A NOVEL MULTIHOP BASED PROTOCOL FOR DEVICE-TO-DEVICE COMMUNICATION FOR COGNITIVE RADIO WITH MACHINE LEARNING ALGORITHMS

मशीन लर्निंग एल्गोरिदम के साथ संज्ञानात्मक रेडियो के लिए डिवाइस-टू-डिवाइस संचार के लिए एक नवीन मल्टीहॉप आधारित प्रोटोकॉल

A Thesis

Submitted for the Award of Ph.D. degree

by

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2024

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ABTRACT

The rise in mobile users has increased demand for proximity services with high data rates. A roadmap for dependable and resource-efficient solutions is provided by the fifth generation (5G) of wireless networks, which promises to enhance current technology in accordance with future demands. In order to enable capabilities like live video and data sharing, device-to-device (D2D) communication has been conceptualized as an associated technology of 5G wireless systems. The possibility for device-centric communications utilizing the D2D communication approach is increased by using direct D2D links rather than only cellular links. Offloading traffic from traditional network-centric entities to a D2D network increases network capacity and reduces base station processing. Direct communication between devices improves spectrum efficiency but has drawbacks as well, such as interference. Using the spectrum effectively while reducing the effects of interference could be made possible through intelligent resource allocation algorithms. Furthermore, routing is essential to any wireless network because it allows for path selection, which offers the most efficient way to authorize the data to be transmitted from a source to a target device. Inefficient routing can lead to route flapping and lower overall Quality of Service (QoS). D2D is a technology that, in the meantime, enables connections between the devices with or without full or partial use of the traditional cellular network. Hence, this research introduces two various contributions for the D2D communication like resource allocation and efficient routing strategies. The first contribution is the joint channel allocation and relay selection using the Enhanced Hunter prey Optimization and deep reinforcement learning (EnHpo+DRL). In this initially, the channel allocation technique is proposed using the enhanced hunter prey optimization (EnHpo) algorithm. The proposed EnHpo is designed by integrating the conventional hunter prey optimization with the adaptive weighting strategy for enhancing the convergence rate and obtaining the global best solution with balanced randomization and local search phases. Here, the multi-objective fitness function based on factors like priority, bandwidth and transmission rate are considered for the optimal channel allocation. Followed by, the relay selection is devised using the deep reinforcement learning criteria based on the channel gain based on the bit error rate. Here, the relay sub-set selection in the using the deep reinforcement learning enhances the efficiency of D2D communication. The second contribution is the relay based multi-hop routing for the energy efficient D2D communication. Here, the double deep Q learning technique is proposed for discovering the potential paths in this takes into account the energy consumption. Then, the Gannet Chimp optimization (GCO) algorithm is introduced for the selection of optimal path by considering the fitness function based on multi-objective factors for enhancing the performance of the model. The assessment of the D2D communication protocols are evaluated based on various assessment measures like Average Residual Energy, Latency, Network Life Time, Packet Delivery Ratio, and Throughput and accomplished superior outcome.

Keywords: ***5G wireless networks, Device-to-device (D2D) communication, Quality of Service (QoS), Enhanced Hunter Prey Optimization (EnHpo), Energy efficiency Resource allocation algorithms, Throughput.***

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LIST OF ABBREVIATIONS

1.	5G	:	Fifth Generation
2.	D2D	:	Device-To-Device
3.	QoS	:	Quality Of Service
4.	EnHpo+DRL	:	Enhanced Hunter Prey Optimization And Deep Reinforcement Learning
5.	EnHpo	:	Enhanced Hunter Prey Optimization
6.	GCO	:	Gannet Chimp Optimization Algorithm
7.	BSs	:	Base Stations
8.	mmW	:	Millimeter Waves
9.	AI	:	Artificial Intelligence
10.	V2V	:	Vehicle-To-Vehicle
11.	IoT	:	Internet Of Things
12.	FBMC	:	Filter Bank Multi Carrier
13.	CRNs	:	Cognitive Radio Networks
14.	M2M	:	Machine-To-Machine Communications
15.	HetNets	:	Heterogeneous Networks
16.	LTE	:	Long Term Evolution
17.	HSPA	:	High-Speed Packet Access
18.	RATs	:	Radio Access Technologies
19.	MIMO	:	Massive Multiple-Input Multiple-Output
20.	mmWave	:	Millimeter-Wave
21.	SDN	:	Software-Defined Network
22.	NFV	:	Network Functions Virtualization

23.	R1	:	Relay
24.	ANNs	:	Artificial Neural Networks
25.	P2P	:	Point-To-Point
26.	EH	:	Energy Harvesting
27.	EnHpo	:	Enhanced Hunter-Prey Optimisation
28.	UAVs	:	Unmanned Aerial Vehicles
29.	BDI	:	Belief-Desire-Intention Agents
30.	RB	:	Resource Block
31.	SE/EE	:	Spectrum Efficiency/Energy Efficiency
32.	MCDM	:	Multi-Criteria Decision Making
33.	MBMQA	:	Queue Length Multipath-Aware Routing
34.	MARS	:	Multiple-Attributes Route Selection
35.	NARA	:	Network Assisted Routing And Allocation Technique
36.	FINDER	:	Finding Isolated Nodes Using D2D For Emergency Response
37.	MCS	:	Modulation And Coding Scheme
38.	ARS	:	Adaptive Relay Selection Strategy
39.	PPP	:	Poisson Point Process
40.	CEETHCoR	:	Channel Aware Energy Efficient Two-Hop Cooperative Routing Protocol
41.	EH-UWSN	:	Energy Harvesting In UWSN
42.	SNRC -	:	Signal-To-Noise Ratio Combination
43.	IACR	:	Interference Aware Cooperative Routing
44.	Co-DLSA	:	Cooperative Delay And Link Stability Aware
45.	DLSA	:	Delay And Link Stability Aware

46.	QF	:	Quantize-And-Forward
47.	AF	:	Amplify-And-Forward
48.	CEER	:	Cooperative Energy-Efficient Routing
49.	TSCR	:	Two-Stage Cooperative Routing
50.	EDR	:	End-To-End Delivery Ratio
51.	optPRS	:	Optimum Potential Relay Set
52.	CRL	:	Conventional Reinforcement Learning
53.	MAB	:	Multi-Arm Bandit
54.	SINR	:	Signal-To-Interference-Noise Power Ratio
55.	CRP-GR	:	Clustering-Based Routing Protocol
56.	RL	:	Reinforcement Learning
57.	RSS	:	Radio Signal Strength
58.	LMK	:	Light-Weight Multi-Layer Neural Network
59.	DQN	:	Deep Q-Network
60.	CC	:	Central Controller
61.	RLbR	:	Reinforcement Learning-Based V2V Routing
62.	MCC	:	Mission-Critical Communication
63.	APERAA	:	Autonomous Power Efficient Resource Allocation Algorithm
64.	DQN	:	Deep Q Network
65.	MVNOs	:	Mobile Virtual Network Operators
66.	RRM	:	Radio Resource Management
67.	NDS	:	Neighbor Discovery And Selection
68.	AI	:	Artificial Intelligence
69.	NNs	:	Neural Networks

70.	DT	:	Decision Tree
71.	SVMs	:	Support Vector Machines
72.	KNN	:	K-Nearest Neighbor
73.	RNN	:	Recurrent NN
74.	CNN	:	Convolutional NN
75.	FNN	:	Multi-Layer Feed-Forward NN
76.	RECOME	:	Relative Core Merge
77.	EnHpo	:	Enhanced Hunter Prey Optimization
78.	DNN	:	Deep Neural Network

INTRODUCTION

CHAPTER - 1

INTRODUCTION

1.1 Introduction

The fourth generation has achieved its highest point due to the rapid interchange of data due to the rise in usage of cellular devices. The use of 4G networks is enhanced by the availability of smart cellular gadgets, high-quality calls, and very dependable media data [1]. Device-to-device (D2D), which was regarded as one among the newest models utilized in cellular network, is believed to be one of the current models needed to support today's modern technologies and applications in order to accomplish the minimal latency in data with the increase in data rates while sharing information [2, 3]. The challenges in data latency and data rate in the cellular communications are solved reliably and effectively by fifth generation (5G), which makes use of D2D technology. The D2D connections bypass the base stations (BSs) and access points and are considered as a potential method for allowing mobile devices to communicate within devices [4].

The rapid expansion of applications and services that utilize the position to locate and connect with nearby users is the crucial feature considered in the D2D since it lowers the communication costs [5]. D2D is incorporated with various technologies like millimeter waves (mmW), Artificial Intelligence (AI), Vehicle-to-Vehicle (V2V) technology, Internet of Things (IoT) for elevating the performance of the network; still, these approaches faces several challenges that limits the efficiency in communication [6, 7]. Due to the fact that cellular user and user share same resources in the same space, there is interference while deploying D2D technology. In addition to energy consumption, D2D technology also faces issues with security, optimization, radio resource allocation management, and peer delivery and finding of efficient routing path [8]. Thus, there is a need for energy efficient protocol for the better communication between the devices.

1.2 Background

The next generation network in wireless communication is termed as 5G. As subscriber demand for faster data speeds to support mobile applications, 4G networks is shortly supplanted by 5G [9]. Filter Bank Multi Carrier (FBMC) Multiple Access or Non- and Quasi-Orthogonal, and Beam Division Multiple Access (BDMA) are only two examples of the improved technologies it incorporates. Visible light communication (VLC), mmWave communication, Cognitive Radio Networks (CRNs), and Massive MIMO are considered as a few of the technologies that have been combined to create 5G [10]. Due to the dependence on the BS, the first four generations were considered as network centric. However, 5G is moving in the direction of a device-centric approach, where the devices themselves set up and manage the network [11]. The 5G networks utilized D2D communication as a fundamental element to accomplish lower latency, better throughput, higher spectral efficiency, and improved system capacity as the outcomes [12]. Figure 1.1 presents a high-level summary of the wireless communication periods and the services they enabled.

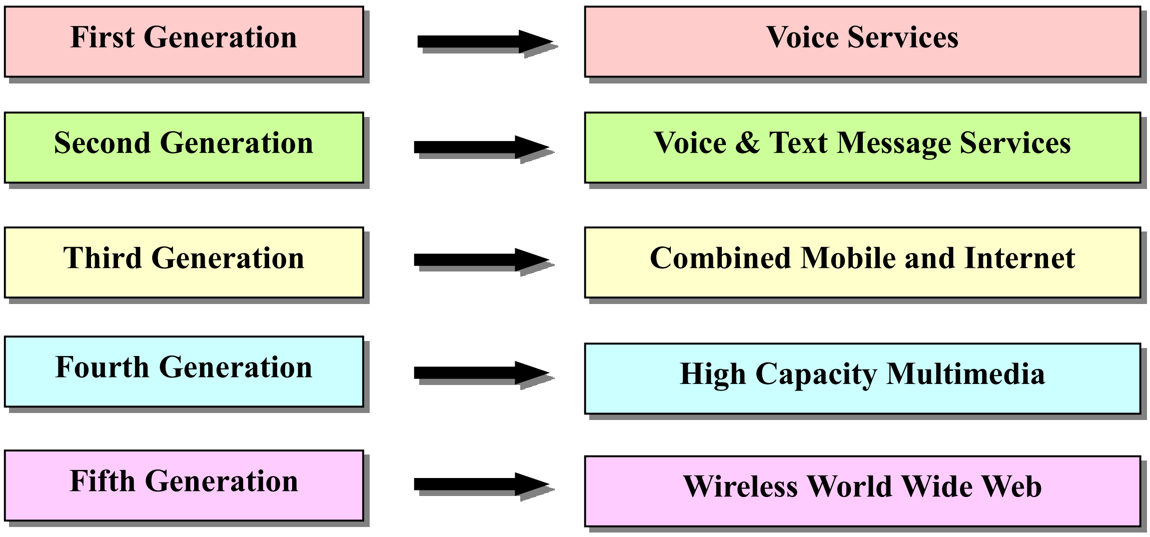


Figure 1.1: **Generations of Wireless Communication**

Peer-to-peer (P2P) applications requiring high data rates were given a better solution for the efficient communication with the introduction of 5G technology [13]. IoT, D2D, machine-to-machine (M2M) communication, and heterogeneous network (HetNets) are only a few of the created technologies that would go through standardization as part of the development of 5G networks. The goal of 5G standardization initiatives is to determine the fundamental structure of 5G in accordance with the requirements of commercial potential and new applications. In order to help 5G evolve, network operators have shown a strong interest in developing a 5G network [14]. One of the objectives of 5G is to improve mobile broadband, bringing with it applications like sharing of videos in live and virtual reality. With the P2P networks, traffic from cellular networks is considered under 5G [15].

The fundamental concept of the 5G is to reduce the load on BSs by using direct communication among the mobile user devices [16]. One contender for upcoming 5G networks is said to be D2D wireless networks. The effectiveness of the spectrum is increased through direct communication between mobile user devices, but there are drawbacks as well, such as interference. Using the spectrum effectively while reducing the effects of interference might be made possible through intelligent resource allocation algorithms [17, 18]. There may be a variety of chances for new applications and services in networks that include mobile user devices like smart phones to control the interference. Combining cellular installations like femtocells with D2D communication networks has offered an intriguing area of research [19]. The D2D connections may improve cellular reuse even while high capacity network access enabled by femtocells. But system performance might be hampered by interference problems in a setting where D2D networks, macrocells, and femtocells exist [20]. Both femtocell and macrocells in the BSs might support D2D pairs in effective resource allocation and modify usages of power in accordance with the acquisition of desired quality-of-service (QoS) [21].

1.3 Key Technologies of 5G

To provide effective communication between the devices, numerous new technologies are employed to 5G systems, some of them are:

(i) Heterogeneous Networks (HetNet): Different nodes have various Wi-Fi, Long Term Evolution (LTE), High-Speed Packet Access (HSPA), and radio access technologies (RATs) technologies. Here, the different characteristics of the networks has distinct coverage area and transmission power, there is a need for the a multitier network with distinct properties for each tier [22]. The issue concerning the capacity is solved through the incorporation of hyper-dense tiny cells with the 1000x capacity that is realized with HetNet. The utilization of tiny cells like femto, pico, or microcells within the cellular system, the design of HetNet is made through the cellular network overlaying. However, area's spectral efficiency (b/s/Hz/m2) of HetNet is much higher [23].

(ii) Massive Multiple-Input Multiple-Output (MIMO): A few hundred co-located antennas with the spatially multiplex criteria are used in this technology to serve several users within the single time-frequency resource simultaneously [24]. When an array has a large number of antennas, its aperture and resolution both expanded. In order to maintain the transmit power to be set at any low level, the antenna arrays makes the power transmission efficiently through concentrating on the targeted receivers [25]. As a consequence, intra- and inter-cell interference are greatly reduced with enhanced Energy Efficiency and throughput are accomplished through the MIMO based approach [26].

(iii) Millimeter-wave (mmWave): Ultra-broadband wireless pipe was offered by the network due to the numerous amounts of spectrum that is currently available in the mmWave bands. Tens of antenna elements were packed into a single square centimetre due to the tiny antenna diameters ($\lambda/2$) and their close proximity (also about $\lambda/2$) [27]. By implementing this at both the User Equipment and the BS, it will be possible to achieve significant beamforming gains in very small regions, thus increasing the capacity of the system. On the other hand, these bands' path losses are somewhat higher than those of traditional sub-3GHz bands [28]. Additionally, these bands' penetration losses concerning the buildings are significantly larger, making it impossible for indoor users to use outdoor RATs. Radio connections can be interfered with by moving objects or persons since these bands propagate in the Line of Sight direction. mmWave is the most promising spectrum for future networks despite these limitations since it supports huge MIMO and has a lot of available spectrum [29].

(iv) Software-defined network (SDN): The network's flexibility, scalability, and affordability may all be dramatically increased by utilizing SDN, which offers three essential characteristics: abstraction, programmability, and logically centralized intelligence [30]. The data plane is separated from the network control plane by the SDN for acquiring the more resources in the user plane. The efficient resource allocation provides greater bit rates than the relatively low bit rate offered by the control plane. In addition, the network's centralized Controller may configure several networking approaches such as access control, forwarding, and routing enables the dynamic network topology reconfiguration and readjustments for those mechanisms [31]. A further benefit using the programmable central controller is that it makes the simple and rapid framework to adapt the cutting-edge networking technologies like the IoT, cloud computing, and others [32].

(v) Network Functions Virtualization (NFV) and Networking Slicing: Network as a Service (NaaS) components may really be shared and offers the virtualized networking functionalities at the network edge using the NFV [33]. As a result, network operations may be devised using virtualization approaches in software that can operate without a hardware requirement concerning the server. In order to virtualize various functions and services, the operator's basic hardware can be divided into a logical structure that can support both processing and network hardware requirement [34]. Thus, actual network functioning components are virtualized for supporting many tenants and applications by enabling functions and services for expanded operations as needed with decrease in maturing and Time to Market with Capital Expenditure savings.Due to the removal of obstacles caused by proprietary hardware, new networking services can be deployed much more quickly [35]. The capability of a model to create and operate several logical functionalities as virtually distinct business functions on a same physical fremework is known as network slicing. The 5G network will include network slicing as a crucial part of its design even if it is currently being implemented in select Enterprise scenarios [36].

(vi) Device to Device (D2D) communications: D2D communications allow an effective offloading for the traffic from BSs and efficient spectrum use in 5G [37]. The expectations for D2D in a cellular network are as follows:

- Minimal Latency
- Higher throughput
- Enhanced spectral efficiency
- Improved system capacity

Due to D2D's lack of the base station involvement in the D2D communication, the base station's burden is significantly reduced. Therefore, the base station needs less power overall using the D2D communication protocol.

1.4 D2D communication Types

The Outband and Inband are considered as the two various categorization of the D2D communication systems by considering the usage of spectrum, which is depicted in Figure 1.1 [38]. The communication performed within the spectrum with the license is termed as Inband D2D communications. In contrast, the communication performed beyond license is termed as Outband communication, which means usage of unlicensed spectrum.

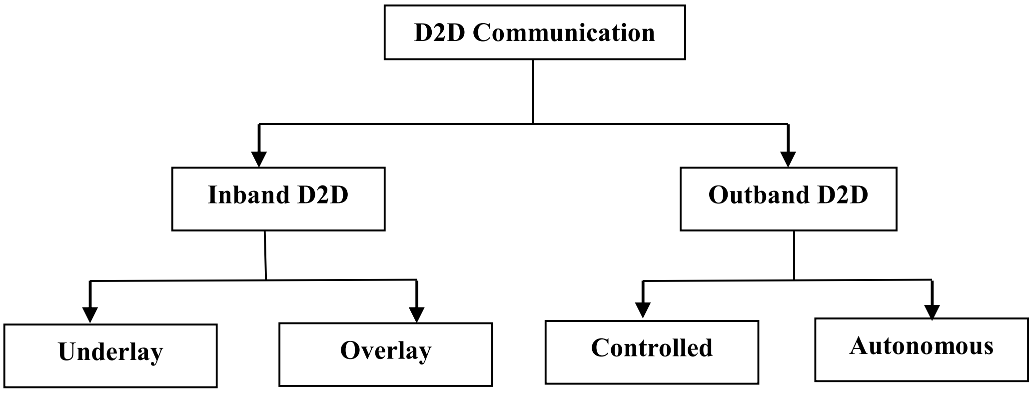


Figure 1.2: **D2D Communication Types**

1.4.1 Communication in terms of Inband: The Overlay and Underlay are the two various categories of Inband communication devised for the D2D communication within the spectrum under license.

- **Underlay**: In this category, the communication is devised between the cellular and equipment link directly through the set of direct links for exchanging information based on the cellular spectrum [39]. The spectral efficiency is increased in this criterion because D2D user equipments compete with opportunistically access resources and cellular user equipments used by cellular users. The D2D transmitter employs the resource blocks that are designated for direct contact with the cellular users as opposed to other users. The excellent spectrum efficiency is acquired by the underlay based interaction, which improves the performance of cellular networks; nevertheless, it interferes with D2D communication and vice versa in cellular networks [40]. Even though sophisticated resource allocation techniques can be used to overcome this restriction, the base station will experience increased computation overhead as a result.

- **Overlay**: In this category, the communication is devised between the cellular and equipment link through the dedicated band based on the cellular spectrum. Besides, a specified section concerning the cellular spectrum was set aside for D2D communications while considering the overlay based communication. Here, both communications methods are performed in different spectral bands, the interference issue gets minimized [41]. The advantage of the communication is the improved power control and scheduling capability for direct D2D communication with better signal strength and spectral efficiency while considering the relay-assisted communication criteria. The primary drawback of overlay inband communication is the possibility of inefficient D2D resource consumption, which lowers system throughput and reduces resource utilization in the section of the cellular spectrum designated for D2D communication [42].

1.4.2 Communication in terms of Outband: The communication among the equipment through the unlicensed spectrum is performed through the Outband communication. The autonomous and controlled Outband are the two various categories of Outband communication.

- **Controlled**: In this category, the communication is controlled by BS by controlling the radio interfaces. The cellular network utilized in this category manages the coordination of Wi-Fi Direct, ZigBee, or Bluetooth based radio interfaces. To ensure that D2D users may properly compete and use the ISM band resources, spectrum allocations are already assigned to them [43]. For the accomplishment of the QoS criteria, BS can also give certain users' transmissions priority. The system's resource management and throughput therefore function better as a result of the priority based transmission. Increased signaling overhead due to the growth in network capacity is this approach's most considered downside and higher latency affects the network performance [44].

- **Autonomous**: In this category, the communication is managed by the radio interfaces for making communication between devices. The BS controls the cellular connectivity in this type of communication, while the D2D communication is managed by the devices themselves [45]. The traffic on the cellular network is greatly reduced by this method, and since no significant adjustments are needed for the deployment of BS, it is also a desirable option concerning the mobile service providers and operators [46]. The system's signaling overhead is decreased by the D2D network, which is also in charge of allocating resources to newly inserted devices. Because of this built-in advantage, BS deployment is also made simpler because the devices may distribute various traffic requirements and lowers the overhead [47].

1.5 Types of Outband D2D Communication

The D2D communication among the devises without the licensed spectrum are categorized into four various types based on the communication links.

Relay based communication with BS control: In this category, the device communicates the BS when there exists a cell edges or areas of poor coverage. Here, the BS has the full control over the devices, and the device closer to the BS act like a relay node for making communication between the devices [48]. The resource required for the information exchange is assigned by the BS and the illustration is depicted in Figure 1.3.

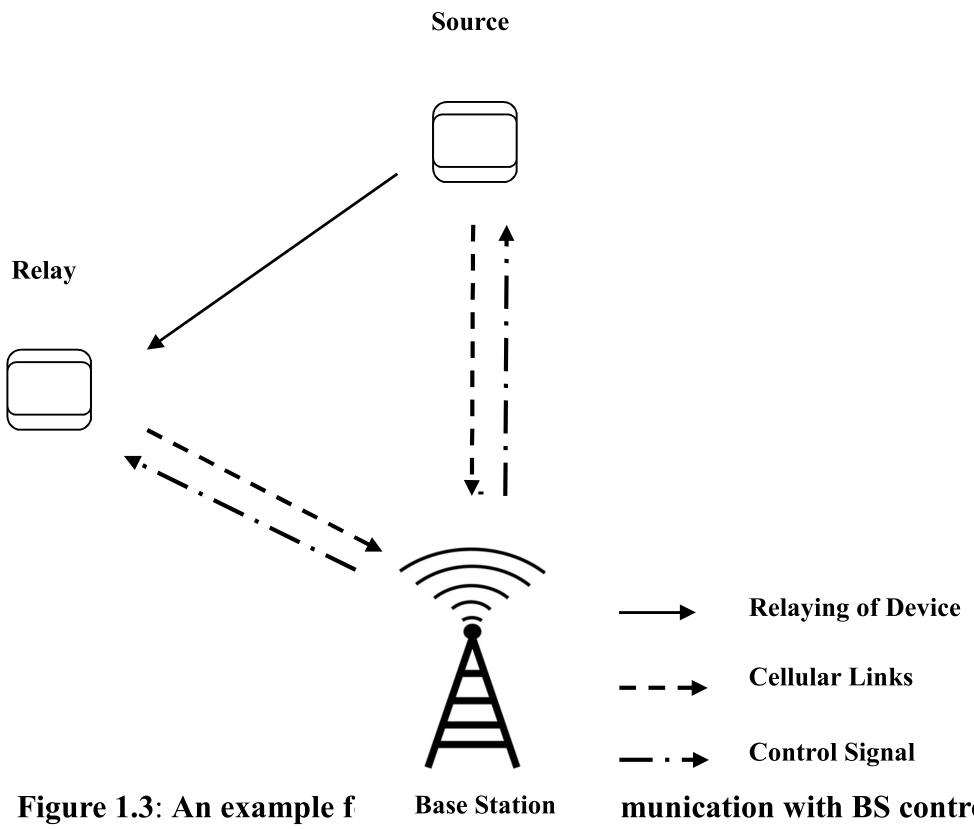


Figure 1.3: **An example f munication with BS control**

BS based direct communication: Effective communication between two devices is achieved using the BS's control, as demonstrated in Figure 1.4. In this case, management of interference and distribution of resource are carried out through centralized control for obtaining uninterrupted communication [49].

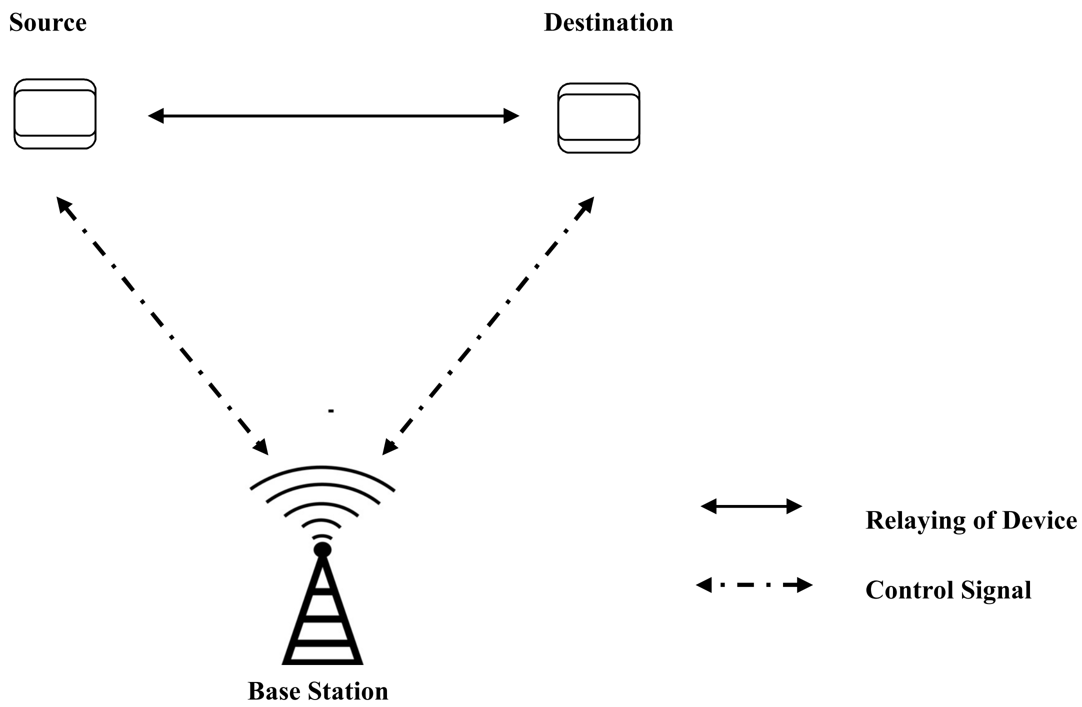


Figure 1.4: **An example for BS based direct communication**

Device Control based communication: The D2D communication in this type is not managed by the BS. The communication between the devices is devised through a relay, as indicated in Figure 1.5, and distributive manner based control is carried. Here, the device will be in charge of controlling the communication through efficient management of interference, call setup, and resource allocation [50].

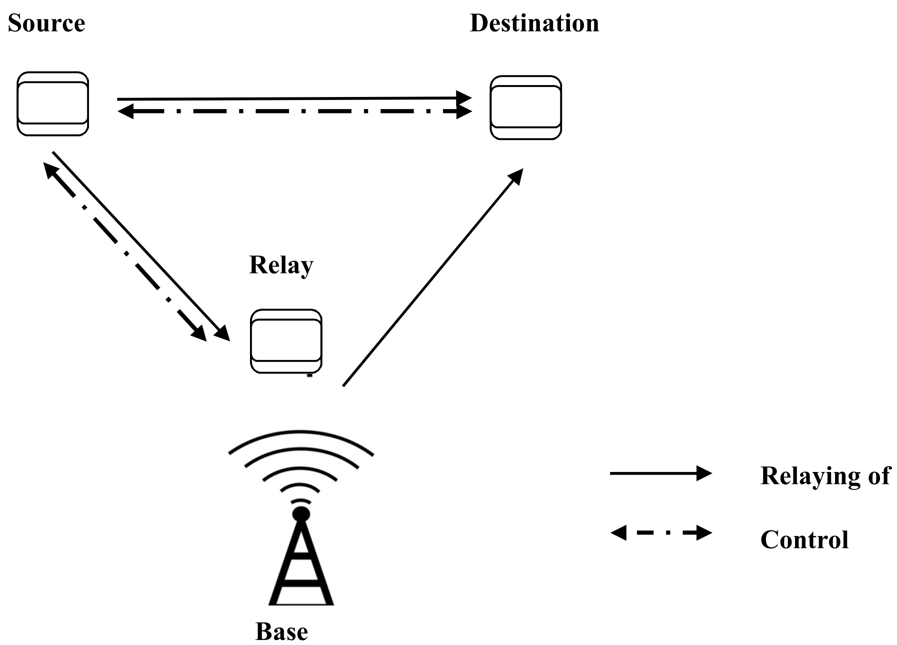


Figure 1.5: **An example for Device Control based communication**

Communication without BS control: Figure 1.6 illustrates the devices interaction without the BS's intervention. The equipment itself therefore handles management of interference and call setup [51].

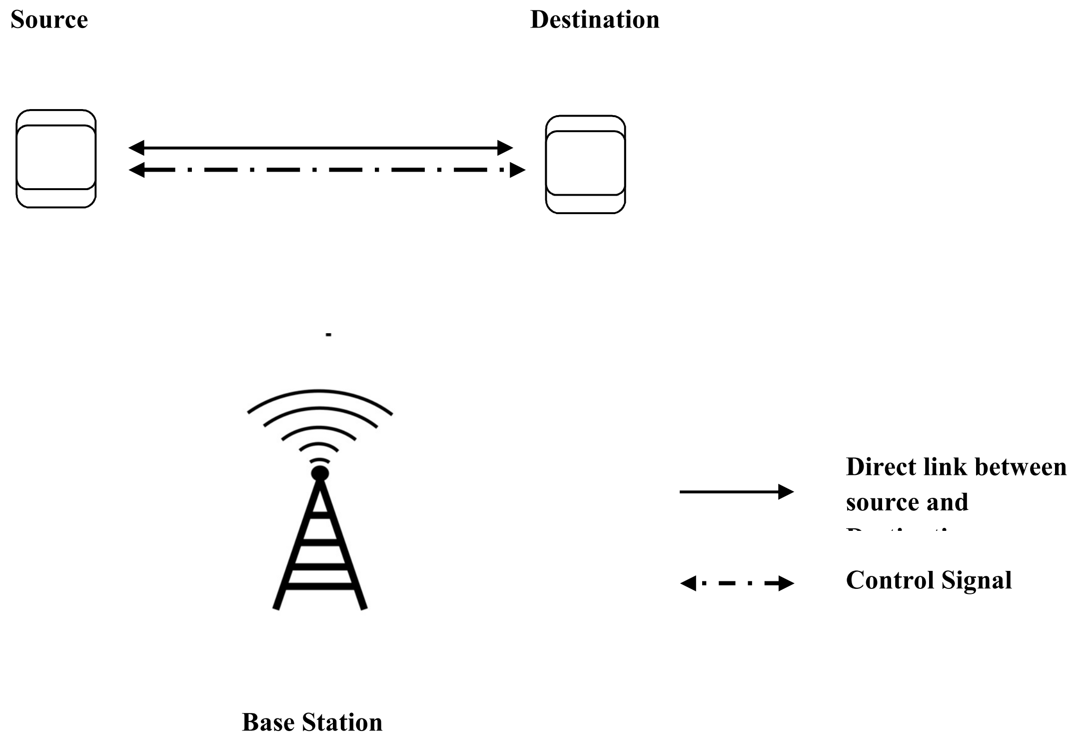


Figure 1.6: **An example for Communication without BS control**

1.6 Types of Relay selection Communication

To support 5G technologies by considering the efficiency of routing, direct D2D communication is incorporated into cellular networks. The BS handles the direct communication of two devices over a control link. Relay devices can then be used for device communication [52]. As shown in Figure 1.7, this research takes into account a number of D2D communication system models both directly and via various networked relay techniques. Following is a list of these models:

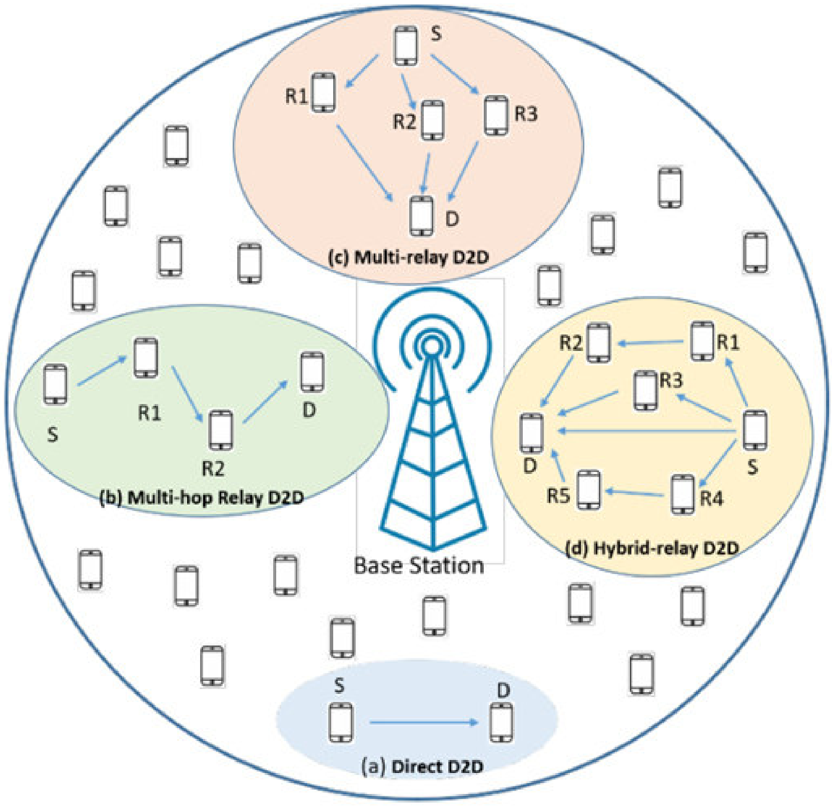


Figure 1.7: Relay Selection categorization

1.6.1 Direct D2D or Single hop

Single hop D2D communication is devised among the source and destination devices directly. It enables the device link with or without BS control and the cellular networks to connect two nearby devices for communication. Device discovery is required for direct transmission between the equipment. For short-range communication, the D2D communication model is considered as a better suited model [53].

1.6.2 D2D multi-hop relay

For transmitting information to the destination, the source device engages in communication with numerous relays in sequence (R1 and R2). The source directly communicates the destination device for sharing the information signals through the relay during the initial stage of communication [54]. Followed by, the relay (R1) transmits the signal that received during the initial stage to the nearby relay (R2), which then transmits it to the final relay (Rk). At the final stage, the information is transmitted to the intended device. The maximum ratio combining technique is used to integrate the signal shared over the multi-hop relay network and direct link at the target device [55].

1.6.3 Multi-relay D2D

To forward information to the indented device, the source delivers data simultaneously to several relays (R1, R2,..., Rn). Here, a number of parallel relays are set up as the source and sends information signals directly to the relays initially. The information signal that received from some of the relays have picked up and is executed in the second stage in accordance with the protocol in use, and it will then be sent on to the target device [56, 57]. The next stage involves the processing of the information signal that shared by some of the relays have been picked up in accordance with the protocol in use before sending it on to the intended recipient. The information signal is combined at the intended device using the maximum ratio combining method after being received directly and through numerous relays [58].

1.6.4 Hybrid D2D relay

Using a multi-hop relay architecture, this strategy involves sharing data from the source both directly with the intended receivers and with a number of relays, which subsequently forward the data to the recipients. Initially, the source simultaneously transmits its information to all neighboring relays [59]. The information signal is directly transmitted via one or more relays in the next stage to the indented recipient. After arriving at the destination, one or more relays also send data, hop by hop, to additional relays. The final step is for the destination to employ the maximum ratio combining method to combine all of the information signals from the relay [60].

1.7 D2D Communication Types

(i) Peer and Network Discovery: By considering the restricted and open discovery techniques, D2D communication devices can find nearby counterparts more effectively. In contrast to restricted discovery, when a device is not able to identify without the BS's consent, open discovery allows for the discovery of a device even when it is in close proximity to other devices [61, 62]. It is possible for D2D users to recognize nearby devices using the network discovery process, which is considered as a crucial component of D2D communication. For sharing data to various devices, the devices communicate using beacon signals. In addition, an exchange information about the channels state is also devised to enable pair grouping among the devices in the network. Device-centric and Network-centric networks are the two subtypes of network discovery structures [63].

(ii) Synchronization: In order to synchronize frequency and time, BS periodically broadcasts; here, the devices linked in the same BS utilizes the common broadcast for obtaining the synchronized D2D communication. The presence of proximity leads to the utilization of local synchronization in place of global synchronization when a device has to find and connect with a peer in a D2D network in order to save energy [64].

(iii) Mode Selection: The next stage of D2D communication among the devices is the exchange of information with one another after discovering the end device, but if the direct communication among the device is noisy, then the cellular communication can be utilized for noise-free communication that has less interference or noise [65]. In order to achieve performance goals such as better spectrum efficiency and low latency, two devices might choose between cellular or D2D communication [66].

(iv) Devices Connectivity: In order to make connection between the devices, the device determines whether the D2D devices are within range. For this two various conditions needs to be satisfied: (i) the incoming request should be from the BS and (ii) the throughput supplied is larger as compared to the cellular communication [67]. Besides, the resources are allocated for making the communication between the devices after checking the transport conditions by the BS. When one of the devices initiates a connection, the communication between the devices is employed without any support from the BS by the gateway tunnels relay. For D2D and cellular communication along with the cellular communication's bearer, the radio resource control is maintained by the BS [68].

(v) Resource Allocation: The allocation of radio resources is a crucial step in D2D communication since it determines the establishment and sustains direct connections between two D2D devices. The cellular devices doesn’t use the resource blocks utilized by the other user. While considering the outband communication, the resources already reserved by the application domains like medicine, technology, and science prevents the usage of bands by the nearby D2D users [69]. As shown in Figure 1.3, D2D communication schemes like V2V, VANET, MANET, and WiFi direct, use an architecture resembling an ad hoc network to enable additional applications such as live streaming, public safety, intelligent transportation systems, and autonomous vehicles. Despite the fact that these D2D communication schemes deliver various applications to users and the network in different ways, they are similar in that they do so. Flexible, adaptable, and guaranteed quality of service (QoS) is offered by the multi-hopping communication between the devices [70].

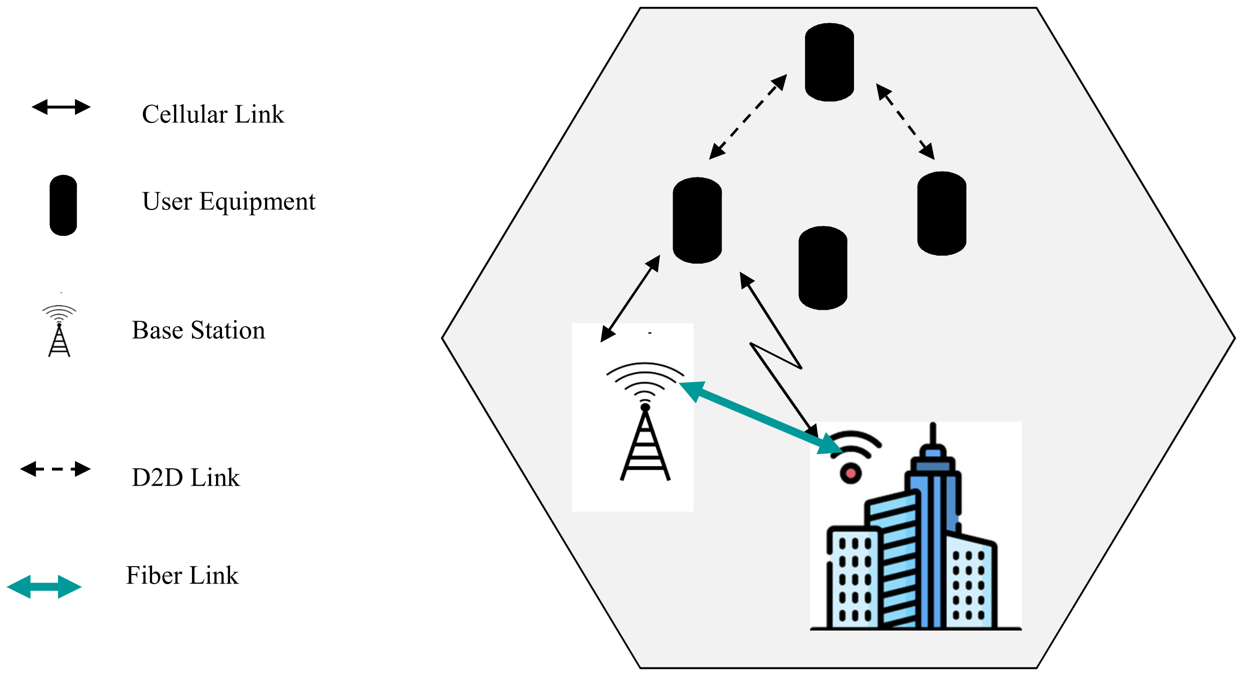


Figure 1.8: Communication schemes for resource allocation

1.8 Routing Protocol Types

The multihop-multipath routing protocols concerning the D2D communication of the 5G networks is detailed in this section.

1.8.1 Downlink Spectrum Resource Sharing

In contrast to outband resources, inband resources can be managed and dispersed more easily, hence inband D2D communications have received a lot of attention among the users [71]. Here, while generating the communication between the two end users using the inband based D2D communication based on the spectrum resource sharing provides the resource management through the reusing strategy [72]. Due to the usage of the same spectrum resource, the Inband always results in interference from the transmission of the D2D communication to the cellular user, but it is not exist in the outband based strategy. Inband and outband were considered for D2D multihop-multipath communications using the multiple modes based technique. However, managing and controlling radio interfaces on this method is extremely complex, making it impossible to find the best solution for sharing spectrum resources [73]. For obtaining the simplicity in radio interface control and administration, D2D multihop-multipath communications were conducted in the inband. Besides, co-channel interference has attracted more research in D2D multihop-multipath communications because of its adaptable design that only depends on the interference [74]. With one D2D hop and reduced interference concerning the co-channel, a cellular user may share its spectrum resource in a simple manner. The signal to interference-plus-noise ratio at cellular user must be greater than or equal to a specified threshold in order to permit multiple D2D hops in separate directions to utilize the same spectrum resource shared by a cellular user [75].

1.8.2 Caching

A caching mechanism utilizes the macro BS and small cell BSs for sharing the contents using the D2D multihop-multipath communications. However, while sharing many contents through the cached in end users generates the dense 5G networks [76]. To reduce the workload of the macro BS and the small cell BSs and raise the system's QoS is highly essential, which is devised through the cached contents in end users. All of the caching methods, nevertheless, involve proactive caching, which assigns the optimal source to provide the user's destination. In the context of D2D multihop-multipath communications, more reactive caching strategies with higher efficiency are devised [77]. On the basis of a prediction model for content popularity, it implies that the contents are stored in the best source user in advance with a specific caching density. Following that, D2D multihop-multipath D2D communications are immediately established to fulfil a destination user's request for the content [78].

1.8.3 Energy Harvesting

When several end users consent to participate in the data transmission session from the source to the destination user, the biggest issues with D2D multihop-multipath communications exists in the network. Here, the end users are required to consume some of the remaining energy in order to facilitate D2D multihop-multipath connections [80]. Energy harvesting is the method that has the most chance of rewarding the end user for their energy usage. In addition to serving as an information transmission node, a relay end user also functions as an energy harvesting node by consuming energy from the macro BS [81]. Also, an energy transfer node prevails in nonfunctional areas transfers' energy to the subsequent relay node. Repeated transferring of information between the source and destination higher energy consumption was possible. Thus, for reducing the higher energy consumption by the model, there is a need for energy efficient routing protocol [82].

1.9 Need for Energy Efficient Protocol

For better network management, the consideration of energy usage is essential while establishing a network of greater scale. At the moment, higher than 0.5% of all energy was used by mobile network worldwide. Thus, from the perspective of environmental considerations and network maintenance, the reduced energy requirement is one among the main elements of 5G design. As devised by [83], a dense network with smaller cell sizes will invariably need network energy. Because the network is using smaller cells more often, forwarding and idle power usage will likely account for most of the network's consumption of energy. Network functional virtualization and Software-defined MAC are two components of a hypothetical framework for 5G developed by [84]. By adopting these strategies, [83] designs a 5G system with lower latency that uses less energy. They agreed with the authors of [84] that logically separating the data and control planes may help create the adaptable and sustainable 5GrEEn approach that is outlined in [85]. The 5GrEEn design aims to produce a network infrastructure that is energy-efficient, utilized for various traffic conditions, and required to provide more capacity. Nowadays the energy efficient protocol is devised using the deep learning methods due to the promising outcome.

1.10 Machine Learning based Routing Techniques

A critical intelligence enabler for the future networks is the machine learning (ML) that has recently emerged as a powerful tool [86]. It is clear that the foundation of 5G and future mobile networks, including 6G, will utilize the ML algorithms for efficient communication. In order to effectively manage networks by making better decisions, mobile networks have already produced a significant amount of data. Artificial intelligence (AI) and ML present a best opportunity in this instance because they can deliver insightful data analysis using the accessible data [87, 88]. The ability of AI/ML techniques to predict future events, learn from past events, and adapt to operational contexts is their most promising outcome. With AI/ML, customers may choose the structures which are most beneficial for the constantly regulate connectivity among numerous cells, and choose the most appropriate the intended cells to guarantee uninterrupted service [89]. Using AI/ML, BSs may optimize network and system factors, such as mobility variables, to offer balanced load. By learning the information that has been collected, the use of AI/ML techniques can yield useful insights. It is possible to learn numerous capabilities to enable prediction, decision-making, and optimization to balance demands in 6G networks [90, 91].

Resource allocation-related problems in numerous unpredictable ML contexts have been successfully addressed by RL, which has been explored and implemented more and more. For long-term operations, RL-based algorithms use learning criteria to update about the changing and dynamic environment to enhance the optimal decisions [92]. As an illustration, an RL-based approach has been created and implemented for performing the scheduling process in cloud settings for lowering the level of congestion and delay concerning the execution. It has been suggested that several RL based approaches are utilized to increase the efficiency, such as reducing data centre energy use [93]. Deep RL (DeepRL) techniques that achieve remarkable results in complicated management domains recently benefited from the collaboration among deep learning and RL that may further develop their resources. This clearly demonstrates their superiority in making decisions in these types of challenging environments. In order to optimize work scheduling in the data centre, for instance, a DeepRL method is created [94]. A Deep RL technique is used to produce the best job-virtual machine planning in the cloud, which addresses the allocation of resources issue. RL-based algorithms are successfully used in various areas of information technology to solve the variable scheduling of tasks issues [95]. These key findings reveal a practical approach to use the RL paradigm in addressing resource allocation issue in 5G network. In order to resolve resource allocation and routing issue in the context of D2D communication, RL-based solutions are frequently used [96].

1.11 General Frame work of RL based D2D Communication

Figure 1.9 shows an illustration of the D2D communications based on DRL framework. A D2D transmitter is regarded as an agent while considering the D2D interaction. D2D users are numerous within a cell. An agent-based system is considered as the scenario. Several D2D and cellular users are present in the surroundings [97]. The D2D transmitter acts, taking into account a number of criteria for effective routing during the duration of interaction among environment and the agents. After that, the rules are updated for improved D2D communication along with the state, action space, reward functions and state [98].

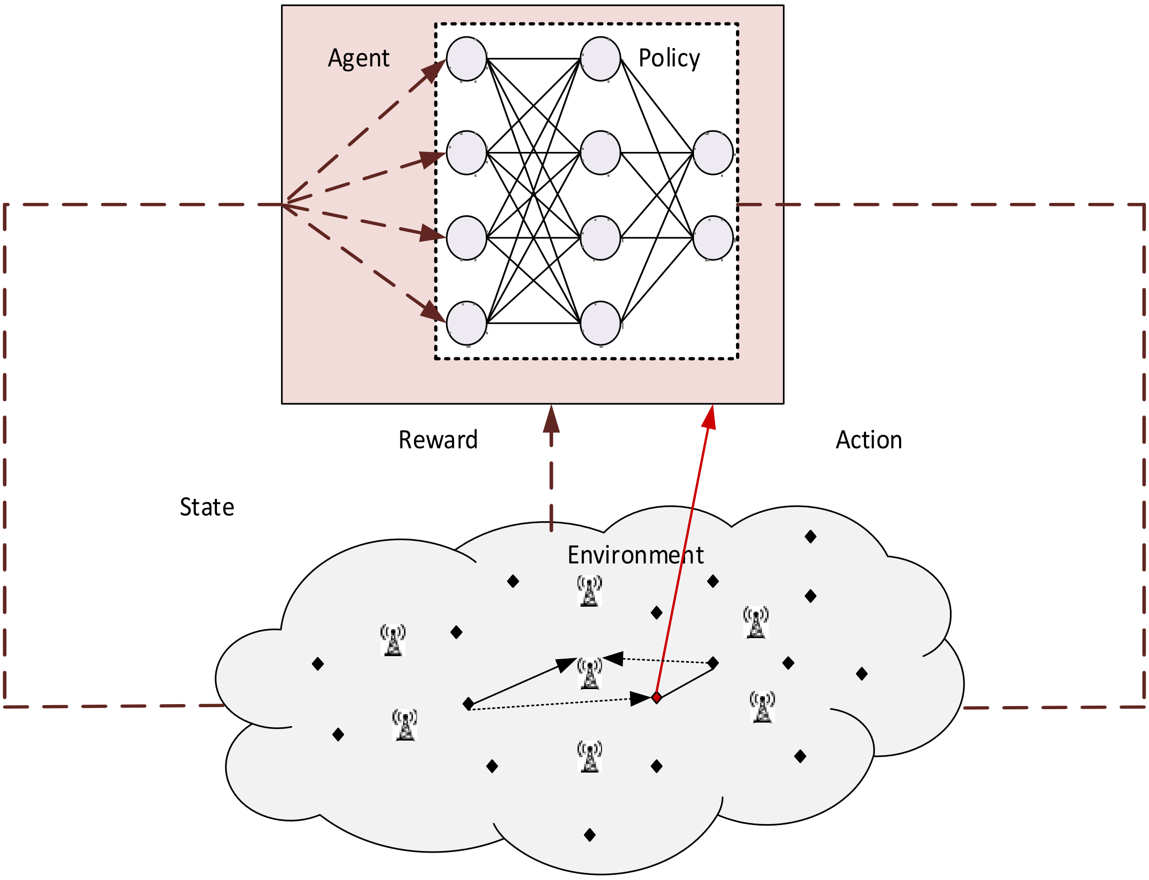


Figure 1.9: General Frame work of RL based D2D Communication

With the goal to maximize a reward, agents use the RL process to discover what to perform or the best way to correlate events into actions. The deep Q-network (DQN) has emerged as an established manifestation of deep RL (DRL) that combines DL within RL and requires agents to take actions based on information that is not organized. Wireless communication system optimization and decision-making issues have led to the widespread application of DRL. It makes sense to transition from DRL to RA through a number of time steps since it serves as an effective method enabling decisions sequentially [99]. In real-world communication systems, it has been speculated that employing DRL remains an effective method to determine resources for D2D equipment in a less complicated, less optimum way. Artificial neural networks (ANNs) in agents undergo extensive training during the training phase for a wide variety of scenarios. Subsequently, during the real functional stage, agents simply monitor occurrences and use trained ANNs to come up with less-than-ideal answers to RA problems. To route

D2D communication effectively, RL-based machine learning techniques are therefore frequently used [100].

1.12 Challenges in D2D Communication Protocol

Reduced data flow in the transmission channel is the primary goal of cellular networks deploying D2D. It is thought that by recycling cellular resources, under-laid D2D communication can increase the quality of networks while also increasing spectrum efficiency [101]. Compared to pure cellular networks, D2D underlaid interaction increases spectrum efficiency and offers additional incentives for local coverage. Without the use of a BS, D2D makes it possible for two roughly remote devices to communicate [102]. Spectral efficiency rises when the delay is decreased. The efficacy of D2D interactions remains significantly impacted by the distance among two equipment. Different routing strategies have been put forth by researchers from all over the world to improve the QoS quality for D2D interaction. The primary obstacles in choosing the best route include contention window size, connection quality, battery life, and mobility of relay devices [103]. Equipment moving around the network at first causes the structure of the network to change in an unanticipated way. Network packets are discarded as a result of the network stability being negatively impacted. Furthermore, the battery capacity of each device is limited, and once the battery is depleted, the system is rendered inoperable. The connection quality condition of the chosen paths also has an impact on how devices move throughout the network. The concurrent packets of data being delivered from the source to the identical path cause information in the relay equipment, which is the final effect [104].

1.13 Need for new model

Maximizing the efficacy of D2D interaction has attracted significant scientific interest due to the growing significance of reduced-energy mobile connectivity in 5G systems. Utilizing energy optimization optimal energy efficiency is accomplished using the D2D interaction. The energy-efficient routing technique is a solution to the optimization issue for energy efficiency, which aims to achieve its full potential. In case of optimizing the consumption of energy in connectivity, branch and bound method has become a well-known technique. Besides, the deep learning methods provide the promising outcome due to the enhanced learning capability. Thus, the energy efficient routing based on the deep learning offers the best solution for D2D communication.

1.14 Applications of D2D communication

Figure 1.10 illustrates a variety of application domains that utilizes the D2D technology based on its benefits. The key circumstances of the D2D technology are covered in the subsequent subsections.

1.14.1 Local voice and data service: There are numerous situations when users in close proximity need to communicate through the voice chat, wherein the users are seated in large cubicles or hallways. Making advantage of the D2D communication, the network performance is improved particularly by reducing user-to-user latency to satisfy real-time audio requirements. Likewise, D2D communication offers the local data service, when two devices or users within the coverage area, needs to share the information. Under such circumstance, the D2D communication elevates the user's data rate and limits the latency. Thus, the D2D energy efficient protocol offers the better service for making the local voice call and data service [106].

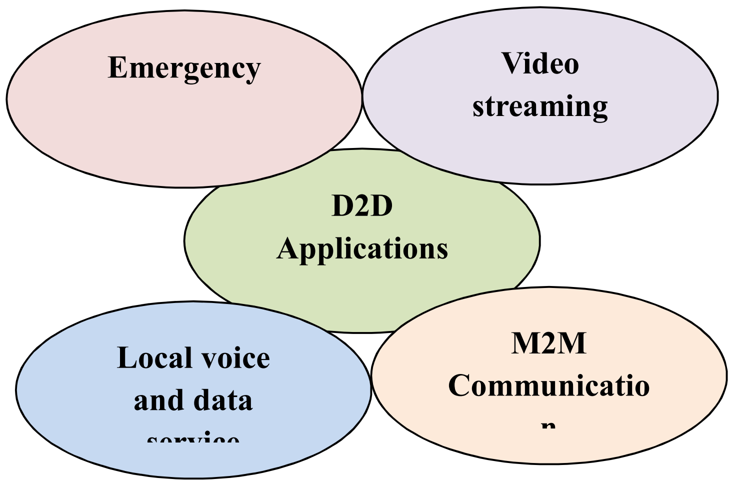


Figure 1.10: Applications of D2D Communication

1.14.2 Video streaming: Sharing the real-time compressed video data over the Internet is referred as video streaming. Accordingly, for viewing the video, it is not necessary to download the full content; prior to its full download, the viewer can watch the video through the video streaming. For this, a continuous stream of data is used to send video instead, which is promptly played upon its arrival at the back. Thus, one of the major internet traffics considered in the current scenario is the video streaming. Approximately 90% of internet traffic is due to the videos as per the 2019 report of Cisco. Point-to-Point

(P2P) video streaming is a kind of video streaming which reduces amount of traffic that a network can handle. All users in the communication range are encouraged by P2P video streaming to directly interact with other users and exchange their content. Examples of P2P video services include PPLIVE and PPSTREAM. The PPSTREAM are utilized by larger than 32,210,000 people per day were reportedly in China in September 2012; while considering theP2P video streaming, there were larger than 60,000,000 total users. Between devices that require sharing video streaming, D2D technology can offer greater performance improvement than typical cellular networks. The same device in same cell or nearby cells can also use similar applications like video conferencing or video chat [107].

1.14.3 Machine to machine (M2M): Without the intervention of humans, M2M communication takes place between devices or equipment that resemble machines with communication and computation operations. M2M communication utilizes sensors to track specific consequences and give commands for actions. Wireless networks are used to transmit the recorded events to servers, which then performs various functioning likeanalyze, executes, and automatically command and direct other equipment using the information based on the learned knowledge. End-to-end machine communication is provided through the network for efficient communication. Industrial machinery, automated vehicles, environmental monitoring, smart houses, and other items are some well-known instances of M2M technology. The D2D technology is used in the M2M communication when two devices are closer within a particular area. By utilizing the superior channel quality of short-range D2D links, D2D communications can increase network effectiveness. Furthermore, machines' batteries can be kept running longer by reducing gearbox power. As a result of D2D traffic being routed directly, the overall M2M network latency gets reduced. Additionally, for local M2M traffic, the network may have less evenly distributed load on the data servers [108].

1.14.4 Emergency networks: Natural catastrophes may cause connection failure for a protracted period of time in a particular area. Here, a large amount of local traffic data needs to be sent among the users unfortunately. The rescuers, for instance, need to communicate with them constantly and needs to share the visual and audio data. In the same way, doctors and nurses working in medical area require access to patient medical records from their hospital and may require remote consultation and assistance from certain professional. The news must also be reported quickly by reporters and journalists, among other things. Broadband services can be temporarily provided for all of these needs using the D2D technologies that built on emergency networks. In order to form a small network and share data among themselves, several devices are capable of communicating with one another.D2D technology has been used by certain researchers to analyses this situation and provide a solution. A D2D is utilized to save energy in the uplink and downlink to extend the life of the network when disaster scenarios were taken into account. The simulation results for the suggested solution indicate reduced energy utilization, lower latency, and improved Quality of Service. By acting as relay nodes, intermediate nodes build connectivity between the source and the destination. Energy Harvesting (EH) is used in relay and cluster heads node, is another technique for extending node life. The results of the simulations demonstrated that the EH-based D2D protocol works better over the course of a node's lifetime due to the cluster heads' and relay nodes' increased energy efficiency. It also provided a larger coverage area [109].

1.15 Objective

The objectives of the research are:

- To design a optimal best routing in D2D communication by considering the joint Relay assignment and channel allocation technique.
- To design a energy efficient cooperative routing protocol which uses deep learning technique.
- To design a optimal best path using hybrid optimization algorithm by considering the multi-objective fitness functions.
- To design a deep learning based possible path identification to avoid the over optimistic issues in conventional RL methods.

1.16 Contribution

The contributions of the research are:

Design of Optimal Channel Allocation: The enhanced hunter-prey optimisation (EnHpo) is used to devise the best channel allocation by taking into account the multi-objective fitness function based on transmission rate, bandwidth, and priority.

Design of joint channel allocation and relay selection for D2D communication: Deep reinforcement learning is used to perform the combined channel allocation and relay selection, with the relay choice being made depending on the chosen channel gain.

Double Deep Q-Learning: The double deep Q learning is introduced for the detecting paths from source to destination. In the proposed double deep Q learning, the estimation of Q-value and reward are estimated using two several Deep CNN models in avoiding the over optimistic problems.

Gannet Chimp Optimization: The Gannet chimp optimization (GCO) was designed by hybridizing the hunting behavior of Gannet with the chimp in identifying the optimal best path D2D communication.

1.16 Organization

The organization of the research is:

Chapter 1: The introduction of the cooperative routing protocol for D2D communication concerning the 5G networks along with its applications and challenges are detailed in Chapter 1.

Chapter 2: The detailed analyses of conventional D2D communication techniques are presented in Chapter 2.

Chapter 3: The architecture and challenges of the D2D communication in the 5G cellular networks is detailed in Chapter 3.

Chapter 4: The Cooperative Device-to-Device Communication using Joint Relay Assignment and Channel Allocation using deep learning

Chapter 5: A Multi-objective hybrid optimization based Energy Efficient D2D communication with deep reinforcement learning routing protocol is presented in chapter 5.

Chapter 6: Concludes the research with the main findings accomplished along with the detailed future scope.

LITERATURE REVIEW

CHAPTER - 2

LITERATURE REVIEW

2.1 Introduction

Device-to-device (D2D) communication, which is being used in boosting information speeds, decrease connection delay, and enhance bandwidth and efficiency of energy, is considered to be one of the emerging technologies in cellular wireless networks. According to published research, D2D resource optimization schemes are being used more often to handle interference effectively and improving efficiency of various network across a wider range of projects [111]. The transition of cell communication networks from 1G to 5G was brought about by expanding network capacity to satisfy users' expanding requirements [114]. A single data centre must be used to host both the training data and the inference procedures for the majority of the machine learning methodologies as well as solutions for communication networks now in use [119, 121]. Yet, it becomes not feasible for all of the communication equipment which are involved in learning to send every bit of their gathered data to an external data center or a cloud that can then use a centralized learning algorithm for data analysis due to privacy restrictions and constrained communication facilities for transfer of information in connections. To expand, centralized algorithms for machine learning include intrinsic drawbacks that restrict utilization, such as a considerable signaling burden, a rise in technical difficulty, as well as elevated delay when addressing problems with communication. Furthermore, new wireless networking paradigms such as cognitive radio networks, industrial control networks, D2D communications, and swarming networks based on unmanned aerial vehicles (UAVs) are inherently utilized for enhanced communication. In addition, given potential applications, centralized methods might not be appropriate for tasks requiring fast response times, such operating a self-driving car or directing a robotic surgeon [134]. Thus, the D2D communication based on cellular networks is consider for the efficient communication between the users.

2.2 Categorization of 5G Communication techniques

The categorization of the D2D communication techniques is devised based on the methods utilized for enhancing the performance of the model. Three various categorization of the conventional cellular communication in 5G networks are Machine learning based techniques, D2D communication techniques and Cooperative communication techniques. Figure 2.1 illustrates the categorization of 5G Communication Techniques.

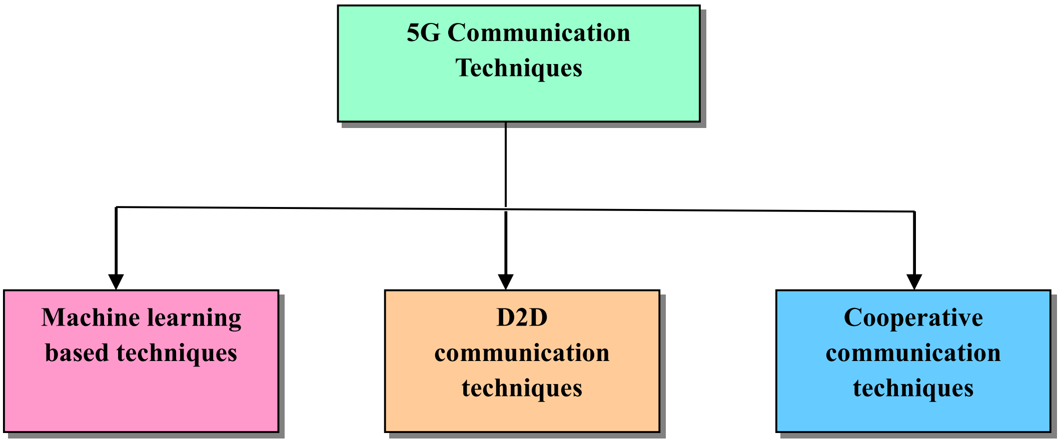


Figure 2.1: **Categorization of 5G Communication Techniques**

2.2.1 D2D Communication Techniques

Some of the D2D communication techniques are explained in this section.

Distributed Artificial Intelligence Solution: Routing problems in various D2D communication was solved by Belief-Desire-Intention (BDI) agents that utilized the designing of an AI-based D2D communication system by [110]. Without altering the hardware at user equipment or BSs, the agents were already integrated at the user equipment. The expectations or intentions concerning the planned responsibilities, wants or desires concerning the motivational approaches and convictions or beliefs concerning the informative states of mind were considered as three various fundamental mental structures considered by the BDI software agents while designing the agents. In its simplest form, the BDI model depends on two basic criteria's like mean transmit thinking and thought. While mean send thinking has series of activities to perform, as an effort to satiate desires, thought processes are the means by which the agent produces its aim on the basis of its desires and convictions. The D2D needs were defined together in the created model. Hence, the designed method considers the transmission mode of each user device and constructs the optimum routes to the BS via clusters and relays using the proof-of-concept algorithm. It was depicted that the devised system would guarantee both the minimal computing burden and enhanced spectral efficiency using the simulations.

Mixed Strategy: [112] developed a mixed strategy-based algorithm for D2D communications that allocates resources efficiently while using both the energy and spectrum. The designed method minimizes the power consumption of user equipment while increasing the efficiency of the entire spectrum. As an interpretation of a mixed strategy non-cooperative game, a distributed algorithm based on a novel mathematical game theory model was introduced, in contrast to earlier works on resource allocation issues that exclusively took centralized strategies. By reducing power consumption and interferences through intelligent resource block (RB) allocation, the solution provided by the designed model improves the joint spectrum efficiency/energy efficiency (SE/EE) trade off. According to the random network behavior, the designed model enables users to adopt more precise assumptions to maximize its utility. The outcome of the method shows that the suggested method outperforms earlier methods based on the convergence time and number of users supported by the method for communication. As an example, the method can be followed by a supplementary strategy to enable multi-hop D2D, in which relays must be carefully chosen for obtaining the sustained and effective data transmission with improved communication capabilities.

EMBLR: For solving the issues and improve network performance in D2D communication a novel approach based on energy, mobility, queue length, and link quality-aware routing (EMBLR) strategy was developed by [115]. Additionally, to choose the relay equipment in an ideal path, a multi-criteria decision making (MCDM) method was used. The hybrid and Dijkstra algorithm multi-path concept of routing was utilized by the developed EMBLR routing approach irrespective of the existing routing approaches. Besides, the designed method to select the best route was designed in accordance with the full combination of device parameter metrics like devices queue length, quality of link, consumption of energy and mobility. Here, for the selection of the optimal best route from the enormous routes identified based on link cost parameter that was measured according to the evaluated relay equipment's parameter value through the MCDM decision factor. Consequently, the choice of the best route between the equipments was made using the MCDM measure for enhancing the energy efficiency. The suggested routing strategy considerably improves network performance, as shown by extensive simulation that was done.

MBMQA: For the IoT 5G networks based on D2D communication, a Mobility, Battery, and Queue length Multipath-Aware (MBMQA) routing strategy was developed by [116] to address these major issues in routing. The device selection estimated value was employed using the back-pressure algorithm approach to reroute flow of packet. For the load balanced best route identification in the designed D2D communication framework, a Multiple-Attributes Route Selection (MARS) metric was utilized. In case of limiting the energy consumption of individual devices and assures the mobility would not affect packet routing, the designed model found many final routing pathways to the destination while distributing workload across all devices. By considering accessible factors for each node such as the size of device queue length, mobility details, and battery's energy level was considered for the route computation. The offered information was quantified in order to choose the optimum path among several paths to the target equipment. A multiple characteristics route selection metric is also provided. The developed MBMQA routing method therefore seeks to choose the best route from source to destination devices that eliminates consumption of energy, traffic loads were balanced among the equipments and acquired the route stability and enhances network while transmitting the data. The acquired simulation outcomes, demonstrate that the introduced MBMQA routing approach eventually elevates quality of service (QoS) and performance of the network when compared with conventional approaches.

NARA: While considering the 5G cellular infrastructures, an efficient routing approach for the D2D communication was developed by [118] using the Network Assisted Routing and Allocation technique (NARA). While considering the D2D communications, NARA increases network coverage and minimizes interference through the new resource block allocation technique. When determining routes for mobile devices, NARA takes into account the channel quality between nearby active D2D interactions while using a graph coloring technique to simulate the resource block (RB) allocation issue and interference minimization. Using the shortest path Dijkstra algorithm, NAR builds multi-hop routes to the user request from the BS. NAR actively chooses several paths before settling on the optimal best path using the CQIs of the user equipment neighbors. The NAR routing strategy considerably decreases the overall volume of messages and eliminates flooding criteria, which also lowers power usage. To assess the behavior of routing and resource allocation, the developed model made use of the Rayleigh fading channel and the UMa propagation model concerning the UMa channel model.

FINDER: While considering the disaster area for reducing the loss of damage and life to property a novel framework was designed by [122] using the Finding Isolated Node using D2D for Emergency Response (FINDER) to find and link the remote Mobile Nodes (MNs). A crucial D2D network was created if the cellular link was lost due to an emergency and the MNs under the damaged BS utilizing the concept of D2D communication. A nearby Wi-Fi access point or a BS can connect the MNs for providing an active network in the disaster area. To improve the energy efficiency of individual nodes and to enhance the lifetime of the network, a multi-hop D2D communications by considering the optimization was implemented. Furthermore, the number of nodes that are actively participating in the network was minimized through the dynamic clustering criteria, and the quantity of packets in the network was minimized through the data aggregation. It was advantageous to get help from the Software-Defined Networking (SDN) controller during disaster scenario at the BS for obtaining the reliable and intelligent to the MNs. The best path to use for maximization of efficiency was the path chosen with fewest hops and the highest link quality. In picking the neighbor node two various factors like the hop-count and connection quality were therefore taken into account from the list of the available paths. The likelihood of choosing a node as a neighbor node was higher for those with fewest hops and strong network quality. The short description of the cooperative communication method is presented in Table 2.1.

Table 2.1: Short description of the D2D communication techniques

Reference	Technique Used	Performance Measures	Advantages	Disadvantages
Ioannou, I., Vassiliou, V., Christophorou, C. and Pitsillides, A. **[110]**	Distributed Artificial Intelligence Solution	Computation time, Spectral Efficiency, and Total power	Numerous problems like routing issues including interference management, and power control were resolved by developed method.	The performance of the model analysis using a dynamic network scenario was not evaluated to depict the robustness.
Sawsan, S. and Ridha, B. **[112]**	Mixed Strategy	Average interference, Spectral efficiency, and Energy efficiency	For converging the algorithm, the designed model utilizes only fewer iterations.	As power consumption for data routing elevates, the energy efficiency first elevates with spectral efficiency and then declines. Energy efficiency first raised while attempting to cut down on energy, but it then starts to decline monotonically since power reduction has a negative impact on spectral efficiency.

Tilwari, V., Dimyati, K., Hindia, M.N., Mohmed Noor Izam, T.F.B.T. and Amiri, I.S. **[115]**	EMBLR	Convergence time, energy, packet delivery, delay, and throughput	The recommended structure was extremely favorable for public life, for instance in the event of a calamity when the communication for survival may be formed with the extra installation of drone-based disaster response models.	Due to interference prevails in the spectrum-sharing communication, which lowers the outcome of the model as the D2D link interferes with cellular links and other equipments that use the similar spectrum resources.
Tilwari, V., Hindia, M.N., Dimyati, K., Jayakody, D.N.K., Solanki, S., Sinha, R.S. and Hanafi, E. **[116]**	MBMQA	Throughput, delay, PDR, and energy	Higher energy efficiency was achieved by the MBMQA system that acquired the reduced quantity of loss of packets and provided a larger quantity of packets using the specified amount of energy.	The challenging aspect of the model was its lower system data rate.
Bastos, A.V., Da Silva, C.M. and da Silva Jr, D.C. **[118]**	NARA	Number of routes	The outcome of the devised model reveals that NARA acquired minimal message loss.	Resource allocation, power management, fairness, in sectored cell areas, and other route loss situations were not examined, nor were the resource allocation procedure improved to strengthen the

				integrality of the factors and provide the best possible outcome.
Thomas, A. and Raja, G. **[122]**	FINDER	Delivery probability, overhead ratio, average residual energy	According to the outcome of the deployment, designed model FINDER increases network lifetime and decreases energy usage during routing.	The network lifetime and energy efficiency may be further increased by extending to enable wireless energy harvesting from radio frequency.

2.2.2 Cooperative Communication Techniques

Some of the cooperative communication based methods are detailed in this section.

Relay Probing: [123] introduced a multi-hop relay probe strategy for mmWave D2D routing by considering relay nodes concerning the multi-band mmWave. To estimate the likelihood of the dispersed relay nodes SNR of the mmWave based on both non- line-of-sight (NLOS) and LOS route availability. The gathered μW signals received signal strengths (RSSs) of the relay nodes were employed in this technique. Here, the potential multi-hop path's relay nodes detection simultaneously using hierarchical search technique based on a probabilistic metric. The spectral efficiency of the route from the source to destination among the several paths was enumerated to maximize the efficiency. The relay nodes positioned inside the previously chosen multi-hop paths were devised to employ online relay probing in the offline phase. In order to demonstrate the value of multi-hop routing and the connection among improved amount of explored paths and improving the resulting spectral efficiency, the assessment was carried out. The superiority of the introduced route probing approach over the introduced method was devised to validate the mathematical conclusions acquired by the simulation analysis. The unmanned aerial vehicle (UAV) network was considered as one application for which the designed approach may be employed. Due to the UAV's high degree of dynamicality and its excessively low power capacity, multi-hop UAV-to-UAV routing with low energy consumption and high throughput was accomplished by the introduced model.

DSPA: Using the cellular communication and dual connectivity of D2D among cluster head for solving the problem of link disconnection was addressed in a cellular D2D-assisted relay strategy was introduced by [124] to forward data. The relay selection was employed using Maximum Weight Bipartite Matching in the suggested technique named D2D Relay Node Selection and uplink Power Allocation (DSPA). When data was being sent to BS via DSPA from active low-battery CHs, the CHs' uplink transmission power requirement was reduced. The initial step was to create a technique with energy usage criteria with or without D2D interaction. By considering the KM technique for the active CHs, a bipartite matching problem was then solved to determine the optimum D2D relay nodes. By considering both with and without D2D communication, the estimation of the CH's energy usage was estimated through the numerical value. In this, the BS can identify any CH with low battery levels at any particular time. Here, the DRNs were utilized for transmitting the data with multi-hop interaction. Same modulation and coding scheme (MCS) index were retained to conserve CH's transmission power; still, maintaining same throughput. According to the presumption concerning the data transmission by considering the inactive CH that provides assistance to the others in sending data to the BS, wherein the inactive CHs will be changed depending on the schedule period using the cooperative communication system. The overall transmission energy gets saved through the optimal D2D coverage range calculation for each sensor node density.

Adaptive relay selection algorithm: The multi-relay network model with cooperative out-bands technique using the concept of the adaptive method formulation was designed by [125]. Here, for a cooperative model, connection distance and channel gain were considered by the introduced adaptive relay selection (ARS) strategy for the efficient communication. A Rayleigh fading channel was utilized with QF protocol employing multi-relay was used to establish the framework for the design of introduced technique. Additionally, the suggested scheme's precise closed-form energy efficiency and throughput formulations have been developed for optimal communication. Based on the findings, it was summarized that the introduced ARS method acquired minimum distance, maximum channel gain and better throughput. Additionally, the introduced ARS has the potential to lower overall usage of energy that directly affects the final degree of energy efficiency. Besides, with regard to power distribution or connection space, the designed ARS design delivers the maximum energy efficiency.

PPP realistic model: To precisely analyze the arbitrary operation of the cooperative communication, the Poisson point process (PPP) approach with stochastic geometry was adopted by [126]. Since transmitters and receivers are components of stochastic point processes, they must be taken into account in stochastic modeling. While considering the variable cell size, the stochastic modeling was ineffective for topologies where, the hexagonal approach was not appropriate for the construction of heterogeneous network topologies. In order to forecast the probabilistic factors such as SINR, BS mapping, coverage probability, load distribution, and cell interference employs stochastic geometry as a suitable method for a randomly built heterogeneous network. While considering homogeneous random models as a network, the D2D and cellular users were used in the realm of relay nodes (RNs) design. Poisson and independent were considered as the two related phenomena in choosing the relay node. The outage probability, ergodic capacity, success probability, and SINR considered by the introduced technique during the cellular network simulation. In order to create an interference-free network, the suggested approach makes use of the D2D user, cellular user, relay node, and BS for the placement of the model. As metrics for assessing the outcomes with regard to densities of node and different SINR pre-defined values outage probability, ergodic capacity, and success probability of the D2D users.

Markov chain framework: D2D relays that already existed in the network were considered as the state of the Markov chain in a framework for D2D cooperative relay created by [127]. The assumption based on the premise of probabilistic D2D cooperation, the calculation of the network's long-term average D2D relays number as a function of the switching probability of the devices was employed. The objective was to evaluate ideal switching probability of the uplink D2D cooperative transmission and to acquire the highest possible levels of dependability and throughput using the designed D2D-relay configuration. The findings demonstrate that the network's average throughput and reliability may be maximized by using optimal switching possibilities and an average amount of D2D relay. The level of collaboration, density of network, and area of coverage all has a significant impact on the achieved outcomes. In general, equipment likes changing from one category to an alternative if the total throughput and dependability were higher than they would be if it remained in that group. With the objective to maximize the network's throughput and dependability, the ideal switching probabilities, which mean the number of device in every group were often affected by congestion in the network, disruption, orthogonality factor, transfer of power, and equipment batteries.

A Stackelberg Game Approach: A two-hop D2D relay selection was proposed by [128] using a Stackelberg Game Approach for obtaining energy and spectral efficiency in communication. The connection of out-of-coverage (OOC) devices was the primary objective of the model. A distributed two-stage approach has been created depending on the Stackelberg game to incorporate each of the participating equipment, in contrast to earlier systems where the relay was chosen either centrally or privately. Initially, the spectral efficiency of the intermediaries has been maximized by matching the OOC devices (OCDUs) with them, and then the bandwidth needed for every device was identified. To determine the ideal management of power, a power control stage was then evaluated. A superior result was obtained when the performance of the suggested strategy was analysed in terms of number of devices in the cell, spectral efficiency, and energy efficiency. Comparing the simulation findings to current approaches, considerable improvements were evident. Gains in energy and spectral efficiency were always maintained at the optimum distance and power level. The interferences among the co-channel interactions was obtained smaller as a result of energy mitigation and acquired spectral and energy benefits. The spectral and energy loss brought on by the usable signal gain decline cannot be made up for below the ideal value. Thus, the better outcome was offered by the introduced model when the transmitter and receiver were closer.

Inter-clustering: In order to enhance the outcome of the model for boost energy efficiency in cooperative D2D networks, [129] developed a relay selection approach utilizing the two inter-clustering model. Two various inter-clustering techniques were created by providing the appropriate methods for each model. To build a multi-relay network, simultaneously delivers training bits to several relays by the source of each cluster. The max-min strategy was used at this stage to choose a relay from the group. Next, the source transmitted this data to the top relay, which subsequently relayed to the CH. The CH that was most near the BS had been meant to be identified. After that, the CH transmits the data to the BS, which in turn passes it on to a different CH. The data passes according to the idea of a D2D multi-hop immediately after the most effective route has been chosen. Different clusters are present in the mobile network in the inter-clustering paradigm according to the second technique, in contradiction. The progressive relay-selection approach is used to pick several relays as cluster heads from among an extensive amount of types of equipment operating as senders. Following the selection of the CH, the source sends data to the destinations of the BS and CH of other clusters. For information to be transferred from one cluster to the intended cluster, inter-clustering model II needs minimal operations. As per the investigation, Inter-clustering Model II had the best throughput performance and was the most energy-efficient. The application of this concept was therefore appropriate while considering5G overlay D2D interactions.

Delay Aware Hybrid Routing: Geographic routing and clustering routing were combined to create a hybrid cluster based D2D cooperative routing strategy [130]. The algorithm's major goal was to create communication between devices with comparable levels of mobility in order to lessen the impact of mobility since there was a solid connection between those moving at the same speed. In this routing, we form a cluster with nodes of equal velocity to lessen the effect of mobility on the link reliability. Based on the node's location, we then chose the cluster head for the subsequent hop, which is the node that is within the source's transmission coverage area and close to the destination. When the SNR within the CH being lower compared to the established threshold due to travelling and route circumstances, cooperative interactions was employed to improve the network efficiency. An individual of the equipment in the group was chosen as the CH since it has a number of equivalent mobility modules. To enhance the efficiency of the system, the CH assignment was established using threshold-based and geographic routing cooperative communication was made available inside the cluster. Based on the findings of the simulation, it was determined that the suggested routing strategy performed better in terms of outage probability, energy usage, and end-to-end transmission latency.

CEETHCoR: In order to create a lightweight paradigm with the goal of lowering transmitting energy, [131] presented the channel aware energy efficient two-hop cooperative routing protocol (CEETHCoR). CEETHCoR derives the properties of cross-layer protocols. Three levels make up the protocol design: network, MAC, and physical layer. Additionally, unlike other research that modify data transmission in a one-hop way, our work performs data delivery in a two-hop transmission by using an integrated relaying for 2 successive one-hop cooperative conversations. In order to decrease packet collisions, handshaking of RTS/CTS interchange was carried out at the MAC layer. For example, by fully using the broadcast aspect of wireless signals, the connection quality was routinely evaluated to enable more precise relay selection. Here, the broadcast aspect of radio signals (both data as well as control signals) was completely used for two key goals: determining the connection quality and cooperatively coordinating between two subsequent one-hop communications. The goal of an optimization methodology developed to find the most effective approach was to reduce the communication efficiency for every network pathway. While the ideal cooperative protocol for routing has been discovered, it proved unworkable due to the required a lot of processing, involving gathering two-hop neighbor data as well as regulation. Using the path consciousness along with the energy efficiency criterion obtained using the lemma, the lightweight technique CAEECR was developed to overcome the problem. Because the selection of relay method was focused on establishing reliable and resilient connections for control signals and information packets, the ideal latency efficiency was achieved to its minimized packet retransmission.

EH-UWSN: The Energy Harvesting in UWSN (EH-UWSN) protocol for routing concept was presented by [132]. An efficient, high-performance, as well as small-footprint networking system called EH-UWSN took into account the coordination of data packet transfers across relay nodes to save energy. The devices had the capacity to recharge the batteries directly their external environment via harvesting energy, which served the dual purposes of reducing energy use and extending network lifespan. A Signal-to-Noise Ratio Combination (SNRC)-based mixing strategy was used at the sink node. The hand-off sensor and the receiver both receive data from the source nodes. The hand-off node strengthens the acquired signal to produce an instantaneous copy repetition of transmitted data. The main concept is to transmit copies of data using several techniques. Additionally, which is referred to as a beneficial diverse assortment. The system's capability and unwavering state are both improved by this cooperative arrangement. As a result of longer network lifetime and better throughput at the destination, simulation findings demonstrate that EH-UWSN has spent much less energy than Co-UWSN.

IACR: The Interference Aware Cooperative Routing (IACR) was described by [133] by considering the cost of the route as an outcome of the signal disruption that a network node generates and receives. The weighted total of the interference that was both generated and obtained has been employed to determine the metric value. The reception interruption component in the suggested routing measure guarantees that the information gets transmitted over a minimal interfering route, providing strong SINR on the destination. On contrary, the produced interruption concept chooses the data connection that delivers lowest disruption to the network. QoS for each network user gets better because a consequence of the aforementioned approach. According to the design, while units were added to the network, the system's consumption of energy rises. Still, IACR required less power than conventional methods since the devices cooperate as well as produce minimal interference to one another, hence lowering network-wide disturbance. Nodes in the network may communicate at a reduced rate of resource, which reduces the amount of energy they use since disruption in the system lowers.

Co-DLSA: [135] has developed two relaying techniques for the information transmission approach: Cooperative Delay and Link Stability Aware (Co-DLSA) and Delay and Link

Stability Aware (DLSA). Being a modification of the previous DLSA path detection scheme, Co-DLSA incorporated the relaying technique of cooperative routing along with the fair-relay-strategy (FRS) and red-black (R-B) routing tree to boost network efficiency. The major goal aimed to reduce the network reliability score by means of an interrupted node with minimizing loss of transmission and latency. In conclusion, all procedures produced results at various percentage levels of difficulty; however, its efficacy was inadequate in comparison to the recommended task. The relay method was deployed to accomplish cooperative routing through partitioning the relay nodes within the system as well as introducing a three-layered technique with relay, aerial, and ground strategy to act as a link separating them in minimizing the evaluation of the network reliability; in this case, the smallest number was regarded as to be optimal since it signifies the least amount of discontinuations have taken place. Likewise to this, the smallest transmission loss generally denotes the highest efficiency. The least amount of latency and packet loss, when compared to other factors, imply the highest performance. The top protocol overall was Co-DLSA, which excelled in every assessment criteria.

Hybrid K-Means Clustering: For cluster-based networks, a technique for cooperative collection of information and relay that increases lifespan has been put forth by [136]. Employing an innovative K-means clustering method incorporating K-means clustering and Huffman coding techniques, the suggested lifetime-enhancing cooperative collecting information and relaying method divides each node into cluster. Decreased information transmission costs across multiple cluster sections to the central BS have been obtained by making optimal use of specialized relay cooperative multi-hop interaction via network coding methods. In terms of transmission lengths and remaining energy measures, the choice of the relay node is presented as an NP-hard task. Relaying node location and remaining energy were employed to frame the node's relay allocation as an NP-hard issue. An approach based on the gradient descent technique has been suggested to address the NP-hard issue. The resulting region's accumulated packets have been jointly routed in multi-hops through the centralized BS during the last stage, where the data was cooperatively processed using random linear coding. Applying this methodology will improve relaying node identification and increase transmits success rates in a variety of cluster-based systems. Additionally, devoted collaborating relay nodes continually help the CH nodes to transmit their collected information by having advantageous locations and sources of energy. The payload packets are furthermore randomly network encrypted at every single hop between the points of origin to the recipient. The findings demonstrate that the suggested approach enhances throughput and durability while reducing delay and consumption of energy.

Multiple-Relay Cooperative Networks Using Hamming Coding: By employing Hamming codes, [137] gave an examination of cooperative networks with multiple-relay for enhancing the energy effectiveness. In this, Quantize-and-Forward (QF) and Amplify-and-Forward (AF) protocols were taken into consideration for multiple-relay networks. The multiple-relay networks used three different forms of Hamming codes with varying lengths. The system characteristics and network model were taken into account for evaluating the consumption of energy, which was assessed based on energy for depicting the efficacy of the model based on the energy. The energy efficiency of hamming code increased with the number of bits enhancement. For the acquisition of the lower BER, a longer Hamming code was employed in a cooperative network since it has a more adaptable minimum distance between the code-words and was resistant towards transmission noise.

CEER: By introducing the Cooperative energy-efficient routing (CEER) technique by [138] hoped to elongate the life of network and build a trustworthy one. By resolving the hotspot problem, the sink mobility strategy was used to cut down on the consumption of energy. To transport information to the intended node, the recommended approach employs the sink portability mechanism. As a result of the information being transmitted directly, consumption of energy could be reduced. The nodes would transport information immediately to the intended node if it was within range of communication. Dependability of information was not guaranteed when it was sent over a single link. Thus, the suggested technique makes advantage of the cooperative transmission of information system to decrease end-to-end latency and improve reliability of the network. The intake nodes were placed in every sector of the territory, which had been separated by several pieces enabling more accurate installation. For the purpose of cutting down on consumption of energy, nodes with sensors produce information and transfer it to the intended node. The network's dependability has been established by using a cooperative method. The maximum remaining energy and the shortest route are both significant factors that were used to choose the sender's location and receiver. By using direct communication to send information from sender to receiver that consumes less energy and retains the nodes active for an extended amount of time, the CEER technique reduces the overall amount of participating nodes.

TSCR: An energy-efficient two-stage cooperative routing (TSCR) system was put out by [139] to lengthen the lifespan of the network and increase energy efficiency simultaneously. This work utilized a core helper to choose the helper set and hence it was significant and unique because it initially investigates a two-stage cooperative (TSC) communication approach for cooperation. The model contrasts with the current methods due to the various design objectives. The incorporation of residual energy's coefficient of weighting into the cooperative transmission based on the two-stage link cost formulation impact the accomplishment of desired goal. The optimization of each link's two-stage link cost by choosing the best assistance set. At last, a distributed TSCR scheme was developed by considering two-stage link cost with optimization in reducing the cost of path and to determine the minimal distance route among sender and indented user. Here, in the designed approach, the sender shares the source packet to the destination via the path identified by the TSCR approach. The various demands concerning the flexibility of the model was accommodate through the consideration of fading conditions. Through simulation result, the advantages of the TSCR protocol were compared to the other schemes in terms of energy efficiency, delay, network lifetime, and network residual energy. The short description of the cooperative communication techniques is presented in Table 2.2.

Table 2.2: Short description of the cooperative communication techniques

Reference	Techniques Used	Performance Measures	Advantages	Disadvantages
Mohamed, E.M., Elhalawany, B.M., Khallaf, H.S., Zareei, M., Zeb, A. and Abdelghany, M.A. **[123]**	Relay Probing	Coverage probability, SNR, throughput, spectral efficiency		To further enhance the mmWave multi-hop relay probing procedure, reinforcement learning-based machine learning technologies must be explored.
Barik, P.K., Singhal, C. and Datta, R. [124]	DSPA	Energy efficiency, hop gain, and churn rate	The intended DSPA approach achieved the lowest battery energy usage of the low-battery active CHs employing an alternate cluster head with superior signal reliability to transmit information.	The designed method acquired minimal network lifetime.
Raziah, I., Yunida, Y., Away, Y., Muharar, R. and Nasaruddin, N. [125]	Adaptive relay selection algorithm	Energy efficiency, energy consumption, and throughput	In cooperative out-band D2D multi-relay infrastructure, the developed Adaptive relay selection strategy uses fewer resources compared to the highest channel gain or shortest path techniques.	The BPSK modulation was used to get the improved throughput efficiency since the throughput assessment utilising M-QAM was complicated. To enhance the reliability of a cooperative D2D

				network, M-QAM modulation was recommended for throughput study.
Qamar, F., Dimyati, K., Hindia, M.N., Noordin, K.A. and Amiri, I.S. [126]	PPP realistic model	Outage probability, and success probability	To ensure more dependable communications, a powerful interference control system was developed.	Adjacent-channel interference and device noise degrades the performance of the model.
Driouech, S., Sabir, E. and Bennis, M. [127]	Markov chain framework	Throughput, and switching probability	The optimal transition possibilities and typical quantity of D2Drelays were utilized to maximise efficiency and dependability.	The cost of improving dependability nevertheless involves an increase in delay.
Selmi, S. and Boullègue, R. [128]	A Stackelberg Game Approach	Energy Efficiency	Based on the results of simulations, it can be shown that the suggested architecture improves overall capacity, spectrum efficacy, and energy utilisation with a manageable computation.	High power transmissions from the BS cause substantial interference to close D2D conversations.
Nasaruddin, N., Yunida, Y. and Adriman, R. [129]	Inter-clustering	Throughput, and Energy Efficiency	According to simulation findings, the inter-clustering architecture was boosted by favourable connection path circumstances and had a low data	The network architecture impacts the network's energy use since only the best relay node was chosen to carry signals through the relay to the

			transfer error rate.	intended location, rather than every relay node.
Devulapalli, P.K., Pokkunuri, M.S. and Babu, M.S. [130]	Delay Aware Hybrid Routing	Delay, Energy consumption, number of hops, and bit error rate (BER)	The information and beacon signals were both compressed using an approach called compressed sensing, which significantly reduced the node's energy usage.	Failed to consider the effect of imperfect synchronization for enhancing the performance.
Tran-Dang, H. and Kim, D.S. [131]	CEETHCoR	Packet delivery ratio, energy consumption, end-to-end delay, energy efficiency	The received SNR may be significantly enhanced even when same transmission power was applied for both relay and direct link, it has been demonstrated that the cooperative transmission strategy was useful in improving reception quality of the information.	Considered only one or two relays for communication
Ahmed, S., Ali, M.T., Alothman, A.A., Nawaz, A., Shahzad, M., Shah, A.A., Ahmad, A., Khan, M.Y.A., Najam, Z. and Shaheen, A. [132]	EH-UWSN	Network stability, lifetime, energy consumption	When compared to Cooperative Routing Scheme for UWSNs (Co-UWSN), the developed has used up to three times as minimal energy during data transfers.	Minimal Network lifetime was accomplished by the method.

Waqas, A., Mahmood, H. and Saeed, N. [133]	IACR	Energy consumption, throughput	When there are a lot of nodes in the framework, the efficacy of the suggested approach gets better. Considering dense edge computing-enabled 5G networks, the suggested approaches could thus provide an effective interference-aware routing option.	The basic SINR at the lowest interference paths cannot meet the threshold level at because the efficiency of the paths has been impacted by the path-loss factor; thus, a significant outage was detected.
Hussain, A., Shah, B., Hussain, T., Ali, F. and Kwak, D. [135]	Co-DLSA	Delay, Throughput, Network stability, and packet drop	Due to the usage of a relay approach as a cooperative system, routing schemes have the capacity to function in cooperative environments.	Strong routing techniques were necessary for both airborne and terrestrial nodes, as well as for obtaining node regional security, scalability, and QoS optimization.
Agbulu, G.P., Kumar, G.J.R. and Juliet, A.V. [136]	Hybrid K-Means Clustering	Delay, Energy Consumption	Achieved superior results with regard to of decreased consumption of energy with longer lifespan and higher information transmission rates with decreased delay.	

Nasaruddin, N., Adriman, R. and Afdhal, A. [137]	Multiple-Relay Cooperative Networks Using Hamming Coding	Energy Efficiency	As a result, adding Hamming coding into the multiple-relay Quantize-and-Forward technique proved an effective way to boost effectiveness while boosting energy efficiency.	As the relay distance ratio rises, the Amplify-and-Forward network has to use more reinforcement power to avoid having its power consumption level rise along with it.
Ahmad, I., Rahman, T., Zeb, A., Khan, I., Othman, M.T.B. and Hamam, H. [138]	CEER	Number of alive nodes, delay, energy consumption, throughput	While the receiver remained out of transmission spectrum, CEER chose the closest neighbour node having the highest resource and bit error rate (BER) during transmitting information to the destination that reduces the system's consumption of energy.	Failed to consider the significant attributes during the relay node selection that enhances the energy efficiency.
Cheng, J., Gao, Y., Zhang, N. and Yang, H. [139]	TSCR	Residual energy, network lifetime, end-to-end delay, energy efficiency	Comparing the new TSCR system to the existing ones, simulation results further demonstrate that it may increase energy utilisation and longevity of the network.	Interference between different data flows was higher for the designed model.

2.2.3 Machine Learning based Techniques

Some of the machine learning based approaches is detailed in this section.

RL-ID2D: Rather than a direct uplink communication, the proposed method leverage two-hop communication protocol for narrowband Internet of Things (NB-IoT) applications that were applicable for healthcare-IoT services based delay-sensitive measure [113]. To attain best end-to-end delivery ratio (EDR), the optimum potential relay set (optPRS) optimization challenge is put forth. Additionally, the introduced model uses reinforcement learning (RL) based on Q-Learning to choose the best cellular relay, which helps to upload sensitive data to BS through the NB-IoT user device. Here, the eventual increase in energy efficiency is accomplished by choosing the best relay with the highest EDR using the designed RL-intelligent-D2D (RL-ID2D) method. The agent was acted depending on the Q-value, which was increased to allow for further exploitation. Here, while maximizing the immediate payoff, the agent to behave greedily in the exploitation phase to elevate the reward. The ambiguity in exploration was acquired from the fact that action was unknown and will result in a higher reward. Still, it was preferable to investigate non-greedy action while considering several time steps, in which exploitation was utilized that was represented in its outcome, which is that elevating the exploration improves the EDR.

CenTri: In 5G network scenarios, CenTri was developed by [117] utilizing a integrated path selection approach utilizing heterogeneous nodes concerning the small-cell from macro-cell BS for traffic offloading of white spaces. The ultra-densification, heterogeneity, and availability of dynamic channel were considered as only a few of the significant aspects of 5G network that it supports. Using the dynamic reinforcement learning (DRL) and conventional reinforcement learning (CRL) techniques, the D2D communication was designed. The constant learning rate was utilized by the CRL; but, the dynamic learning rate was utilized by the DRL that fluctuates in response to main user activity levels. Eleven USRP/GNU radio sets were used as test subjects in the designed protocol. In order to give more realistic circumstances, each USRP unit comprises a minicomputer named RP3. The findings of the analysis demonstrate improvements in many qualities of service (QoS) measures when compared to TRL, including a route breakage with minimal number, a smaller end-to-end latency, and higher packet delivery ratio. Despite having a lower throughput and packet delivery ratio, routes with more intermediate nodes also have greater end-to-end delays.

I-D2D: When it comes to information distribution based on improved in-depth coverage, enormous MTC's necessitates the ultra-reliability [117]. Data transmissions and repeating control allows NB-IoT to meet the need concerning the reliability. One of the main features of NB-IoT was its ability to use less energy. Still, the basic approach of more frequent repeats of the data and control signals uses higher power. For elevating the information transmission, a unique D2D communication connection was utilized as a routing strategy that provides the user equipments with minimal repeats and two-hop route. In this case, to access the best relay by considering the best PDR was performed through the identification of the relay using the dynamic intermediate node selection technique. A Multi-Arm Bandit (MAB) system may be used to perform the learning process for choosing an ideal relay. Based on the channel conditions and relay's location such the Signal-to-Interference-Noise power Ratio (SINR), the relay’s quality variations was examined. In order to get the least amount of latency and a trustworthy PDR while using less energy, the best relay was chosen.

CRP-GR: The clustering-based routing protocol (CRP-GR) [120] was crucial in heterogeneous 5G-based smart healthcare because it ensures quick data transmission to the BS from the sender. Energy optimization and QoS were acquired using game theory to choose an energy-efficient CH and reinforcement learning (RL) to choose the optimal multipath route. In order to identify equilibrium criteria, clustering game theory based CH selection was designed with a mixed strategy that considers several characteristics. While selecting the CH, several factors like mobility speed of the node, remaining energy, spacing between the BS and nodes were considered. The idea behind the information sharing was to use RL with Q-learning to create an energy-efficient multipath routing. Using a deduced iterative approach for the Q-table, multipath routing based on Q-learning identified for obtaining energy-efficient distance and pathways. The ideal cluster head (CH) and path (path of least resistance) for data transmission was chosen using the designed approach for sharing information from nodes to BS through CH. Conversely, the energy wastage in the network exists due to the consideration of arbitrary CH and path selection strategies that require additional computation and a long transmission range, which was avoided in the designed model. The suggested strategy reduces the network nodes and energy consumption as a result. The devised model enhances the effectiveness of the nodes based on energy-saving efforts and minimizes energy dissipation.

Fast Connectivity Construction: In order to meet the low latency requirement concerning the mobility, a smartphone has the capability of intelligent actions, DNN computation, and can process the context acquisition [140]. A small-scale neural network that was trained using a small batch of data and requires little computational effort using the introduced DNN. Signal state and connectivity context were considered as the two types of context utilized in the training phase of the introduced DNN training data set. The information concerning the links MAC layer like network layer routing path and MAC layer link were employed for the connectivity context. Radio signal strength (RSS) values were used to measure the signal status context. A light-weight multi-layer neural network (LMK) was utilized for the data learning. Here, the data gathered from the social networking domains or from the smart industry was utilized for learning the LMK for joining the mobile device in the network. After gathering the data acquired from the network, the LMK learns the data. By this way, the LMK was updated to the current scenario through the learned data. By considering the RSS value acquired from the real world issues, the contexts like signal and connectivity were considered for making the communication between the devices. The pre-trained LMK receives requests from the mobile device for forecasting the route based on the updated routing table for making the connection. Followed by, the execution of the networking control plane was devised by the mobile device in the network layer based on the updated table. At last, the information was ready to send data to other equipment through the established connection through the D2D communication. Based on evaluation results, it can be concluded that the introduced framework offers low latency data transfer and reliable communication.

Optimal DQN: An agent can choose the optimum action for a given state with the help of the Deep Q-network (DQN), which was designed based on DNN and reinforcement learning [141]. In order to increase flying ad hoc energy efficiency, longevity, and network stability, this method introduces an intelligent cluster-based routing strategy. To provide a balanced improvement in the performance of the local and global networks, the introduced strategy provides the recency of information among the distributed controller (DC) and central controller (CC). In order to forecast state action values, DNN gives agents the ability to learn the states based on mobility of agent and residual energy. The

DNN learns in real time using small batches of experiences. Improved convergence rate was acquired for the most appropriate path by considering the three characteristics based on the lower mobility and residual energy. While considering the dynamic environment for enhancing the prediction of state-action values, training was first conducted using the delayed reward concerning the replay memory. In addition, when the episodes rises, the fading variable employed was shifted to the tendency towards intensification away from diversification. Third, to train and minimize a loss function, replay memory with run times small batches were considered for the state estimation. It has been demonstrated that the introduced system improves energy efficiency when compared to random approaches and conventional reinforcement learning.

RLbR: The strain on the 5G cellular network was greatly reduced by a unique reinforcement learning-based V2V routing (RLbR) architecture developed by [143]. The V2V network was designed by considering the non-real time traffic offloads. The concentration on RA of 5G in the suggested architecture enhances the efficacy of communication. The figuring of presence or absence of the real-time traffic was performed by the SDN controller. The V2V network carries non-real-time traffic and cellular network carries real-time traffic. On top of an SDN controller, the relevant algorithms and strategies may be installed as an application, making it simple to upgrade owing to its plan. The application of the reinforcement learning in the routing algorithm to assess the nearby device's quality was utilized for choosing the best path. While considering the environmental conditions, the Q-Table's convergence rate was accelerated through the forward packets by considering the position factor PF. Several simulated conditions were used to evaluate efficacy of the model. The outcomes show that the suggested structure offloads traffic from the designed framework. There were also evaluated more comparisons with the available routing techniques to depict the superiority of the outcome. In terms of average latency, delivery ratio, average energy consumption, and network longevity, the findings demonstrate the effectiveness of the RLbR algorithm.

Improved D2D MIMO Deep Learning Model: With the use of artificial intelligence, [144] developed a mode selection method with highly effective and low complexity for D2D mmWave communications. The best mode in the event of mmWave transmission blockage or a small mmWave coverage area was estimated using deep learning strategy. The best mode for information relaying was then predicted with highly reliable using the suggested deep learning model. Here, nearly usage cases in the offline phase were utilized for training the model. Possible D2D transmitters choose their method of transmission during the mode selection process based on a number of factors. It utilizes the cellular uplink or specialized D2D communication, wherein the intermediate node utilized for the transmission was considered as BS. A high-efficiency and low-complexity based optimum mode selection problem was addressed by the developed deep learning model.

Resource allocation and power control method: By considering a complex D2D communication scenario, [145] suggested a DRL based approach for solving the issues using a combined power control and resource allocation approach. In this, the power management and channel selection concerning the surroundings were considered as joint optimization issue in the introduced model for training the transmitter of D2D model. Here, the consideration of channel reuse led to an increase in transmission power from D2D users and an increase in interference for cellular users. For satisfying service expectations and maximizing system capacity, the introduced model utilizes power control techniques and multi-channel selection approaches for learning the introduced model. With the inclusion of the RL approach, the issue concerning the decision-making was solved effectively. The decision-making issue was considered as a more challenging task by the D2D user's ability to choose a best path among several channels in a communication situation. This was because the state and action spaces were a quite wide task in reinforcement learning. The introduced deep RL (DRL) approach was designed particularly for situations with large state and action spaces to choose the best route that may greatly speed up learning process. Additionally, the algorithm's speed does not suffer as more multiplexed channels were considered by the introduced model. In order to send services as quickly as feasible without interfering with cellular users' regular interaction, D2D users can choose from a variety of channels depending on the different types of Mission-critical communication (MCC) service needs. Each agent may learn from the outcomes of simulations to meet the cellular communication requirement while maximizing the overall system capability and minimizing D2D communications disruption.

APERAA: The underlay Inband D2D communication model's uplink resource allocation was carried out in [146] with the optimization of transmit power by considering various restrictions such as SINR, BER, and so on. Using the BER constraints, the power control and resource allocation were assured by the introduced model for solving the transmit power limitations. Autonomous Power Efficient Resource Allocation Algorithm (APERAA), performs effectively by solving the issues in power regulation and resource allocation utilizing the Lyapunov optimization along with an iterative strategy. The uplink D2D connection based on frequency band distribution was provided autonomously by the SVM-based ML algorithm. The outcome of the method show that, in comparison to the most widely used algorithms, the system's total capacity was higher. The considerable separation between BS and D2D users along with the separation between the D2D users were supported by the introduced model. The test results for the random data set with SVM-based training demonstrate exceptional accuracy, and also demonstrated in the assessment based on simulation depicts that the accuracy in terms of resource allocation elevates with the elevation in number of D2D devices. In order to offer autonomous resource allocation for IoT healthcare applications and services, the devised approach may be used in 5G networks.

Joint Deep Reinforcement Learning: [147] suggested a hybrid approach that combines an unsupervised learning network and a deep Q network (DQN) using the distributed resource allocation approach to efficiently improve wireless spectrum utilization, boost network capacity, and decrease interference. The channel allocation in the unknowable and dynamic environment was first solved using a DQN algorithm in a distributed way. In order to provide a channel power management system in an optimal manner to elevate the sum-rate of the spectrum transmit by considering relevant constraint processing, power control based on unsupervised learning method was built using a deep neural network. Using a small amount of state information gathered locally, the suggested algorithm utilized each transmitter to make power control and channel selection as a learning agent. In contrast to conventional centralized methods, the devised approach utilizes the information concerning the network that was gathered instantaneous global criteria. The distributed algorithm's transmit power was within the permitted range, demonstrating the model's dependability.

Improved DRL: An innovative dynamic reinforcement learning-based slicing framework and optimization solutions were created by [148] for vehicular communications applications by considering low latency and bandwidth-hungry needs. In order to facilitate effective V2V communication, appropriate resource provisioning approach was used in the model. For several slices, it was intended to strike a compromise between degrees of QoS acquisition and resource use. The three layers and stages of the slicing structure were created in the virtualized network. As an initial step, various resources to slices was allotted by the suggested model for allocating virtual resources using a dynamic deep reinforcement learning strategy. For processing the particular application, slicing was devised in the mobile virtual network operators (MVNOs) by dividing it into several segments in its physical infrastructure. To achieve optimal resource management, adjustments were devised on the MVNOs' resources using a DRL agent. Additionally, it balances the QoS fulfillment and use of resources for slices for better communication. To create the D2D pool, the resources concerning the D2D components were combined together. The slice resourced resource integration using its specified portion was made in the second stage of the method. Using the distributed algorithm based on multipliers, problem concerning the physical resource allocation based on signaling overhead and computing complexity was transformed into a convex optimization in the third step. Here, the vehicular network's extremely dynamic character issue was addressed by the designed framework. Besides, operational needs, QoS, and performance of the slicing framework were optimized efficiently by the introduced model.

QSPCA: [149] suggests a two-stage power control method called the Two-stage transmit power control approach (QSPCA) for effective communication. The cellular users and several D2D users were taking into account for creating the dataset offline at the initial stage. The attributes like cellular user, D2D location, RB, and D2D user were considered while creating the datasets. To enhance the cellular usage based on the resources allotted by D2D users and the BS utilizing the spectrum were accessible with the help of the offline construction of training datasets. The obtained dataset was employed for the classification purposes using the SVM classifier during the second phase. The data was transformed using the kernel approach to provide the best separation between the results that could be produced. Industrial IoT applications such as mining, production, and factory automation in 5G networks might make use of the D2D transmit power control and minimum delay. The introduced method might potentially be used extensively in areas such increased ultra-reliable minimum delay and time-sensitive networking. The description of the literatures along with the advantages and challenges is depicted in Table 2.3.

Table 2.3: Short description of machine learning based techniques

Reference	Technique Used	Performance Measures	Advantages	Disadvantages
Raja, S., Logeshwaran, J., Venkatasubramanian, S., Jayalakshmi, M., Rajeswari, N., Olaiya, N.G. and Mammo, W.D. [4]	RL-ID2D	End to end delivery ratio	RL-ID2D chooses the cellular relay through an elevated likelihood of demand and excellent EDR, based on simulation outcomes.	The NB-IoT adds a greater quantity of control packet and data retransmissions, which lowers the method's average throughput and energy efficiency while increasing the reliability and coverage area of the connected device.
Gupta, D., Rani, S., Singh, A. and Mazon, J.L.V. [8]	CenTri	Route breakage, Throughput, PDR, and Delay	Load balancing was achieved by offloading traffic from the macrocell layer to the small-cell layer.	With the goal of concentrating on paths with minimal congestion, the delay created by multi-hop connectivity had not been taken into account. Furthermore, the suggested CenTri necessitates additional testing with a greater variety of paths and relay nodes.
Zhang, Y. [11]	I-D2D	PDR, and delay	The developed model chooses the cellular user equipment relay that has	

			the best likelihood of being provided with lowest latency and maximal PDR.	
Kazmi, S.H.A., Qamar, F., Hassan, R., Nisar, K. and Chowdhry, B.S. [31]	CRP-GR	Throughput, packet delivery ratio, residual energy, End-to-end delay, Network Lifetime	Realistic demands increase lifetime of the network and decrease latency by selecting an required learning rate and QoS factor value.	The developed method was not applicable to deal with the emergency situation due to the in-flexibility of the model.
Mangipudi, P.K. and McNair, J. [32]	Fast Connectivity Construction	Latency, Delivery Time, Packet Delivery Ratio	With 100% of the packets delivered, the designed technique can send data more quickly than the usual connectivity scheme.	Higher battery consumption and latency makes the network to degrade its outcome in D2D communication.
Barakabitze, A.A. and Walshe, R. [33]	Optimal DQN	Network lifetime, Energy consumption	Increased network stability leads to increased throughput and less route formation-related signaling overhead.	The model's performance was diminished by an overestimation of Q-value devised through choosing actions with the greatest Q-values.
Sylla, T., Mendiboure, L.,	RLbR	Network lifetime, Energy Consumption, Delivery	The delay associated with the network	The network's overall energy will grow as the quantity of devices participating

Maaloul, S., Aniss, H., Chalouf, M.A. and Delbruel, S. [34]		Ratio, and Latency	was minimal when the number of devices in the network was smaller; because, the path finding within the smaller network was considered as a easier task.	in information transmission increases as well.
Ogbodo, E.U., Abu-Mahfouz, A.M. and Kurien, A.M. [35]	Improved D2D MIMO Deep Learning Model	MSE, Throughput, Energy Efficiency, and Coverage Probability	The designed deep learning based optimal mode selection criteria accomplished an increase in reliability while communicating with the device.	In the event of direct path blockage or significant interference, the developed approach does not ensure that the link between the BS and devices was the optimal link.
Dangi, R., Lalwani, P., Choudhary, G., You, I. and Pau, G. [36]	Resource allocation and power control method	Sum rate, system capacity	The strategy for power selection and resource allocation had the advantage of increasing system capacity overall in accordance with the various MCC functions.	Slower convergence rate

Ioannou, I., Christophorou, C., Vassiliou, V. and Pitsillides, A. [37]	APERAA	Accuracy, SNR, Spectral Efficiency, System Capacity	For devices based on the Internet of Things having independent capability for live care or uninterrupted health monitoring of an individual without experiencing an interruption or latency when connecting to services, the designed model offers an innovative approach in the environment of communication.	The method considered only the uplink channel for resource allocation.
Laguidi, A., Hachad, T. and Hachad, L. [38]	Joint Deep Reinforcement Learning	Spectral Efficiency, and Energy Efficiency	For arbitrary assignments, the technique proved to be more adaptable in terms of average transmit sum-rate.	To directly reduce channel interference between users of mobile devices and BS, the suggested algorithm found it challenging to be implemented.
Khan, R., Tsiga, N. and Asif, R. [39]	Improved DRL	Convergence, resource utilization	Multiple experiments showed that, as compared with current methods, the	Failed to consider the significant features that enhance the efficiency of the model while designing the virtual

			new techniques may increase throughput, slices satisfaction, and resource utilization benefits.	model.
Guo, L., Zhu, Z., Lau, F.C., Zhao, Y. and Yu, H. [40]	QSPCA	SINR, Throughput, and Power	By guaranteeing that the regulated transmission power stays within the restrictions, the newly implemented technique increases the throughput of D2D users.	When the BER rises, the throughput falls as well. But when the BER value increases, throughput gradually declines. Increased SINR is necessary to lower BER. In order to properly analyse the efficacy of the network, the BER factor must be taken into account.

2.3 Research Gaps

D2D communication based on cellular network is an emerging topic of research among researchers nowadays. A lot of research has been done on the D2D communication, but major proposals were faced challenges in obtaining the efficient network model. Some of them are:

- ***Interference***: The main issue with D2D cellular networks that underpin D2D is interference among D2D users and cellular users. D2D connections involving D2D users and cellular users, commonly referred as cross-tier interference, which are considered as the source of unwanted interference. To improve the receipt of intended information at the point of reception, interference has to be significantly reduced. Due to the eNB's strong broadcast strength, D2D users that reuse downstream RBs will experience interference. The communication reliability of a D2D network is reduced when interference accumulates and SINR values declines. In contrast, reduced interference is seen whenever users of D2D reuse upstream RBs since upstream management signalling being weaker than downstream so there is more congestion overhead in cellular networks. Reusing the upstream frequency offers less interference than reusing the downstream spectrum, for this reason.
- ***Device Recovery***: Equipment identifying to connect the communication is an important issue in communication between D2D devices. In D2D technology, there are several device-finding techniques. The two primary methods of device discovery are prosteri and priori and eNB started functioning through interaction with users. Prior to the initiation of interactions among D2D users, the user broadcasts a beacon signal regularly certain times to begin the process of discovery. In order to maximise system gain, eNB finds prospective D2D pairings based on user IP address information and gives users the option to pick D2D connection options. Numerous research publications on device discovery in D2D communication were published. In the cellular network, an integrated approach for full, partial, and off-coverage scenarios are explored.
- ***Mobility***: A thorough examination of the network's mobility system for management is detailed along with an analysis of it impacts on the system's efficiency. Reliability of interaction between devices is significantly impacted by

mobility management. Users of wireless communication systems have allowed roaming about; therefore managing portability becomes an important issue that has to be solved. The wireless cellular technique's operational equipment may relocate, making it impossible to maintain communication uninterrupted. To maintain the infrastructure without disruption an effective algorithm must be developed using the aid of flexibility management. A higher information throughput, reduced latency, and less power consumption are characteristics of the D2D cellular network that underlies it for enhanced mobility.

- ***Security***: It is crucial to consider privacy and security issues thoroughly while adopting and deploying communication between devices on cellular networks. It occurs primarily a result of the integration of several user devices, network architecture, and interfaces to carry out the tasks on one system. To guard from many types of attacks on networks including reply attacks, man-in-the-middle, denial of service, etc., secure wireless communication has to meet the criteria of authenticity, privacy, and availability, as well as confidentiality. During exchange, data has to be secured using an encryption method to prevent attackers.
- ***Energy Consumption***: To increase the total handling capacity and spectrum efficacy of D2D-enabled mobile communications platforms, radio resource management (RRM) problems have to be correctly resolved following device detection and mode selection. To increase the efficiency of the system, a variety of radio resource management strategies were put forth. Upcoming cellular networks will be equipped with the capacity to support a lot of equipment. A 50 billion equipment prediction has been made. The unfortunate result of more communication devices being used is more energy being utilised. The atmosphere's CO2 concentration will rise as a result, harming the ecology and the environment worldwide. Additionally, BSs and access points consume a tremendous amount of energy and emit a significant quantity of radiation, all of which have an impact on human health and the global economy. The environment is therefore taught to hate wireless communication networks. Due to these factors, green communication networks are frequently implemented in 5G networks. In order to be "green," communication must use as little energy as possible and extend battery life. The next generation of 5G cellular networks is predicted to increase energy efficiency by a factor of 1,000. The basic goal of a green network may be achieved by

utilizing a variety of components, including power control, energy harvesting, cloud RAN, and femtocells. D2D technology is one of the key elements that helps green networks. It can take some of BS's energy off of it. The consumption of electricity by devices is also reduced via close-proximity networking. D2D render radiation from BSs obsolete. Also improving energy efficiency is the use of relays with DUs. Due to the fact that battery-powered devices are an evolved kind of D2D user in such networks, energy consumption is one of the key problems that cooperative D2D networking faces.

2.4 Summary

The review of conventional methods concerning the 5G cellular communications is elaborated in this chapter for identifying the challenges faced by the methods while enhancing the efficiency of the network. Here, the three various mechanisms like Machine learning based techniques, D2D communication techniques and Cooperative communication techniques are reviewed. Finally, the research gaps identified based on the review is detailed to develop a novel framework by fulfilling the challenges faced by the conventional methods.

ARCHITECTURE

CHAPTER - 3

ARCHITECTURE

3.1 Introduction

The core idea of the 5G network is to lighten the burden of the base station (BS) by providing direct communication between the devices in the network. Wireless D2D networks is a candidate for the 5G networks, wherein the direct communication between devices increases the spectrum's efficiency, however the presence of interference is considered as its downside [150]. Through better resource allocation algorithms, it may be feasible to make effective use of the spectrum while minimizing the impacts of interference [151]. In networks that utilizes the devices like smart phones, there has been number of opportunities for new services and apps to control the interference. Cellular networks now include direct D2D communication in order to accommodate 5G technologies by taking routing efficiency into account [152, 153]. Using a control link, the BS manages two devices' direct communication through the incorporation of relay devices between the communications.

Reinforcement learning, which has been investigated and implemented in many application domains and has successfully solved resource allocation-related issues [154]. In order to improve the decision-making process over the long term, the information learning criteria is devised by reinforcement learning-based algorithms to maintain the dynamic and changing scenario. A reinforcement learning-based strategy, for instance, has been developed and put into practice for scheduling tasks in cloud environments to reduce execution-related delay and congestion. Several RL-based methods have been introduced to boost efficiency, including a method that lowers the energy consumption of data centers [155]. Recently, deep learning and reinforcement learning have been collaborated to create Deep reinforcement learning strategies that excel in challenging resource management domains [156]. This illustrates the proficiency of deep reinforcement learning strategies in making choices in these kinds of difficult situations.

3.2 Architecture of Cooperative D2D

One of the key feature of the networks of the future is device-to-device (D2D) connectivity, which reduces the overall system's traffic burden and enables traffic offloading. Direct communication among the devices, which bypasses the BS or the core network, is made possible by D2D networks, taking advantage of these features [157]. In addition to traffic, the D2D idea can be used to facilitate communication in emergency scenarios where the BS is broken due to typhoons, floods, and earthquakes like natural disasters. The D2D solves the challenges in this situation by either locating them precisely or connecting them to the nearest operational ground network. By considering the assigned frequency band, the D2D can generally be divided into out-band and in-band communication [158, 159]. The cellular band is either under laid or overlaid by D2D communication in in-band D2D networks. The ISM (industrial, scientific, and medical) channels are used by D2D transmission, which are unlicensed frequency bands in the out-band D2D network. Out-band D2D provides the benefits of no interference and high capacity with cellular users, but because it uses many interfaces, such as Wi-Fi and LTE, it has integration and management issues [160].

Communication between devices offer a number of advantages, but they also cause interruption with devices, particularly for in-band systems. Numerous strategies for power regulation and reusing resources have been put forth in the literature to reduce interruption [161]. The inherent synergy among communication using D2D and the potential millimetre wave (mmWave) band, which ranges in frequency from 30 to 300 GHz, is another inspiring coexistence. The short-range discontinuous communication that distinguishes millimetre waves is caused by their fragile channel. It is a perfect opportunity to coexist with D2D in order to establish minimal mutual interruption, high data throughput D2D lines since it was precisely focused using antenna beamforming (BF) algorithms. Figure 3.1 depicts the D2D communication scenarios concerning the real time application domain [162].

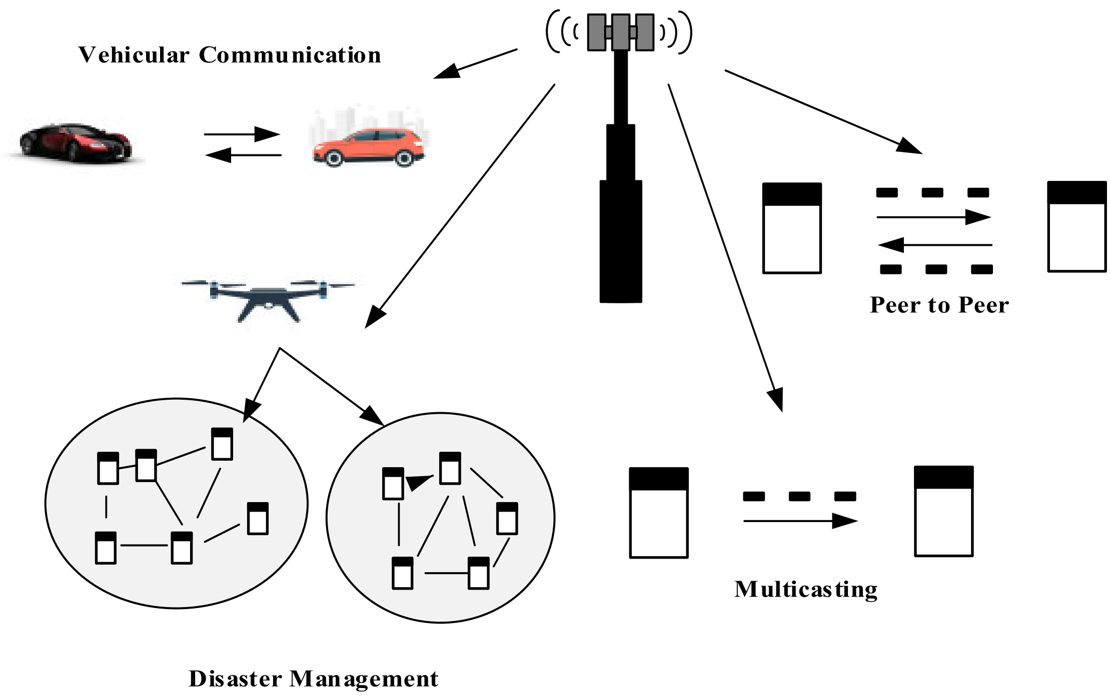


Figure 3.1: Architecture of D2D Communication

The recent advancements in machine learning have made it possible to use D2D communication in several applications such as mmWave beam forming, detection, modulation, channel state information recovery, intelligent radio access (RA), and spectrum management [163]. Still the issues like coverage extension of D2D relaying based multi-hop routing, resource allocation, D2D pair matching, and neighbor discovery and selection (NDS) prevails in the D2D communication are solved using the machine learning technique. Artificial intelligence (AI) has a branch called machine learning (ML) that enables computers in learning from examples and data without having to be explicitly programmed [164]. By utilizing various training methods, which are often divided into the following types:

Supervised-Learning: In the supervised learning phase, the learning is devised by considering the historical data sample pairs and maps the output for the concerned input using the machine learning strategy. The two various categories of the supervised learning are the classification and regression tasks [165]. Using linear or sigmoid function approximations, the forecasting is devised for the real-valued outcomes using the logistic or linear regression models. The approaches like boosting and bagging meta-algorithms, random forests, neural networks (NNs), and several other fundamental regression methods considers diverse methodologies for performing the regression tasks [166]. Data samples are classified using classification models into one of different classes. Various approaches like decision tree (DT), support vector machines (SVMs), are K-nearest neighbor (KNN), utilized for D2D applications based on the classification approaches [167, 169]. While utilizing the larger dataset, the artificial deep NNs (DNNs) based on graphical processing units (GPUs) are utilized due to the advancements of machine learning techniques. The methods of supervised learning in the communication domain are Boltzmann machine, Hopfield Networks, recurrent NN (RNN), convolutional NN (CNN), and multi-layer feed-forward NN (FNN) [170].

Unsupervised-Learning: Unsupervised learning model, in contrast to supervised learning, without the use of data labels investigate and uncover the input data's latent structures and patterns. The dimension reduction, density estimation, and clustering are considered as the three subcategories of unsupervised learning [171]. While considering the process of clustering, the machine learning algorithm splits and classifies data samples into clusters or groups, where samples within a cluster are more similar to one another than to samples inside other clusters. Relative Core Merge (RECOME) and K-means clustering methods are examples of these sub-categories [172]. The detection of the high-density regions is devised by mapping the data sample in the feature space through the distribution density of data using the density estimation algorithms. An example for this kind of classification model is the Gaussian mixture model (GMM). When data is transformed to a low-dimensional from a high-dimensional space using the dimension reduction techniques like GGMM, K-means, and principal component analysis (PCA), the data's primary structures are preserved. In many applications, the unsupervised learning methods are widely used [173].

Reinforcement-Learning: Real-time control problems can be challenging to solve using unsupervised and supervised learning approaches. Reinforcement learning is a strong tool for solving these challenges. In a manner similar to the learning capability of the humans, reinforcement learning relies on trial and error [174]. For the action it takes in maximizing the long-term benefits, the agent in a reinforcement learning system is penalized or rewarded. Each phase of the process involves giving the agent recursive environmental feedback to help it decide which course of action to take. The agent's action plan is specified as a policy. Q-learning is one of the most popular reinforcement learning methods [175]. The Multi-Armed Bandit (MAB), on the other hand, is a technique based on reinforcement learning that is gaining more attention, particularly for applications in communication. The exploration-exploitation dilemma is taken on as a player by the MAB problem in its typical settings, which is expressed by a group of actions or weapons. The player or learner chooses one arm at a time and is rewarded with the corresponding, stochastically or non-stochastically modelled, reward [176]. The term "bandit" refers to a situation in which a player is only aware of the prize associated with one arm while the rewards associated with the other arms are still unknown. By choosing the weapons sequentially, the player aims to maximize the overall payout. As opposed to the best single arm, the player needs to reduce regret. The sequential decision-making process, such as network routing, benefits greatly from MAB. However, the reinforcement learning based approaches provides the best solution for the communication related issues [177].

3.3 Challenges

Some of the challenges faced by the cooperative D2D communication based routing are:

Resource Management: Interference control is an important problem in a dense heterogeneous network. This is because many BS are present in the network while considering the underlay spectrum sharing become more challenging than it is for single-tier systems currently in use. The level of interference in cells also varies as a result of various access limitations like private and public. Adaptive resource allocation solutions are also necessary due to the dynamic nature of heterogeneous networks. Resource management in a D2D heterogeneous network is therefore crucial for efficient communication between the devices. Heterogeneous network, interference management is a critical issue. This is because the underlay spectrum sharing becomes more complex than existing single-tier system when multiple BS was involved in the network. Also, due to several access restriction (such as public and private, and so on), interference level varies in cells. The dynamic nature of heterogeneous networks also needs adaptive resource allocation strategies. Therefore, it is difficult to manage resources efficiently in D2D heterogeneous network. In a dense heterogeneous network, interference management is a critical problem. This is because the underlay spectrum sharing become more difficult than the existing single-tier system when multiple BS are involved in the network. Moreover, due to several access restrictions (such as public and private, and so on), interference level varies in cells. The dynamic nature of heterogeneous networks also requires adaptive resource allocation methods. Therefore, it is difficult in managing resources efficiently in D2D heterogeneous network

In a dense heterogeneous network, interference management is a complex issue. This is because the underlay spectrum sharing becomes more difficult than the existing single-tier systems when multiple BS are involved in the network. Moreover, due to various access restrictions (such as public and private, and so on), interference level varies in cells. The dynamic nature of heterogeneous networks also requires adaptive resource allocation strategies. Therefore, it is critical to manage resources efficiently in D2D heterogeneous network. In a dense heterogeneous network, interference management is a critical issue. This is because the underlay spectrum sharing becomes more difficult than the existing single-tier systems when multiple BS are involved in the network. Moreover, due to various access restrictions (such as public and private, and so on), interference level varies in cells. The dynamic nature of heterogeneous networks also requires adaptive resource allocation strategies. Therefore, it is critical to manage resources efficiently in D2D heterogeneous network.

Interference: With regard to security and radio frequency energy harvesting, interference in D2D networks is utilized due to the number of benefits. In order to compromise the receiving signal at a possible listener, the interfering signal can be utilized for security-related friendly jamming. This use of interference specifically ensures data confidentiality by lowering the signal to interference noise ratio at the listener, which causes substantial decoding errors. Additionally, ambient radio frequency energy can be harvested via interference signals. It is possible to charge objects near the cell's edge using this radio frequency energy. However, since the circuitry required for information decoding cannot also be used for energy harvesting, doing so may raise the price of the hardware. Because of this, it is necessary to use a separate energy harvesting module inside the receiver so that the power of the received radio frequency signal is split into two streams: one for energy collecting and the other for information decoding. Additionally, there hasn't been a lot of work done in the D2D literature that makes use of interference effectively for energy harvesting or link security.

3.4 Summary

This thesis chapter details the architecture of the D2D communication along with the challenges for devising a novel techniques for efficient D2D communication. Here, the machine learning techniques for the D2D communication techniques are evaluated along with its challenges.

COOPERATIVE DEVICE-TO-DEVICE COMMUNICATION USING JOINT RELAY ASSIGNMENT AND CHANNEL ALLOCATION USING DEEP LEARNING

CHAPTER - 4

COOPERATIVE DEVICE-TO-DEVICE COMMUNICATION USING JOINT RELAY ASSIGNMENT AND CHANNEL ALLOCATION USING DEEP LEARNING

4.1 Introduction

Modern wireless networks can benefit from relay communication since it enables effective resource utilization. The behavior of the principal users in the cognitive radio network (CRN) will significantly affect the stability of multiple-hop routes connecting cognitive users. This study's deep reinforcement learning-based research proposes a simultaneous channel selection and routing mechanism. Utilizing the improved hunter prey optimization (EnHpo) algorithm, the channel allocation strategy is initially suggested. The classic hunter-prey optimization is combined with an adaptive weighting method in the proposed EnHpo in order to increase convergence and find the optimal solution globally with balanced stages of local search and randomization. The optimal channel allocation is based on the multi-objective fitness function based on parameters like priority, bandwidth, and transmission rate. Then, depending on the channel gain based on the bit error rate, the relay selection is devised using deep reinforcement learning criterion. Here, the efficiency of D2D communication is improved by choosing the relay sub-set using deep reinforcement learning.

4.2 Problem Statement

Femtocells, cooperative networks, intelligent transportation systems, public safety systems, dynamic spectrum access, and smart grid communications are a few examples of CRNs' application domains. However, the model's functioning is still limited by several challenging problems. Researchers have devised a variety of ways for efficient D2D communication among CRN. The loss of information, latency, and enormous consumption of resource were shown to be the limitations of the traditional approaches. The nodes' dynamic nature and the absence of a technique for recovering lost routes are the major reason for the packet loss. Additionally, the network endures a large delay as a result of the new routing paths detected. In order to facilitate effective D2D communication, this chapter presents a combined channel allocation and relay selection method.

4.3 Proposed Methodology for Joint Channel Allocation and Relay Assignment

The cooperative network employs the orthogonal frequency division multiplexing channel (OFDMA) cognitive model with source-destination pairs and numerous relays for joint channel allocation and relay selection. Here, the amount of power used for transmission is fixed, and the device chooses the channel while it is idle to improve communication efficiency between the devices. The channel strength is also thought to be constant for each time slot, and each node is equipped with an antenna. The base station has authority over resource distribution and operational management. The network's latency is initially reduced on the first hop of communication by taking into account variables including bandwidth, priority, and transmission rate. After that, on the second hop, a system for choosing relay nodes based on bit errors is developed to satisfy quality of service specifications. Figure 4.1 presents an example of the two-hop joint channel allocation and relay selection method.

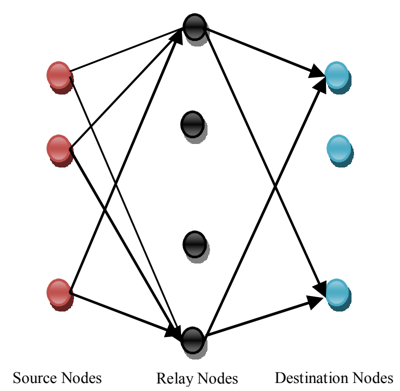


Figure 4.1: System model for the proposed joint channel allocation and relay selection technique

4.3.1 Multi-Objective Fitness Function

The multi-objective fitness function is built with consideration for variables like priority, bandwidth, and transmission rate in order to allocate the optimum channel for D2D communication. In the proposed D2D communication based on joint channel allocation and relay selection, the channels $A_1, A_2,....A_e$ and the bandwidth of $B_1, B_2,...B_e$ are considered.

Priority: Based on the amount of packet loss, the priority of the incoming request is calculated for making the communication more efficient. The node with the quicker packet loss is given a higher priority, and is calculated as follows:

$$A_a = \frac{1}{\min\left\{\frac{D_a - B_a}{D_b}, \frac{C_a - E_a}{S_a}\right\}} \tag{4.1}$$

where, the present size of the data is indicated as E_a, the packets arrives at the node is indicated as S_a, the tolerable delay is notated as D_a, and the device is indicated as a. The delay associated with the node is indicated as B_a, the frames duration is indicated as D_b, and the buffer size is indicated as C_a.

Bandwidth: The bandwidth utilized for making the communication between the devices is notated as B_{G_a}. For making the uninterrupted communication, the bandwidth higher than the B_{G_a} is essential; thus, the requirement of the bandwidth is defined as:

$$A = \left\{A_a \middle| B_a > B_{G_a}\right\} \tag{4.2}$$

Transmission rate: Based on the amount of the data, the transmission time is evaluated, and the best channel allocation is determined by using the highest transmission rate. The estimation of the transmission rate is formulated as:

$$a = \arg\max\left\{g_{a,e} \middle| \frac{f_a}{g_{a,e}} \le T_a\right\} \tag{4.3}$$

where, the transmission rate of device a is indicated as $g_{a,e}$ and available time is indicated as T_a. Thus, the channel allocation's multi-objective fitness function is written as follows:

$$Fit = \{\max(priority, bandwidth, transmission rate)\} \tag{4.4}$$

4.3.2 Optimal Channel Allocation using EnHpo

In order to increase convergence rate, the standard hunter prey optimization is combined with an adaptive weighting method to create the suggested Enhanced hunter prey optimization (EnHpo) algorithm. For the purpose of resolving optimization problems, the hunter-prey optimization takes into account the hunting behavior of the prey species. Gazelle, stag, and deer are the prey species taken into account in this optimization, whereas wolves, leopards, and lions are the predator species that employ the suggested algorithm's method of hunting. In order to get the global optimum solution without becoming stuck at a local optimal solution, the best algorithm has balanced randomization and local search capabilities, which is acquired by the EnHpo. The adaptive weighting technique is added to the traditional hunter-prey optimization to strengthen the randomization criterion and prevent the possibility of premature convergence.

4.3.2.1 Mathematical Modeling of EnHpo

The search agents are located in the search space at random manner, and the viability of the solution is determined by estimating multi-objective based fitness for each hunter. Here, the localization of the hunters is represented as $\left(\vec{P}\right)=\left\{\vec{P_1},\vec{P_2},.....\vec{P_R}\right\}$. Also, the maximal iterations considered for the algorithm is initialized as $\tau^{\max}$. The following is a representation of the hunter's successful solution during the arbitrary phase's randomization phase:

$$P_k = m(1,L)*\left(Max_r - Min_r\right)+Min_r \tag{4.5}$$

where, Min_r and Max_r refers to the minimum and maximum dimension of the solution and the position of the hunter is indicated as P_k and L refers to the variables. The following is the representation of the lowest and maximum dimension of the solution:

$$Min_r = \left[Min_1, Min_2,...Min_L\right] \tag{4.6}$$

$$Max_r = \left[Max_1, Max_2,...Max_L\right] \tag{4.7}$$

Fitness Evaluation: Based on the multi-objective function represented in equation (4.4), the fitness is evaluated.

Randomization: In order to identify the best global best solution for the optimal channel allocation, the hunters explore the prospective areas. In the randomization phase, the hunters' solution is updated as follows:

$$P_{k,h}(\tau+1) = P_{k,h}(\tau) + 0.5\begin{bmatrix}\left(2HW \cdot N_{v(h)} - P_{k,h}(\tau)\right) + \\ \left(2(1-H)W \cdot M_h - P_{k,h}(\tau)\right)\end{bmatrix} \tag{4.8}$$

where, the adaptive parameter is notated as W and the mean of the solutions acquired by the hunters in the present iteration is indicated as M_h. The position updated by the hunters at $(\tau+1)^{th}$ iteration is notated as $P_{k,h}(\tau+1)$ and τ^{th} iteration is notated as $P_{k,h}(\tau)$. The definitions for the W and M_h are expressed as:

$$\begin{aligned} &N = \vec{Y_1} < H; \qquad\qquad u = (N == 0); \\ &W = Y_2 \otimes u + \vec{Y_3} \otimes (\sim u) \end{aligned} \tag{4.9}$$

$$M = \frac{1}{n}\sum_{k=1}^{n} \vec{P_k} \tag{4.10}$$

where, the solution considered as target is represented as N and H is the variable used to get the global best solution by balancing local search criteria with randomization. The random numbers are mentioned as Y_1, Y_2 *and* Y_3 with the limit of $[0,1]$. The value of index is defined as u for $\vec{Y_1}$ that maintains the $(N == 0)$ assumption. Then, the balancing parameter that degrades the value $1 to 0.02$ throughout the equation is formulated automatically as:

$$H = 1 - \tau\left(\frac{0.98}{\tau_{\max}}\right) \tag{4.11}$$

where, the processing iteration is defined as τ and its highest value is indicated as $\tau_{\max}$.

The prey's location is determined by taking into account the mean of the solution found by each individual hunter and the distance between the prey, which is represented as follows:

$$\vec{N_v} = \vec{P_k} \,|\, k\, is\, index\, of\; Max(End)sort(X) \tag{4.12}$$

The Euclidean distance, this is calculated by considering the mean solution of the hunters and the prey. It is given as follows:

$$X(k) = \left(\sum_{h=1}^{L} (P_{k,h} - M_h)^2 \right)^{1/2} \tag{4.13}$$

The prey's position is updated if the distance measurement yields a lower outcome. Based on the assumption, the algorithm has tendency to converge slowly when the output is greater. It is defined as:

$$Z = round(H \times q) \tag{4.14}$$

where, The hunters' population is denoted by q, whereas Z represents the distance-limiting factor. In order to increase the algorithm's pace of convergence, the distance limiting factor is gradually reduced from its original value over the course of iterations. The prey's successful solution is described as follows after evaluating the distance limiting factor:

$$\vec{N_v} = \vec{P_k} \,|\, k\, is\; sorted\; X(Z) \tag{4.15}$$

As a result, the definition applies to the solution of the hunters obtained during the randomization phase is formulated as:

$$P_{k,h}(\tau+1) = I_{v(h)} + HW\cos(2\pi Y_4) \times \left(I_{v(h)} - P_{k,h}(\tau)\right) \tag{4.16}$$

The adaptive weighting technique, which is described as follows helps to eliminate the solution's premature convergence during the randomization step. It is formulated as:

$$Y = (1 - \tau / \tau_{\max})^{1 - \tan(\pi \times (l - 0.5) \times b / \tau_{\max})} \tag{4.17}$$

where, b is added to the hunters' solution when solution updation is not used, is the element that causes the hunters to travel in the direction of the prey. When a solution update is generated by the hunters, however, component b is divided by 2. The adaptive weight factor Y in this instance has a maximum limit of 1 and a minimum value of 0. As a result, utilizing the suggested EnHpo, the hunters' position is updated after adopting the adaptive weighting approach as follows:

$$P_k(\tau+1)_{EnHpo} = Y * P_k(\tau+1) \tag{4.18}$$

where, the solution updation by the proposed EnHpo algorithm is indicated as $P_k(\tau+1)_{EnHpo}$.

Local Search: A local search is designed to find an in-depth solution to the channel allocation problem based on the solution found through randomization. The description of the position update is then given as follows:

$$P_k(\tau+1) = \begin{cases} P_k(\tau) + 0.5[(2 \cdot H \cdot W \cdot N_v - P_k(\tau)) + (2(1-w)W \cdot M - P_k(\tau))] & if\ Y_5 < \eta \\ I_v + H \cdot W \cdot \cos(2\pi Y_4) \times (I_v - P_k(\tau)) & otherwise \end{cases} \tag{4.19}$$

Feasibility Evaluation: The fitness estimation formulated in equation (4.4) is used to assess the viability of the solution found during the local search phase.

Termination: After obtaining the finest possible solution or, the iteration $\tau_{\max}$ comes to an end. Algorithm 4.1 presents the EnHpo algorithm's suggested pseudo-code.

Algorithm 4.1: Pseudo-code for EnHpo algorithm

Pseudo-code for EnHpo **algorithm**	
1	The initialization of parameters $H, \tau^{\max}, \eta, and\ q$ are performed
2	The initialization of parameters Max_v and Min_v are assigned
3	Using equation (4.4) fitness is estimated
4	while
5	{
6	Using equation (4.18) solution accomplished in randomization phase is obtained
7	Using equation (4.19) solution accomplished in local search phase is obtained
8	Re-estimate the feasibility using equation (4.4)

9	}
10	$I = I + +$
11	Return the best solution
12	end

4.3.3 DQL based Relay Selection using channel gain

The DQL is used by the newly devised routing algorithm to determine which relay is the optimal best for making communication between the devices while taking into account the probability of the selected channel. Reinforcement learning helps to solve and improve the problem of the performance of the Markov decision control for the efficient routing. The basic component of reinforcement learning is a learning agent, which is capable of detecting changes in its surroundings and behaving in a way that can have an adverse effect on the controlled environment. In order to improve relay selection performance, the reward signal is specified and instructs the agent to gain larger cumulative values through a trial-and-error process. The well-known reinforcement learning algorithm used Q-learning in its design to address Markov choice issues (Watkins, 1989). As one of the most popular off-policy RLs, q-learning is expected to enhance total reward. Because of this, it is possible to think of the distribution between the given current condition and control action as the ideal value function that guides the formulation of policy. Figure 4.2 illustrates the basic idea that drives Deep Reinforcement Learning.

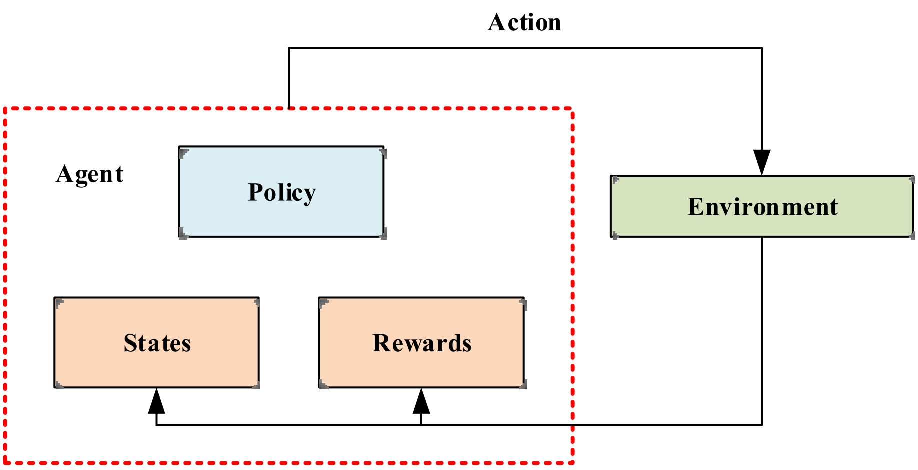


Figure 4.2: Basics architecture of Deep Reinforcement learning

Agent: When making decisions to address problems with uncertainty, the solution is known as the agent. The agent therefore influences the environment (problem). The agent's objective is to maximize rewards since it is essential to do so in order to choose relays with the best efficiency in choosing the available channel assignment.

Action: Actions are the selection best options from many relay for solving the issue. The agent chooses the optimal action out of all the specified actions.

Environment: The newly devised method's relay selection based on channel gain is referred to as the problem since it affects the environment. The environment is changed by the agent's choice in terms of policies, rewards, or states.

Policy: The choice of the right action that contributes to enhancing the reward is the responsibility of the policy.

States: States refer to the collection of parameters that make up the environment.

Rewards: The reward is defined as the feedback of the environment that offers in response to the agent's actions in each state.

4.3.1 Deep Reinforcement Learning

Deep reinforcement learning is the behavior that results from combining reinforcement learning and deep learning. The optimal action is chosen for the relay selection among the different actions that deep reinforcement learning produces for the given state Q . The network parameter is referred to as ϕin this context. In the proposed D2D communication protocol, the relay is chosen based on the channel gain of the allotted channel using deep reinforcement learning. Figure 4.3 illustrates the Deep Reinforcement Learning architecture.

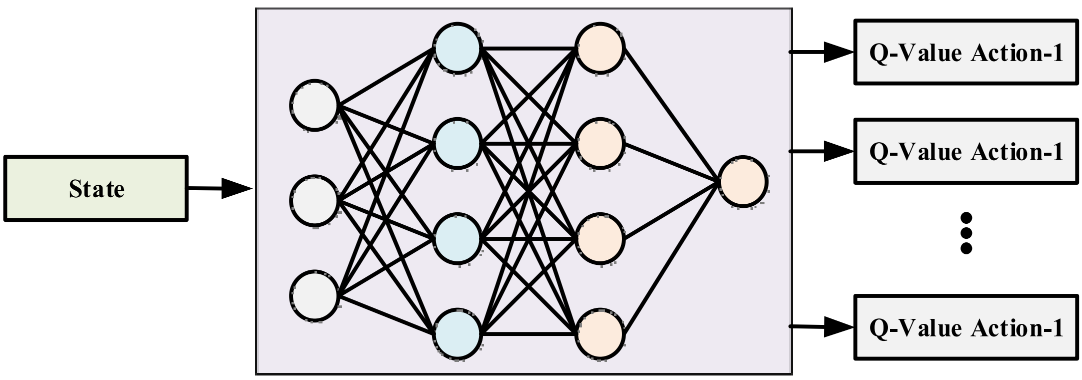


Figure 4.3: Architecture of Deep Reinforcement Learning

Here, the reward $R_{Q,Q''}^{h}$ serves as the basis for the decision-making process about relay selection concerning the state Q. Depending on the action state pair $B_{Q,Q'}^{h}$, the likelihood of selecting the relay is devised, where the action is referred as H. The activity is selecting the optimal relay based on its channel gain for the effective D2D communication in the proposed combined channel allocation and relay selection approach.

Reward and Q value Evaluation: Every decision-making action utilizes an estimated reward, and the action with largest reward selects the optimal relay for making the communication between devices. For the source device m_c, the receiver device m_b is considered for the efficient relay selection. Here, the reward for the action is outlined as:

$$R_{Q,Q''}^{h} = -p - \alpha_1 \left[\left(S_{d,a} \right)_c + \left(S_{d,a} \right)_b \right] + \alpha_2 \left[n(m_c) + n(m_b) \right] \tag{4.20}$$

where, the corresponding action-state pair is notated as $(m\ ,f_s)$, punishment factor is defined as p, the weight factors are defined as $\alpha_1\ and\ \alpha_2$ and $R_{Q,Q''}^{h}$ refers to the factor that defines the reward for the relay selection. If the action fails to choose the optimal relay based on channel gain, the following estimation is devised for choosing its reward function and is described as:

$$R_{Q,Q''}^{h} = -p \times \eta - \gamma_1 \left(S_{d,a} \right)_c + \gamma_2 n(m_c) \tag{4.21}$$

Here, η and $\left(S_{d,a} \right)_c$ represent the drop case of the relay selection and the channel gain taken into account for communication, respectively. After that, the following is the formula for determining the channel gain depending on the required bit error rate:

$$K_a = \underset{a \in \{M_1, M_2, \ldots M_A\}}{\arg\min} \{S_a\} \tag{4.22}$$

where, the destination device is designated as a, and the set of relays used to communicate with it is denoted as $K_a \in D$. Here, the relay selection is assessed using the channel coefficient in reducing the computational complexity of model, and is written as:

$$S_{d,a} = m_e \exp\left(-c_e \frac{q_{d,a} \left| p_{d,a} \right|}{\sigma^2} \right) \tag{4.23}$$

where, the bit error rate is represented as $S_{d,a}$, the power allocation is stated as $q_{d,a}$, the parameters used for modulation and coding are indicated as c_e and m, and the channel coefficient relating to the dth relay to the destination device is indicated as m_e. Relay selection based on channel gain is essential for effective D2D communication in this case. The estimated reward is described as follows:

$$\text{Re}\,ward = B_Q \times R_m^h + B(1 - B_Q) \times R_m^h \tag{4.24}$$

where, the initial channel gain varies from $[0,1]$.

Q-Value: To get the largest reward, the estimation of Q is designed as follows:

$$Q-V(Q,h) = \text{Re}ward + \beta[Q-V(Q,h) + Max_{h'}(Q-V(Q',:))] \tag{4.25}$$

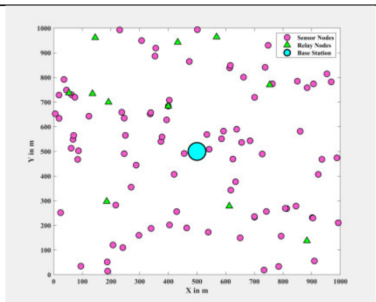
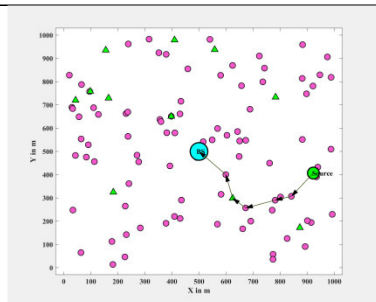
where, the notation of Q-value is represented as $Q-V$ and is exceptionally useful in selecting the most effective relay for D2D communication

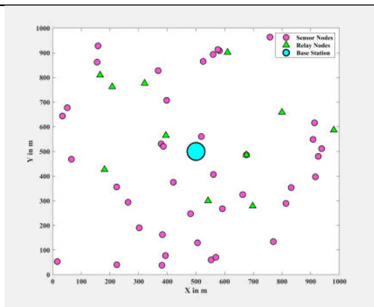
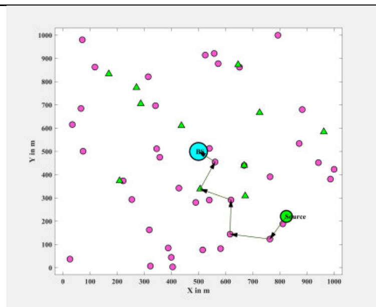
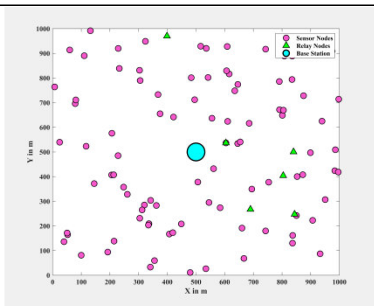
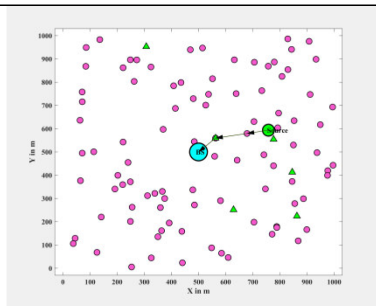
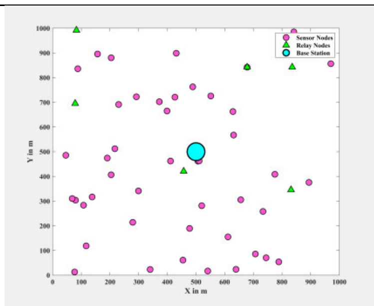
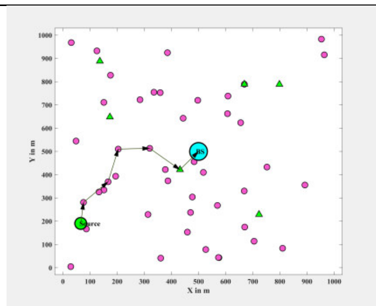
4.4. Result and Discussion

Utilizing the MATLAB programming tool and a variety of assessment metrics, the proposed combined channel allocation and relay selection is evaluated. The performance of the suggested routing protocol is compared here using established resource allocation techniques such as the Game based Framework [178], Decode and Forward method [179], Zigbee/WiFi Routing [180], and DDPG Approach [181].

4.4.1 Simulation Outcome

Figure 4.4 illustrates the analysis of the newly devised joint channel allocation and relay selection approach based on the results of the simulation. In this case, the analysis is employed by altering the network scenario's node count.

100Nodes Network scenario with 10 Relay Nodes		

50Nodes Network scenario with 10 Relay Nodes		
100Nodes Network scenario with 5 Relay Nodes		
50 Nodes Network scenario with 5 Relay Nodes		

(a) (b)

Figure 4.4: **Simulation Outcome: (a) Network Scenario and (b) Routing**

The experimental results are shown in Figure 4(a) for the network scenario and Figure 4(b) for routing for a variety of network situations including 10 relay and100 nodes, 10 relay and 50 nodes, 5 relay and100 nodes and 5 relay and50 nodes.

4.4.2 Performance Evaluation by varying iteration

The analysis of the proposed EnHpo+DRL by varying the number of nodes in the network for various iterations is elaborated here.

(i) Assessment with 50 Nodes and 5 Relay Nodes

Average Residual Energy: The average residual energy by varying the number of communication rounds and iteration size of the newly devised EnHpo algorithm is shown in Figure 4.5. The average residual energy acquired with 500 round is 0.9148 for 20 iterations, which is further reduced when the round increases to 2500 with the average residual energy of 0.6629. Due to the increase in rounds, a greater amount of energy is consumed. However, the amount of residual energy is improved for the model's performance improvement by the increasing the iterations. For example, the average residual energy estimated with 20 iterations and 1000 round is 0.8456, which is 0.8978 when the iteration increased to 100. The detailed analysis is depicted in Table 4.1.

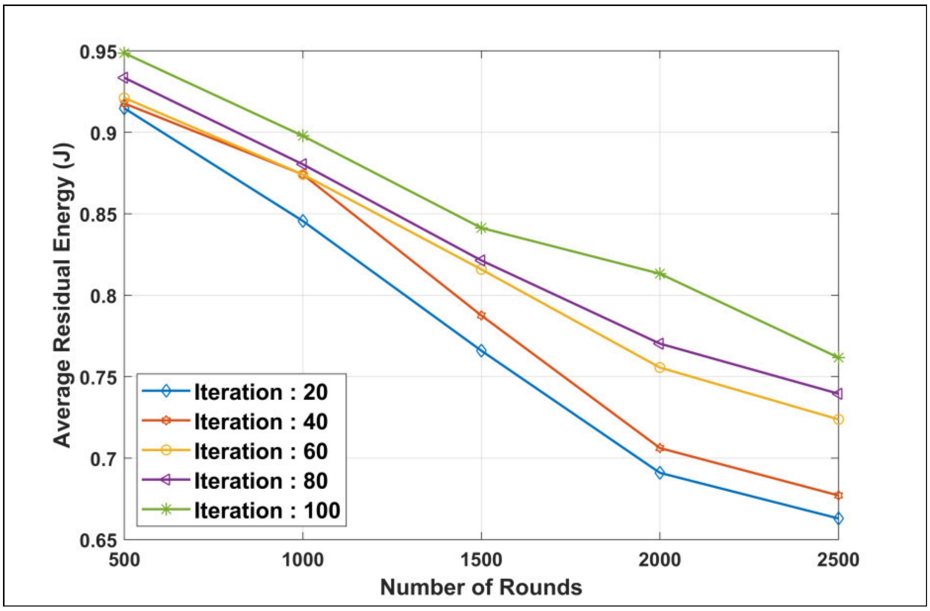


Figure 4.5: Average Residual Energy based on Iteration with 50 nodes and 5 relays

Table 4.1: Average Residual Energy based on Iteration with 50 nodes and 5 relays

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	0.9148	0.8456	0.7659	0.6909	0.6629
Iteration size = 40	0.9177	0.8741	0.7875	0.7062	0.6771
Iteration size = 60	0.9212	0.8742	0.8158	0.7556	0.7238
Iteration size = 80	0.9335	0.8803	0.8213	0.7702	0.7395
Iteration size = 100	0.9486	0.8978	0.8413	0.8132	0.7617

Latency: The latency of the D2D communication depicts the time take for the information to reach the destination from the source. The analysis based on latency by varying the iteration with 50 Nodes and 5 Relay Nodes is portrayed in Figure 4.6. While considering the 20 iterations of EnHpo algorithm with 500 rounds, the latency estimated by the proposed method is 4.197, which is increased to 5.853, when the round is increased to 2500. In contrast, the latency gets minimized with increase in the number of iterations of the algorithm. For example, with 1500 round and 20 iterations, the latency estimated by the newly devised method is 5.434, which is further minimized to 3.637 with 100 iterations. Thus, the increase in iteration elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 4.2.

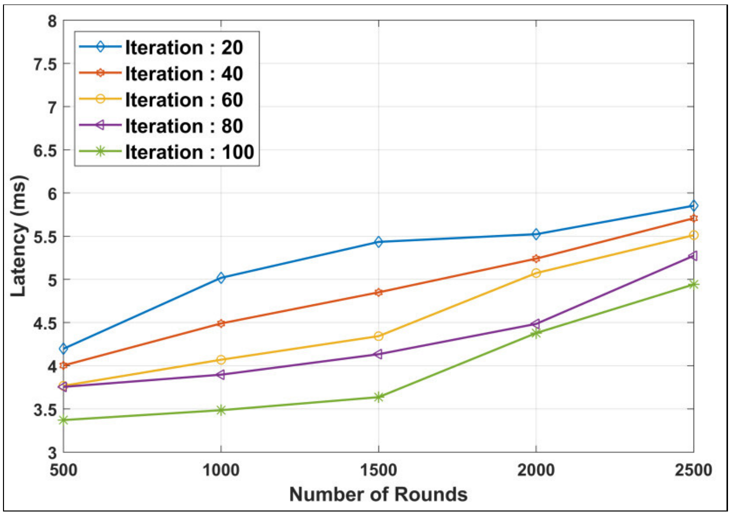


Figure 4.6: Latency based on Iteration with 50 Nodes and 5 Relay Nodes

Table 4.2: Latency based on Iteration with 50 Nodes and 5 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	4.197	5.018	5.434	5.523	5.853
Iteration size = 40	4.003	4.49	4.85	5.24	5.708
Iteration size = 60	3.768	4.07	4.343	5.073	5.512
Iteration size = 80	3.756	3.897	4.134	4.485	5.274
Iteration size = 100	3.372	3.486	3.637	4.379	4.942

Network Life Time: The network lifetime based analysis with 50 Nodes and 5 Relay Nodes by varying the iteration size is depicted in Figure 4.7. The network lifetime estimated by the newly devised joint channel allocation and relay selection protocol is 93.33 with 20 iteration and 500 rounds. The same is 85.36 with 2500 rounds and 20 iterations, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 87.41 with 1500 rounds and 20 iterations, which elevates with 91.51 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 4.3.

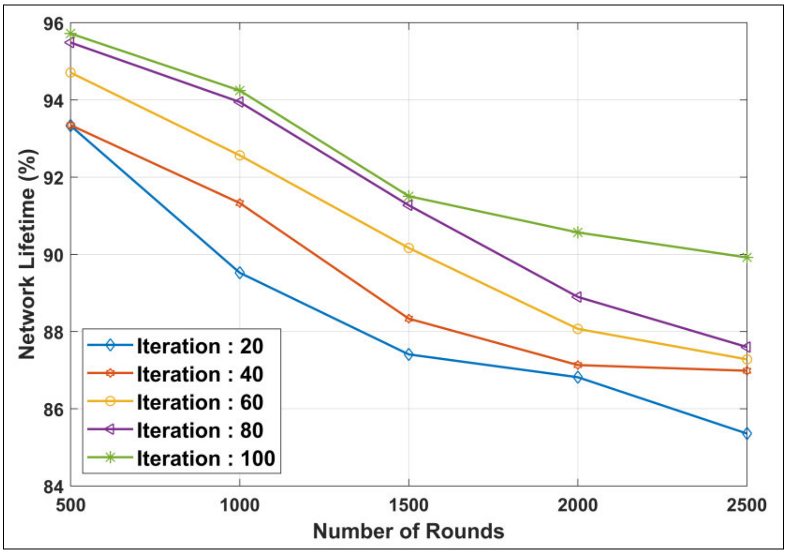


Figure 4.7: Network Life Time based on Iteration with 50 Nodes and 5 Relay Nodes

Table 4.3: Network Life Time based on Iteration with 50 Nodes and 5 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	93.33	89.52	87.41	86.82	85.36
Iteration size = 40	93.35	91.33	88.33	87.13	86.98
Iteration size = 60	94.71	92.56	90.16	88.07	87.28
Iteration size = 80	95.49	93.95	91.27	88.90	87.60
Iteration size = 100	95.72	94.24	91.51	90.57	89.92

Packet Delivery Ratio: The interpretation of the packet delivery ratio for various iteration sizes of the newly devised EnHpo algorithm of the introduced joint channel allocation and relay selection with 50 Nodes and 5 Relay Nodes is depicted in Figure 4.8. For 20 iterations, the packet delivery ration accomplished by the newly devised protocol is 0.989 with 500 rounds, which is 0.8921 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the suggested model is 0.932 with 20 iterations and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 iterations is 0.988with 1000 rounds. The detailed evaluation is presented in Table 4.4.

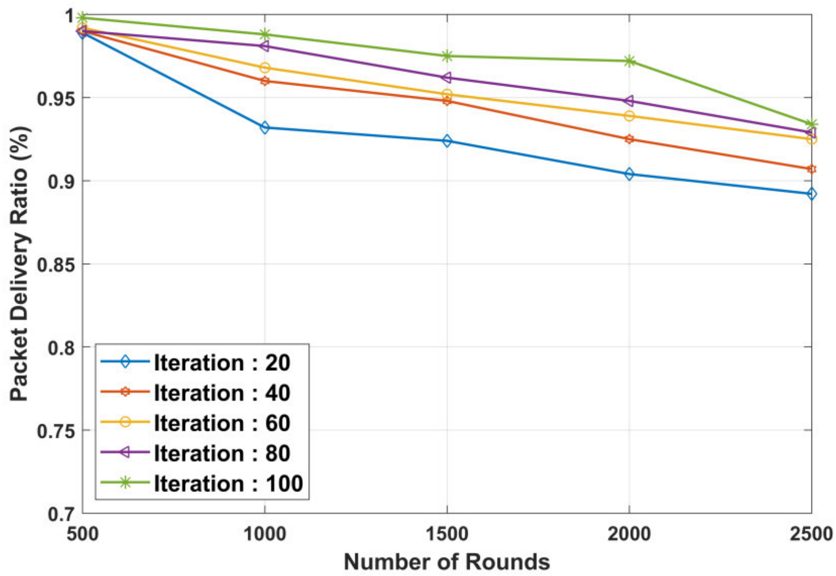


Figure 4.8: Packet Delivery Ratio based on Iteration with 50 Nodes and 5 Relay Nodes

Table 4.4: Packet Delivery Ratio based on Iteration with 50 Nodes and 5 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	0.989	0.932	0.924	0.904	0.8921
Iteration size = 40	0.99	0.96	0.948	0.925	0.907
Iteration size = 60	0.992	0.968	0.952	0.939	0.925
Iteration size = 80	0.99	0.981	0.962	0.948	0.929
Iteration size = 100	0.998	0.988	0.975	0.972	0.934

Throughput: The throughput based analysis of the proposed method by varying the iteration of the EnHpo algorithm is depicted in Figure 4.9 with 50 Nodes and 5 Relay Nodes. The throughput estimated by the newly devised protocol with 20 iterations and 500 communications round is 5923, which is 13959 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 iterations, the throughput estimated by the proposed protocol is 11932. When the iteration increased to 100, the throughput estimated is 17908 that depict the better outcome of the model with increase in iteration. The detailed analysis is presented in Table 4.5.

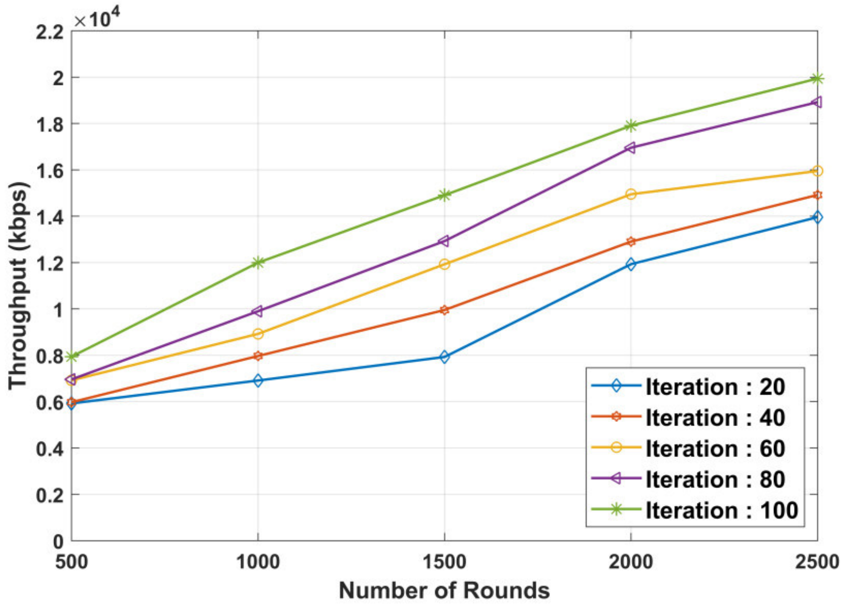


Figure 4.9: Throughput based on Iteration with 50 Nodes and 5 Relay Nodes

Table 4.5: Throughput based on Iteration with 50 Nodes and 5 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	5923	6911	7927	11932	13959
Iteration size = 40	5974	7968	9954	12905	14919
Iteration size = 60	6919	8923	11926	14949	15951
Iteration size = 80	6958	9900	12928	16957	18924
Iteration size = 100	7940	11996	14906	17908	19941

(ii) Assessment with 100 Nodes and 5 Relay Nodes

Average Residual Energy: The average residual energy by varying the number of communication rounds and iteration size of the newly devised EnHpo algorithm is depicted in Figure 4.10. The average residual energy acquired with 500 round is 0.9292 for 20 iterations, which is further reduced when the round increases to 2500 with the average residual energy of 0.6827. Hence, the elevation in the number of rounds consumes more energy. Still, the increase in iteration elevates the performance of the model by enhancing the amount of residual energy. For example, the average residual energy estimated with 20 iterations and 1000 round is 0.8605, which is 0.9160 when the iteration increased to 100. The detailed analysis is depicted in Table 4.6.

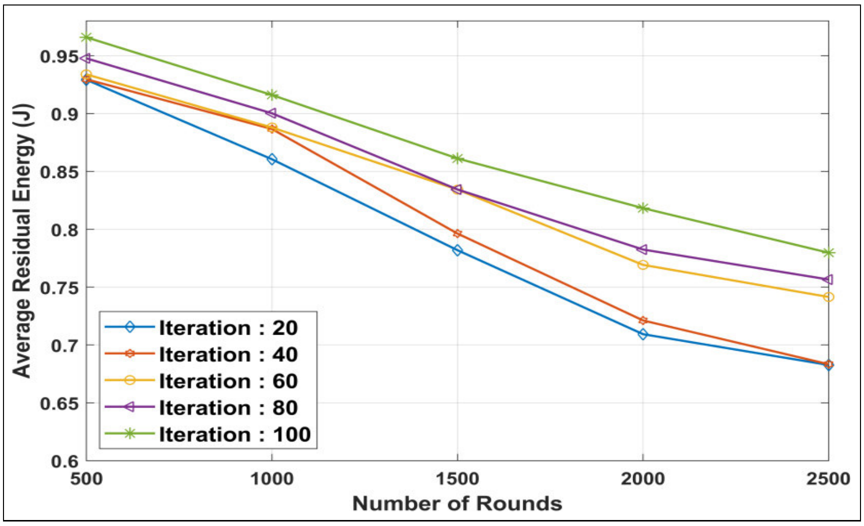


Figure 4.10: Average Residual Energy based on Iteration with 100 Nodes and 5 Relay Nodes

Table 4.6: Average Residual Energy based on Iteration with 100 Nodes and 5 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	0.9292	0.8605	0.7819	0.7093	0.6827
Iteration size = 40	0.9296	0.8866	0.7962	0.7212	0.6833
Iteration size = 60	0.9338	0.8879	0.8342	0.7692	0.7414
Iteration size = 80	0.9477	0.9002	0.8344	0.7824	0.7565
Iteration size = 100	0.9658	0.9160	0.8611	0.8182	0.7797

Latency: The latency of the D2D communication depicts the time take for the information to reach the destination from the source. The analysis based on latency by varying the iteration with 100 Nodes and 5 Relay Nodes is portrayed in Figure 4.11. While considering the 20 iterations of EnHpo algorithm with 500 rounds, the latency estimated by the proposed method is 4.1874, which is increased to 5.8433, when the round is increased to 2500. In contrast, the latency gets minimized with increase in the number of iterations of the algorithm. For example, with 1500 round and 20 iterations, the latency estimated by the newly devised method is 5.4243, which is further minimized to 3.6276 with 100 iterations. Thus, the increase in iteration elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 4.7.

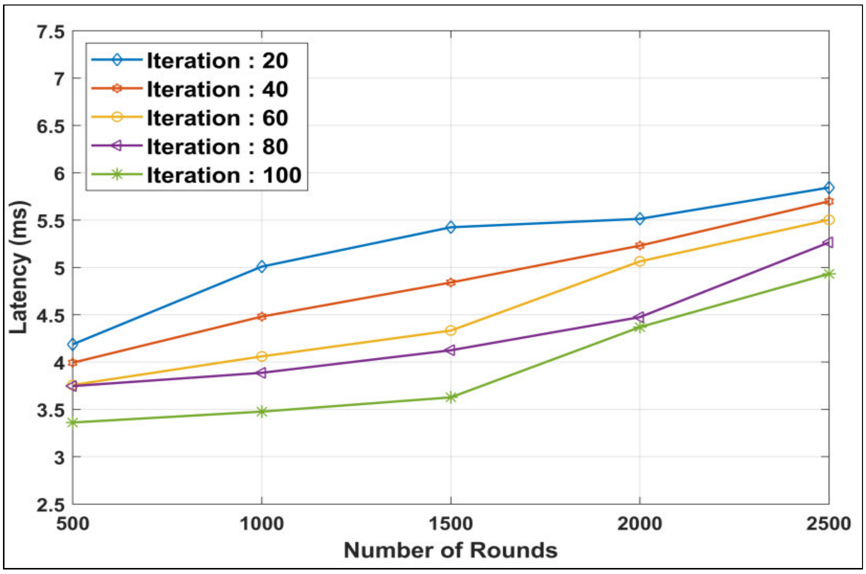


Figure 4.11: Latency based on Iteration with 100 Nodes and 5 Relay Nodes

Table 4.7: Latency based on Iteration with 100 Nodes and 5 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	4.1874	5.0087	5.4243	5.5133	5.8433
Iteration size = 40	3.9935	4.4809	4.8408	5.2301	5.6988
Iteration size = 60	3.7582	4.0605	4.333	5.0639	5.5026
Iteration size = 80	3.7469	3.887	4.125	4.4752	5.2642
Iteration size = 100	3.3621	3.4769	3.6276	4.3697	4.9322

Network Life Time: The network lifetime based analysis with 100 Nodes and 5 Relay Nodes by varying the iteration size is depicted in Figure 4.12. The network lifetime estimated by the newly devised protocol is 94.50 with 20 iteration and 500 rounds. The same is 86.99 with 2500 rounds and 20 iterations, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 89.19 with 1500 rounds and 20 iterations, which elevates with 94.10 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 4.8.

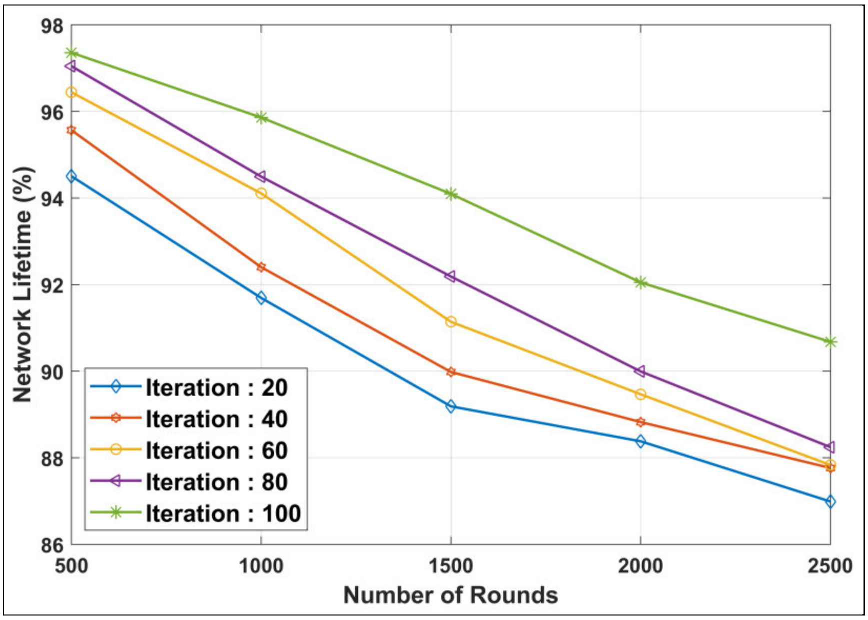


Figure 4.12: Network Life Time based on Iteration with 100 Nodes and 5 Relay Nodes

Table 4.8: Network Life Time based on Iteration with 100 Nodes and 5 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	94.50	91.69	89.19	88.38	86.99
Iteration size = 40	95.57	92.40	89.98	88.82	87.76
Iteration size = 60	96.44	94.11	91.14	89.47	87.83
Iteration size = 80	97.04	94.49	92.19	89.99	88.24
Iteration size = 100	97.36	95.86	94.10	92.05	90.68

Packet Delivery Ratio: The interpretation of the packet delivery ratio for various iteration sizes of the newly devised EnHpo algorithm of the introduced protocol with 100 Nodes and 5 Relay Nodes is depicted in Figure 4.13. For 20 iterations, the packet delivery ratio accomplished by the newly devised protocol is 0.9897 with 500 rounds, which is 0.9012 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the suggested model is 0.9410 with 20 iterations and 1000 rounds. Besides, the packet delivery ratio measured by the suggested protocol with 100 iterations is 0.9908 with 100 rounds. The detailed analysis is presented in Table 4.9.

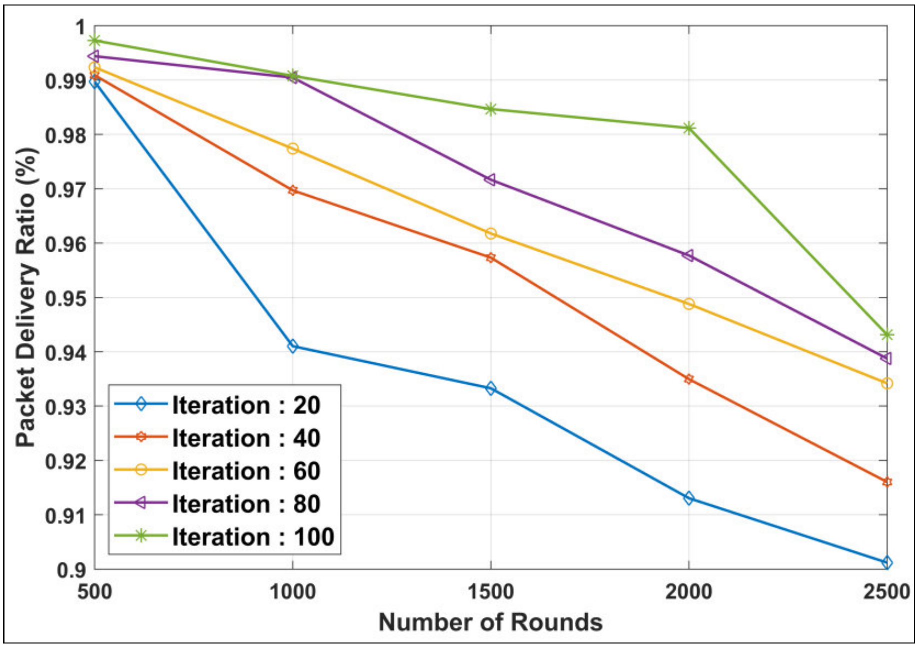


Figure 4.13: Packet Delivery Ratio based on Iteration with 100 Nodes and 5 Relay Nodes

Table 4.9: Packet Delivery Ratio based on Iteration with 100 Nodes and 5 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	0.9897	0.9410	0.9333	0.9130	0.9012
Iteration size = 40	0.9909	0.9697	0.9573	0.9350	0.9160
Iteration size = 60	0.9923	0.9774	0.9618	0.9488	0.9342
Iteration size = 80	0.9944	0.9904	0.9716	0.9577	0.9388
Iteration size = 100	0.9973	0.9908	0.9847	0.9812	0.9431

Throughput: The throughput based analysis of the newly devised protocol by varying the iteration of the EnHpo algorithm is depicted in Figure 4.14 with 100 Nodes and 5 Relay Nodes. The throughput estimated by the newly devised protocol with 20 iterations and 500 communications round is 6501, which is 15224 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 iterations, the throughput estimated by the proposed protocol is 12536. When the iteration increased to 100, the throughput estimated is 18903 that depict the better outcome of the model with increase in iteration. The detailed analysis is presented in Table 4.10.

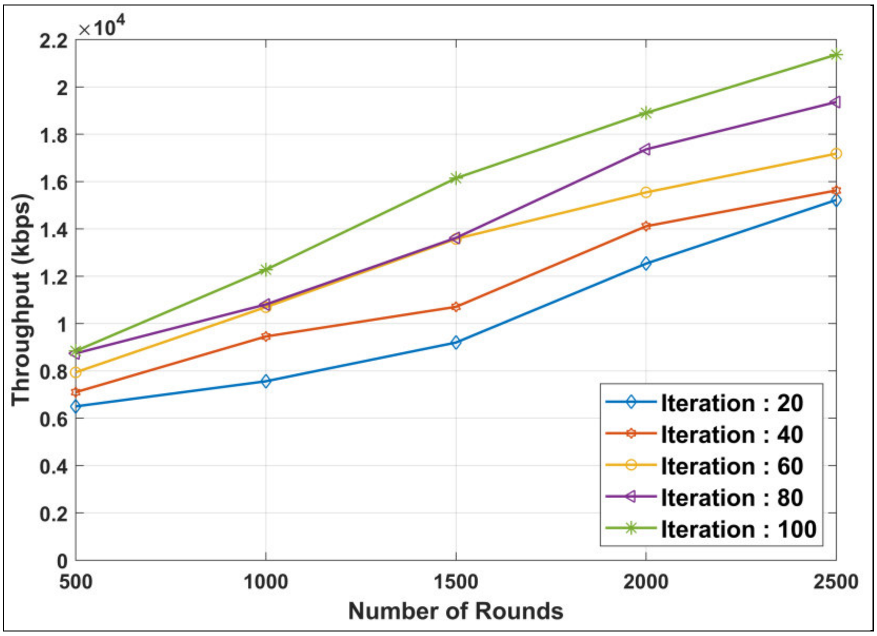


Figure 4.14: Throughput based on Iteration with 100 Nodes and 5 Relay Nodes

Table 4.10: Throughput based on Iteration with 100 Nodes and 5 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	6501	7563	9199	12536	15224
Iteration size = 40	7101	9455	10707	14115	15625
Iteration size = 60	7941	10694	13580	15544	17180
Iteration size = 80	8741	10808	13622	17364	19364
Iteration size = 100	8843	12275	16143	18903	21363

(iii) Assessment with 50 Nodes and 10 Relay Nodes

Average Residual Energy: The average residual energy by varying the number of communication rounds and iteration size of the newly devised EnHpo algorithm is depicted in Figure 4.15. The average residual energy acquired with 500 round is 0.9452 for 20 iterations, which is further reduced when the round increases to 2500 with the average residual energy of 0.7010. Hence, the elevation in the number of rounds consumes more energy. Still, the increase in iteration elevates the performance of the model by enhancing the amount of residual energy. For example, the average residual energy estimated with 20 iterations and 1000 round is 0.8790, which is 0.9529 when the iteration increased to 100. The detailed analysis is depicted in Table 4.11.

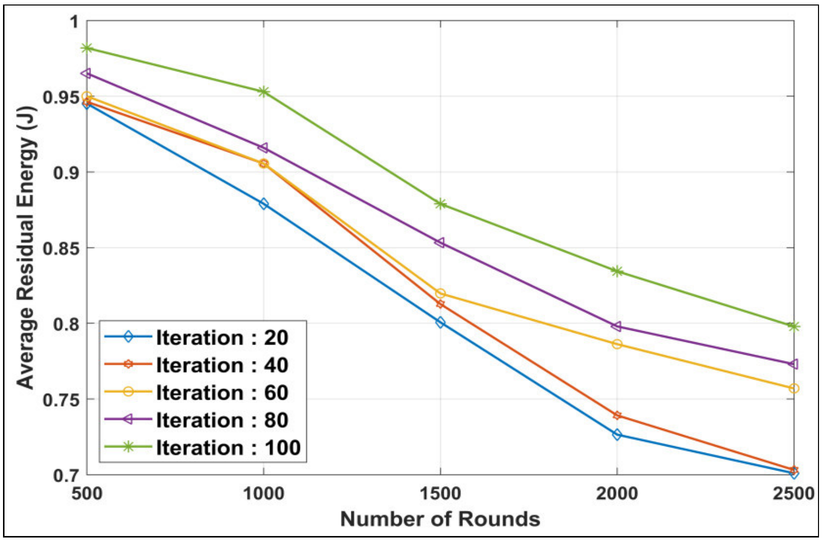


Figure 4.15: Average Residual Energy based on Iteration with 50 Nodes and 10 Relay Nodes

Table 4.11: Average Residual Energy based on Iteration with 50 Nodes and 10 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	0.9452	0.8790	0.8007	0.7265	0.7010
Iteration size = 40	0.9463	0.9055	0.8127	0.7392	0.7031
Iteration size = 60	0.9500	0.9056	0.8197	0.7862	0.7570
Iteration size = 80	0.9651	0.9160	0.8533	0.7979	0.7730
Iteration size = 100	0.9819	0.9529	0.8789	0.8344	0.7979

Latency: The latency of the D2D communication depicts the time take for the information to attain the destination from the source. The analysis based on latency by varying the iteration with 50 Nodes and 10 Relay Nodes is portrayed in Figure 4.16. While considering the 20 iterations of EnHpo algorithm with 500 rounds, the latency estimated by the proposed method is 3.8283, which is increased to 5.5454, when the round is increased to 2500. In contrast, the latency gets minimized with increase in the number of iterations of the algorithm. For example, with 1500 round and 20 iterations, the latency estimated by the newly devised method is 4.5878, which is further minimized to 3.1874 with 100 iterations. Thus, the increase in iteration elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 4.12.

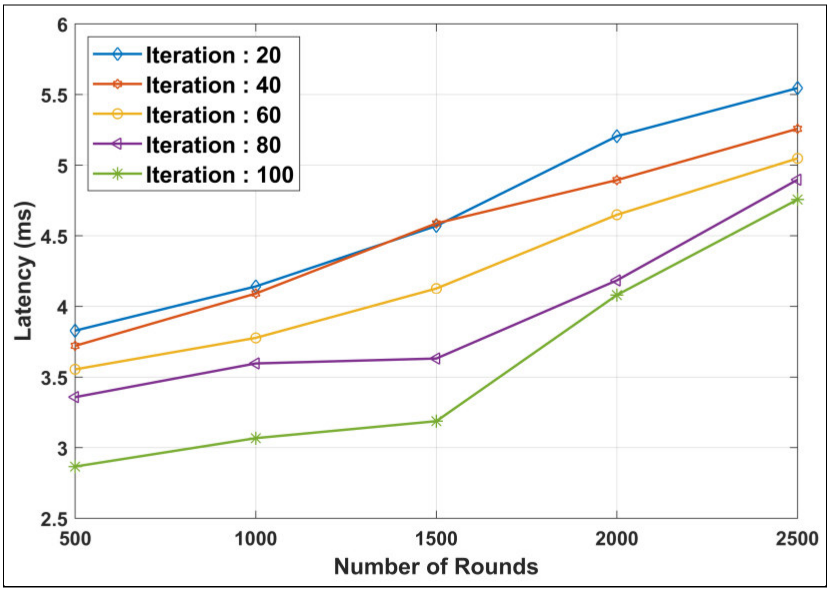


Figure 4.16: Latency based on Iteration with 50 Nodes and 10 Relay Nodes

Table 4.12: Latency based on Iteration with 50 Nodes and 10 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	3.8283	4.1413	4.5878	5.2049	5.5454
Iteration size = 40	3.7207	4.091	4.5696	4.8944	5.2575
Iteration size = 60	3.5542	3.777	4.1266	4.6486	5.0477
Iteration size = 80	3.3575	3.5962	3.631	4.1844	4.897
Iteration size = 100	2.8663	3.0672	3.1874	4.0808	4.7563

Network Life Time: The network lifetime based analysis with 50 Nodes and 10 Relay Nodes by varying the iteration size is depicted in Figure 4.17. The network lifetime estimated by the newly devised D2D communication protocol is 96.19 with 20 iteration and 500 rounds. The same is 88.65 with 2500 rounds and 20 iterations, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 90.00 with 1500 rounds and 20 iterations, which elevates with 95.68 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 4.13.

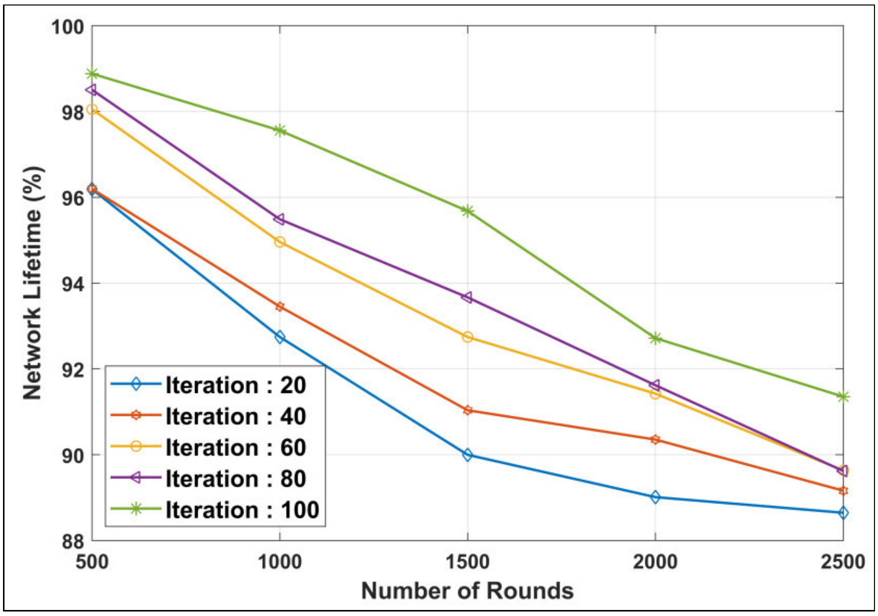


Figure 4.17: Network Life Time based on Iteration with 50 Nodes and 10 Relay Nodes

Table 4.13: Network Life Time based on Iteration with 50 Nodes and 10 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	96.19	92.74	90.00	89.01	88.65
Iteration size = 40	96.20	93.45	91.04	90.35	89.16
Iteration size = 60	98.05	94.96	92.74	91.42	89.62
Iteration size = 80	98.51	95.49	93.67	91.62	89.63
Iteration size = 100	98.88	97.56	95.68	92.72	91.35

Packet Delivery Ratio: The interpretation of the packet delivery ratio for various iteration sizes of the newly devised EnHpo algorithm of the introduced joint channel allocation and relay selection with 50 Nodes and 10 Relay Nodes is depicted in Figure 4.18. For 20 iterations, the packet delivery ratio accomplished by the newly devised protocol is 0.9929 with 500 rounds, which is 0.9037 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 0.9547 with 20 iterations and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 iterations is 0.9952 with 100 rounds. The detailed analysis is presented in Table 4.14.

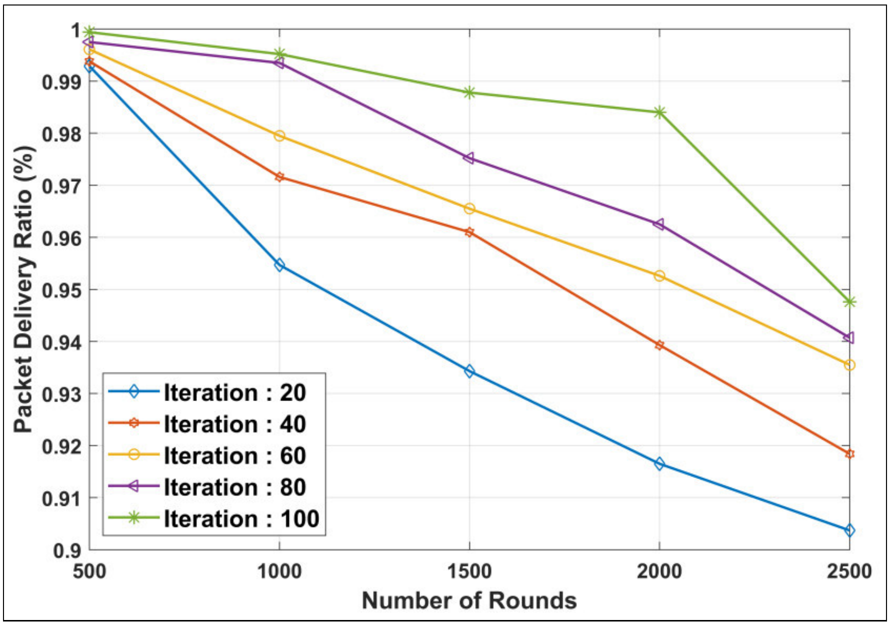


Figure 4.18: Packet Delivery Ratio based on Iteration with 50 Nodes and 10 Relay Nodes

Table 4.14: Packet Delivery Ratio based on Iteration with 50 Nodes and 10 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	0.9929	0.9547	0.9343	0.9165	0.9037
Iteration size = 40	0.9938	0.9716	0.961	0.9393	0.9184
Iteration size = 60	0.9961	0.9795	0.9655	0.9526	0.9355
Iteration size = 80	0.9975	0.9935	0.9752	0.9625	0.9407
Iteration size = 100	0.9994	0.9952	0.9878	0.984	0.9476

Throughput: The throughput based analysis of the D2D protocol by varying the iteration of the EnHpo algorithm is depicted in Figure 4.19 with 50 Nodes and 10 Relay Nodes. The throughput estimated by the newly devised protocol with 20 iterations and 500 communications round is 7264, which is 15868 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 iterations, the throughput estimated by the proposed protocol is 13427. When the iteration increased to 100, the throughput estimated is 19802 that depict the better outcome of the model with increase in iteration. The detailed analysis is presented in Table 4.15.

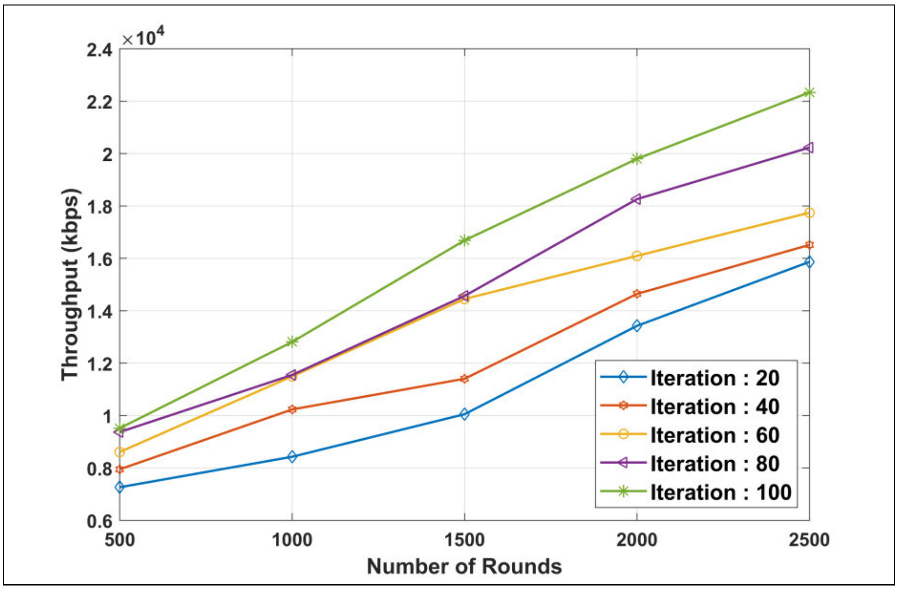


Figure 4.19: Throughput based on Iteration with 50 Nodes and 10 Relay Nodes

Table 4.15: Throughput based on Iteration with 50 Nodes and 10 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	7264	8428	10053	13427	15868
Iteration size = 40	7947	10234	11406	14646	16515
Iteration size = 60	8610	11498	14450	16097	17744
Iteration size = 80	9369	11551	14567	18263	20231
Iteration size = 100	9516	12811	16687	19802	22335

(iv) Assessment with 100 Nodes and 10 Relay Nodes

Average Residual Energy: The average residual energy by varying the number of communication rounds and iteration size of the newly devised EnHpo algorithm is depicted in Figure 4.20. The average residual energy acquired with 500 round is 0.9625 for 20 iterations, which is further reduced when the round increases to 2500 with the average residual energy of 0.7180. Hence, the elevation in the number of rounds consumes more energy. Still, the increase in iteration elevates the performance of the model by enhancing the amount of residual energy. For example, the average residual energy estimated with 20 iterations and 1000 round is 0.8958, which is 0.9504 when the iteration increased to 100. The detailed analysis is depicted in Table 4.16.

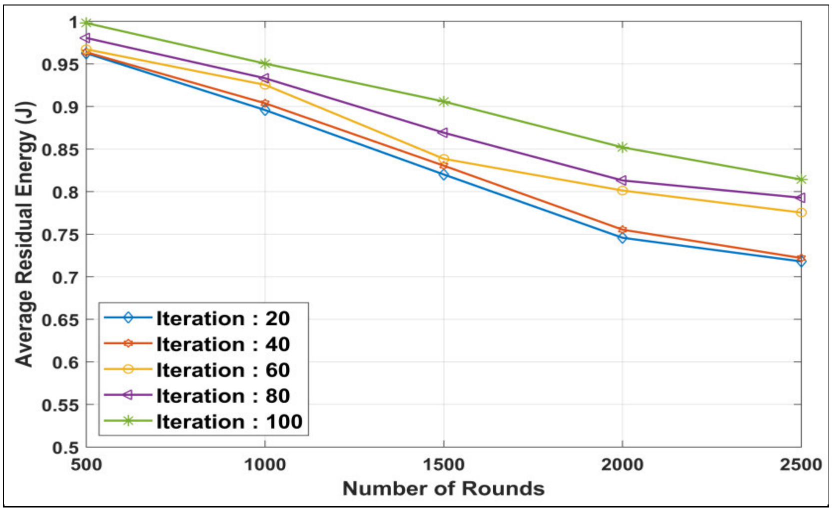


Figure 4.20: Average Residual Energy based on Iteration with 100 Nodes and 10 Relay Nodes

Table 4.16: Average Residual Energy based on Iteration with 100 Nodes and 10 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	0.9625	0.8958	0.8201	0.7457	0.7180
Iteration size = 40	0.9637	0.9038	0.8305	0.7553	0.7220
Iteration size = 60	0.9672	0.9254	0.8385	0.8013	0.7754
Iteration size = 80	0.9805	0.9331	0.8691	0.8131	0.7928
Iteration size = 100	0.9980	0.9504	0.9058	0.8520	0.8142

Latency: The latency of the D2D communication depicts the time take for the information to reach the destination from the source. The analysis based on latency by varying the iteration with 100 Nodes and 10 Relay Nodes is portrayed in Figure 4.21. While considering the 20 iterations of EnHpo algorithm with 500 rounds, the latency estimated by the proposed method is 3.5006, which is increased to 5.1638, when the round is increased to 2500. In contrast, the latency gets minimized with increase in the number of iterations of the algorithm. For example, with 1500 round and 20 iterations, the latency estimated by the newly devised method is 4.6526, which is further minimized to 3.461 with 100 iterations. Thus, the increase in iteration elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 4.17.

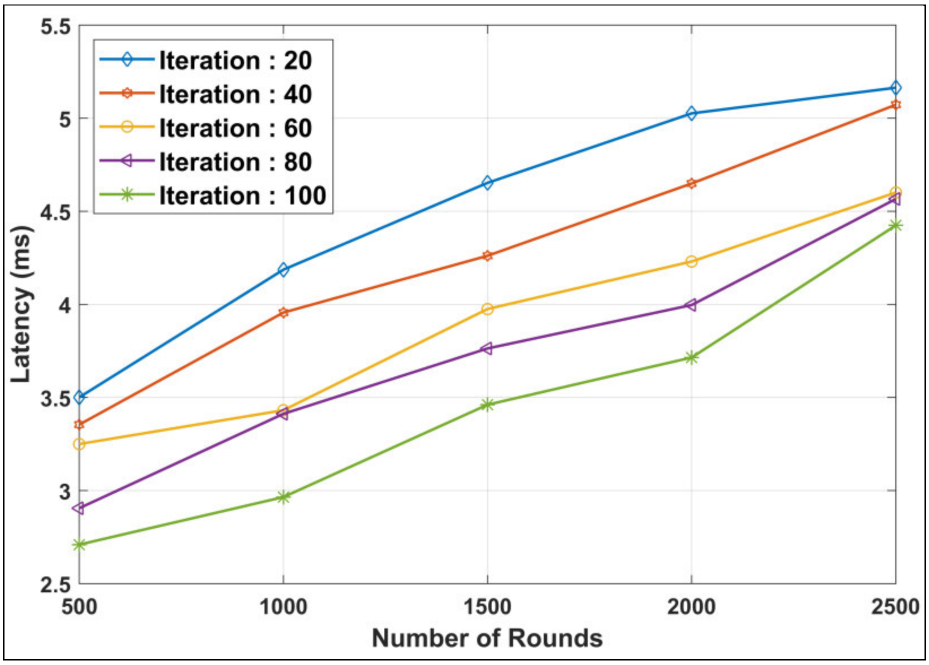


Figure 4.21: Latency based on Iteration with 100 Nodes and 10 Relay Nodes

Table 4.17: Latency based on Iteration with 100 Nodes and 10 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	3.5006	4.1863	4.6526	5.0259	5.1638
Iteration size = 40	3.3541	3.956	4.261	4.6494	5.0722
Iteration size = 60	3.2498	3.4312	3.975	4.2303	4.6007
Iteration size = 80	2.9051	3.412	3.7632	3.9966	4.5661
Iteration size = 100	2.7094	2.9649	3.461	3.7147	4.4243

Network Life Time: The network lifetime based analysis with 100 Nodes and 10 Relay Nodes by varying the iteration size is depicted in Figure 4.22. The network lifetime estimated by the newly devised protocol is 96.95 with 20 iteration and 500 rounds. The same is 90.06 with 2500 rounds and 20 iterations, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 91.40 with 1500 rounds and 20 iterations, which elevates with 96.31 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 4.18.

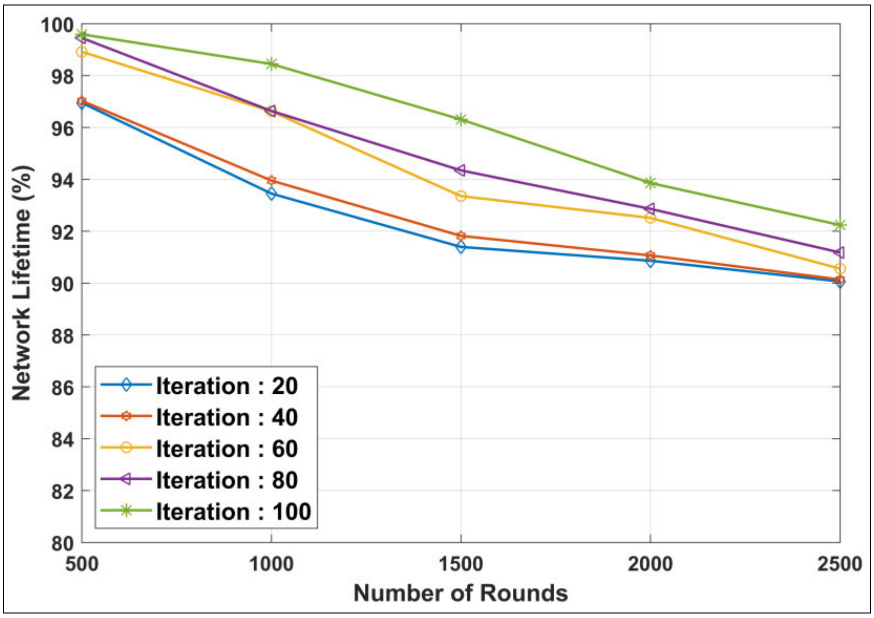


Figure 4.22: Network Life Time based on Iteration with 100 Nodes and 10 Relay Nodes

Table 4.18: Network Life Time based on Iteration with 100 Nodes and 10 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	96.95	93.45	91.40	90.86	90.06
Iteration size = 40	97.03	93.95	91.82	91.07	90.14
Iteration size = 60	98.92	96.62	93.35	92.51	90.56
Iteration size = 80	99.45	96.64	94.35	92.86	91.18
Iteration size = 100	99.59	98.45	96.31	93.86	92.24

Packet Delivery Ratio: The interpretation of the packet delivery ratio for various iteration sizes of the newly devised EnHpo algorithm of the introduced joint channel allocation and relay selection with 100 Nodes and 10 Relay Nodes is depicted in Figure 4.23. For 20 iterations, the packet delivery ration accomplished by the newly devised protocol is 0.9950 with 500 rounds, which is 0.9053 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 0.9581 with 20 iterations and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 iterations is 0.9990 with 100 rounds. The detailed analysis is presented in Table 4.19.

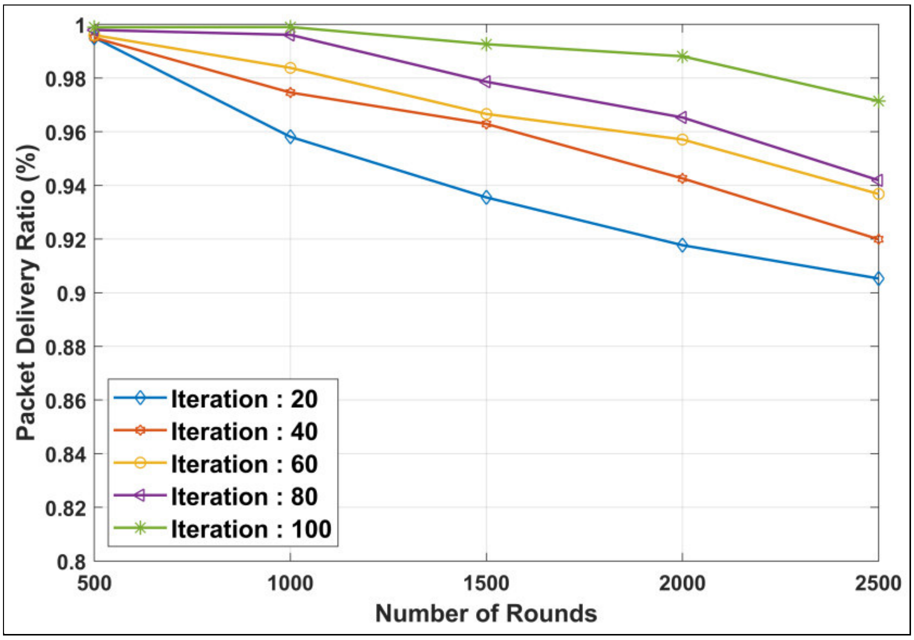


Figure 4.23: Packet Delivery Ratio based on Iteration with 100 Nodes and 10 Relay Nodes

Table 4.19: Packet Delivery Ratio based on Iteration with 100 Nodes and 10 Relay Nodes

Rounds	**500**	**1000**	**1500**	**2000**	**2500**
Iteration size = 20	0.9950	0.9581	0.9355	0.9177	0.9053
Iteration size = 40	0.9951	0.9746	0.9629	0.9426	0.9199
Iteration size = 60	0.9960	0.9838	0.9666	0.9571	0.9368
Iteration size = 80	0.9979	0.9961	0.9786	0.9653	0.9419
Iteration size = 100	0.9989	0.9990	0.9926	0.9881	0.9714

Throughput: The throughput based analysis of the D2D protocol by varying the iteration of the EnHpo algorithm is depicted in Figure 4.24 with 100 Nodes and 10 Relay Nodes. The throughput estimated by the newly devised protocol with 20 iterations and 500 communications round is 8023, which is 16588 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 iterations, the throughput estimated by the proposed protocol is 14222. When the iteration increased to 100, the throughput estimated is 20497 that depict the better outcome of the model with increase in iteration. The detailed analysis is presented in Table 4.20.

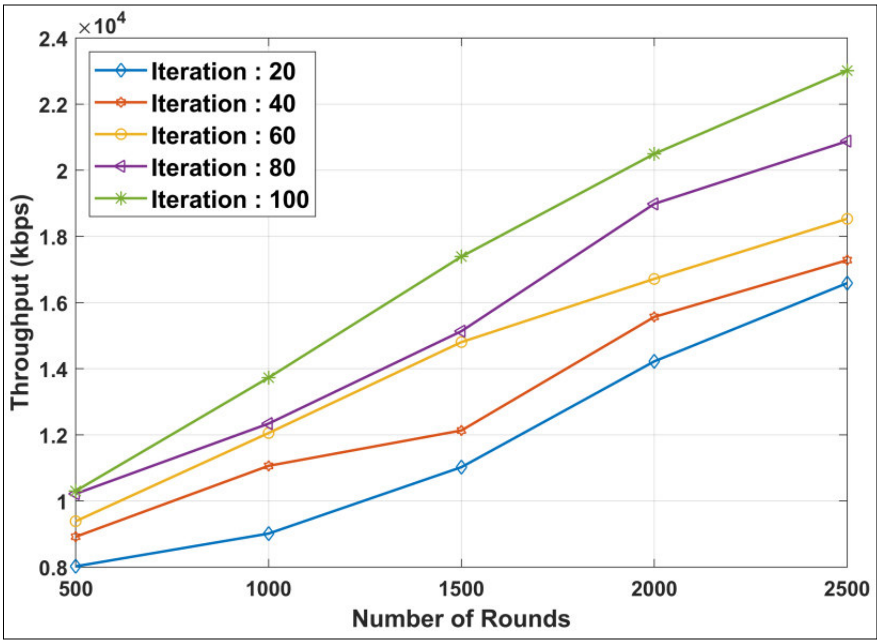


Figure 4.24: Throughput based on Iteration with 100 Nodes and 10 Relay Nodes

Table 4.20: Throughput based on Iteration with 100 Nodes and 10 Relay Nodes

Rounds	500	1000	1500	2000	2500
Iteration size = 20	8023	9013	11022	14222	16588
Iteration size = 40	8918	11062	12132	15565	17282
Iteration size = 60	9387	12054	14804	16716	18534
Iteration size = 80	10216	12338	15134	18985	20881
Iteration size = 100	10303	13728	17389	20497	23015

4.4.3 Comparative Assessment

The comparative assessment is devised by comparing the newly devised joint channel allocation and relay selection protocols for the D2D communication along with the conventional communication protocols like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach methods to indicate the superiority of the proposed model.

(i) Using 50 Nodes and 5 Relays

Average Residual Energy: The assessment based on the average residual energy is depicted in Figure 4.25 with 50 Nodes and 5 Relays. The average residual energy evaluated by the newly devised protocol is 0.9148 with 500 rounds, which is 021.96%, 21.29%, 18.00%, and 11.46% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the average residual energy evaluated by the newly devised protocol is 0.6629, which is 44.47%, 43.29%, 39.89%, and 10.06% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.21.

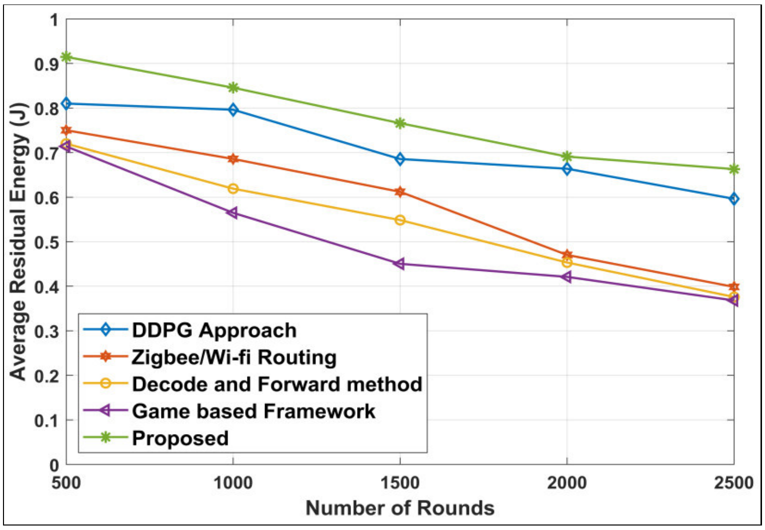


Figure 4.25: Average Residual Energy with 50 Nodes and 5 Relays

Table 4.21: Average Residual Energy with 50 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.81	0.7501	0.72	0.7139	0.9148
1000	0.7962	0.6857	0.619	0.5647	0.8456
1500	0.6855	0.6119	0.5485	0.4503	0.7659
2000	0.6637	0.4702	0.4532	0.421	0.6909
2500	0.5962	0.3985	0.3759	0.3681	0.6629

Latency: Figure 4.26 depicts the latency analysis of the proposed method by considering 50 Nodes and 5 Relays. While considering the 500 rounds, the latency evaluated by the newly devised protocol is 3.372 that is 957.99%, 47.73%, 45.96%, and 13.68% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. Also, the latency estimated by the newly devised protocol is 4.942 with 2500 rounds that is 58.58%, 54.31%, 47.10%, and 40.99% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.22.

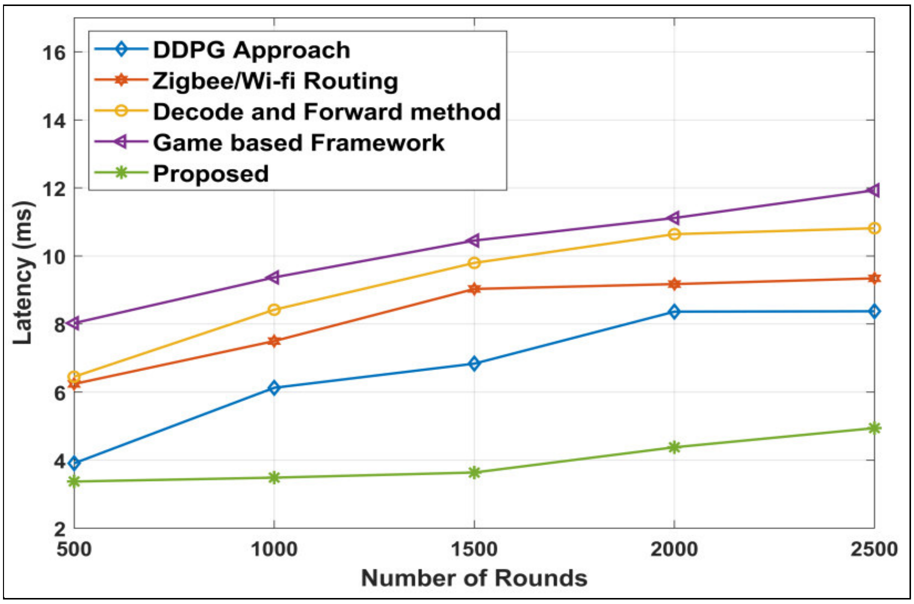


Figure 4.26: Latency with 50 Nodes and 5 Relays

Table 4.22: Latency with 50 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	3.9063	6.2395	6.4506	8.0265	3.372
1000	6.127	7.4992	8.42	9.3706	3.486
1500	6.836	9.0311	9.7966	10.454	3.637
2000	8.3643	9.1743	10.6417	11.117	4.379
2500	8.3755	9.343	10.8161	11.9313	4.942

Network Life Time: The network lifetime analysis is portrayed in Figure 4.27 and its detailed analysis is presented in Table 4.23. In this, the newly devised protocol accomplished the higher network life time of 95.7195; still the conventional methods like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach accomplished degraded network life time of 11.00%, 9.58%, 6.77%, and 5.68% respectively with 500 rounds. Here, the newly devised protocol accomplished 89.9195 Network lifetime with 2500 rounds, which is 15.30%, 13.21%, 11.60%, and 8.85% elevated outcome as compared to the existing like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach.

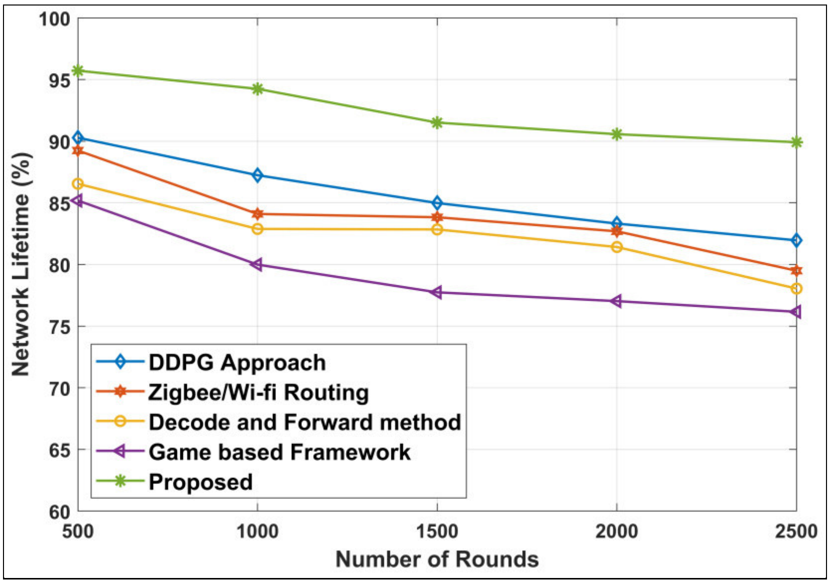


Figure 4.27: Network Life Time with 50 Nodes and 5 Relays

Table 4.23: Network Life Time with 50 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	90.2853	89.2435	86.5465	85.1869	95.7195
1000	87.2405	84.0981	82.8833	79.9888	94.2445
1500	84.9824	83.8301	82.8419	77.7384	91.5069
2000	83.3158	82.6898	81.4155	77.0263	90.5669
2500	81.958	79.4913	78.0443	76.1605	89.9195

Packet Delivery Ratio: The reception amount of information depicts the measure of packet deliver ratio; thus the higher value indicates the better outcome. The analysis of the packet delivery ratio with 50 Nodes and 5 Relays is depicted in Figure 4.28, wherein the newly devised protocol acquired the superior outcome. For example, the newly devised protocol acquired the packet delivery ratio of 0.998 with 500 rounds; still the conventional methods Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach acquired 24.48%, 11.81%, 10.19%, and 7.77% degraded outcome. Here, the newly devised protocol acquired the packet delivery ratio of 0.934 with 2500 rounds, which is 59.46%, 51.00%, 43.17%, and 37.92% superior concerning the Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approaches. The detailed analysis is presented in Table 4.24.

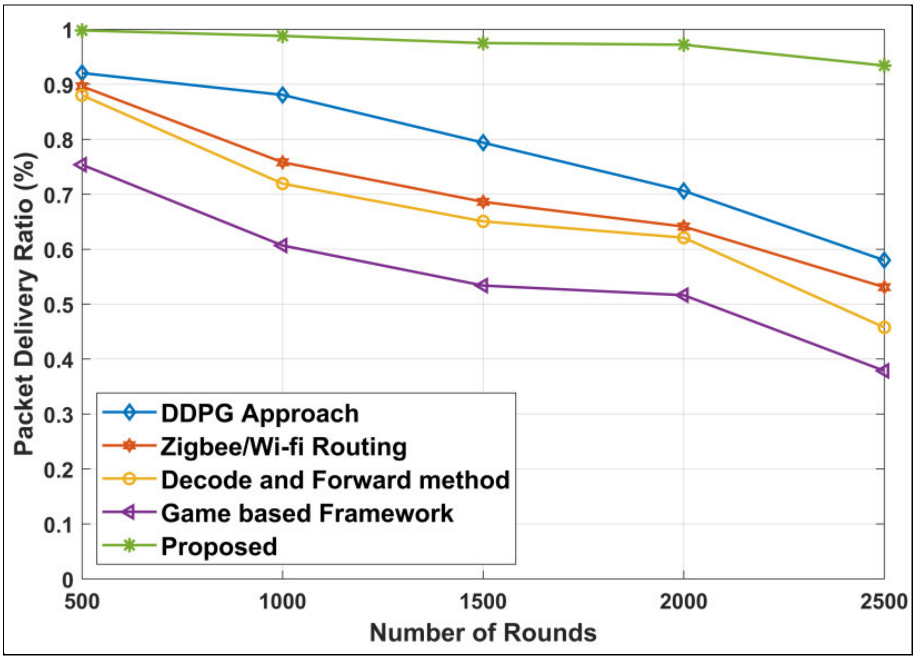


Figure 4.28: Packet Delivery Ratio with 50 Nodes and 5 Relays

Table 4.24: Packet Delivery Ratio with 50 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.9205	0.8963	0.8801	0.7537	0.998
1000	0.8807	0.7581	0.7193	0.6067	0.988
1500	0.7937	0.6861	0.6506	0.5338	0.975
2000	0.7061	0.6411	0.6209	0.5163	0.972
2500	0.5798	0.5308	0.4577	0.3786	0.934

Throughput: The throughput based interpretation with 50 Nodes and 5 Relays is portrayed in Figure 4.29. The throughput evaluated by the newly devised protocol is 7940 with 500 rounds, which is 2.19%, 25.35%, 27.14%, and 61.05% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the throughput evaluated by the newly devised protocol is 19941, which is 6.92%, 29.02%, 32.19%, and 32.61% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.25.

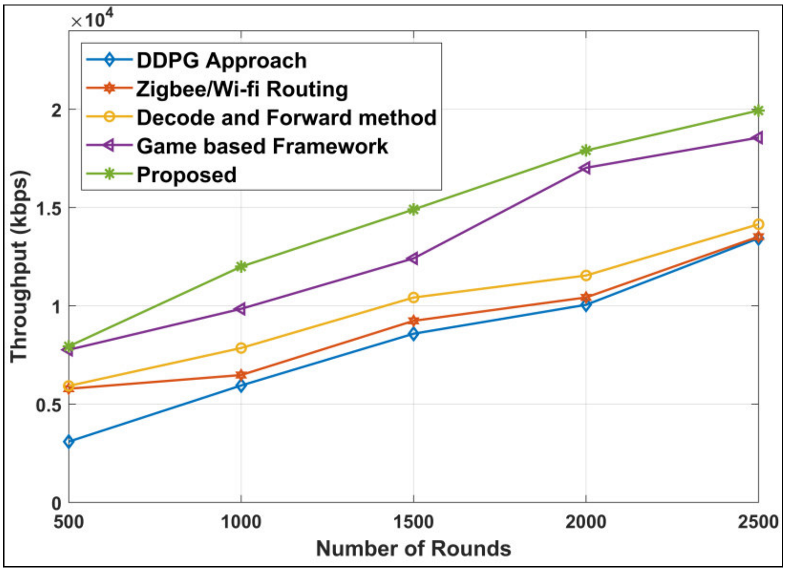


Figure 4.29: Throughput with 50 Nodes and 5 Relays

Table 4.25: Throughput with 50 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	3093	5785	5927	7766	7940
1000	5950	6481	7856	9850	11996
1500	8585	9241	10426	12418	14906
2000	10056	10431	11547	17026	17908
2500	13439	13521	14154	18562	19941

(ii) Using 100 Nodes and 5 Relays

Average Residual Energy: The assessment based on the average residual energy is depicted in Figure 4.30 with 100 Nodes and 5 Relays. The average residual energy evaluated by the newly devised protocol is 0.9658 with 500 rounds, which is 13.32%, 11.65%, 6.54%, and 3.81% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the average residual energy evaluated by the newly devised protocol is 0.7797, which is 40.17%, 37.33%, 34.26%, and 16.11% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.26.

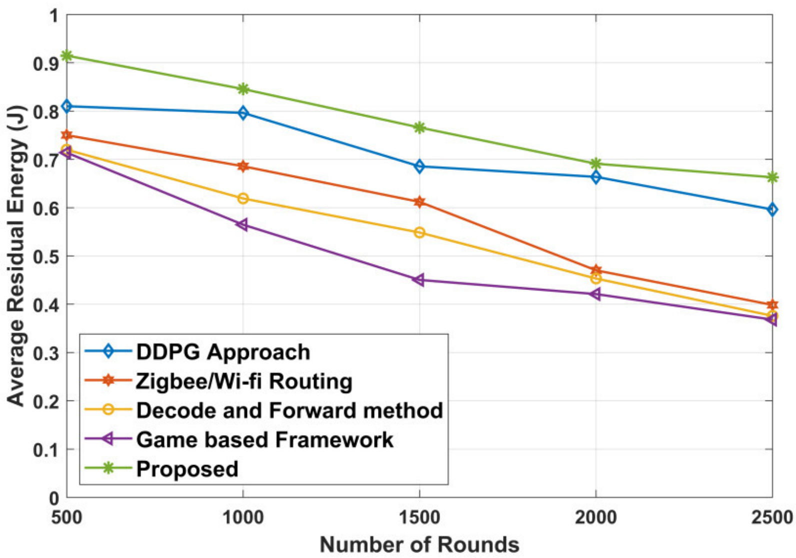


Figure 4.30: Average Residual Energy with 100 Nodes and 5 Relays

Table 4.26: Average Residual Energy with 100 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.929	0.9026	0.8533	0.8372	0.9658
1000	0.892	0.826939	0.6881	0.6387	0.916
1500	0.80191	0.69487	0.6239	0.571	0.8611
2000	0.75696	0.5641	0.5203	0.503	0.8182
2500	0.65407	0.5126	0.4886	0.4665	0.7797

Latency: Figure 4.31 depicts the latency analysis of the proposed method by considering 100 Nodes and 5 Relays. While considering the 500 rounds, the latency evaluated by the newly devised protocol is 3.3621 that is 45.13%, 44.25%, 36.78%, and 9.13% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. Also, the latency estimated by the newly devised protocol is 4.9322 with 2500 rounds that is 56.88%, 50.97%, 44.66%, and 37.25% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.27.

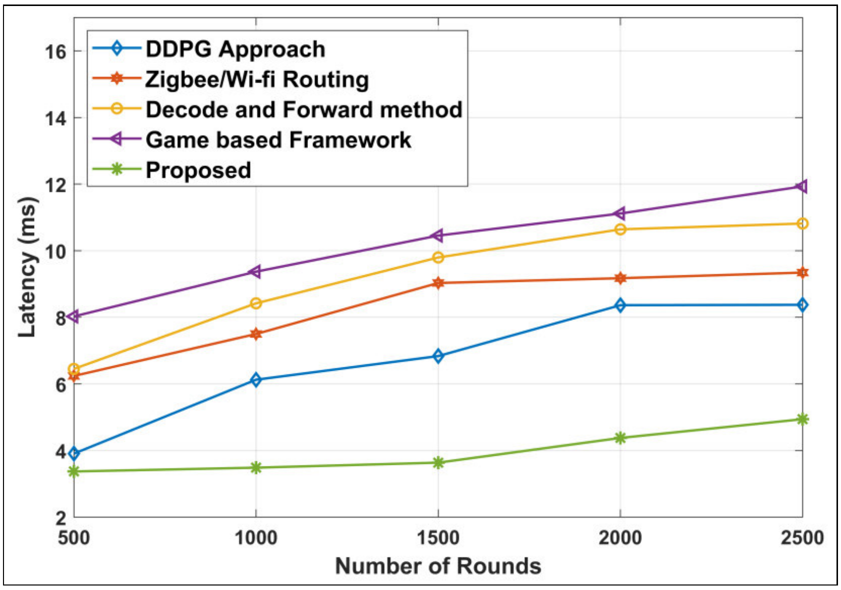


Figure 4.31: Latency with 100 Nodes and 5 Relays

Table 4.27: Latency with 100 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	3.7	5.3184	6.0306	6.1275	3.3621
1000	4.475	6.0644	7.124	7.4176	3.4769
1500	5.731	7.4258	8.1839	9.2048	3.6276
2000	6.9562	8.0865	9.2284	10.2142	4.3697
2500	7.8607	8.912	10.06	11.4379	4.9322

Network Life Time: The network lifetime analysis is portrayed in Figure 4.32 and its detailed analysis is presented in Table 4.28. In this, the newly devised protocol accomplished the higher network life time of 97.3561; but the conventional methods like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach accomplished the degraded outcome of 7.23%, 6.17%, 4.43%, and 1.85% respectively. Here, the newly devised protocol accomplished the higher network life time of 90.6763, which is 8.58%, 8.19%, 7.34%, and 6.53% elevated outcome as compared to the existing like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach.

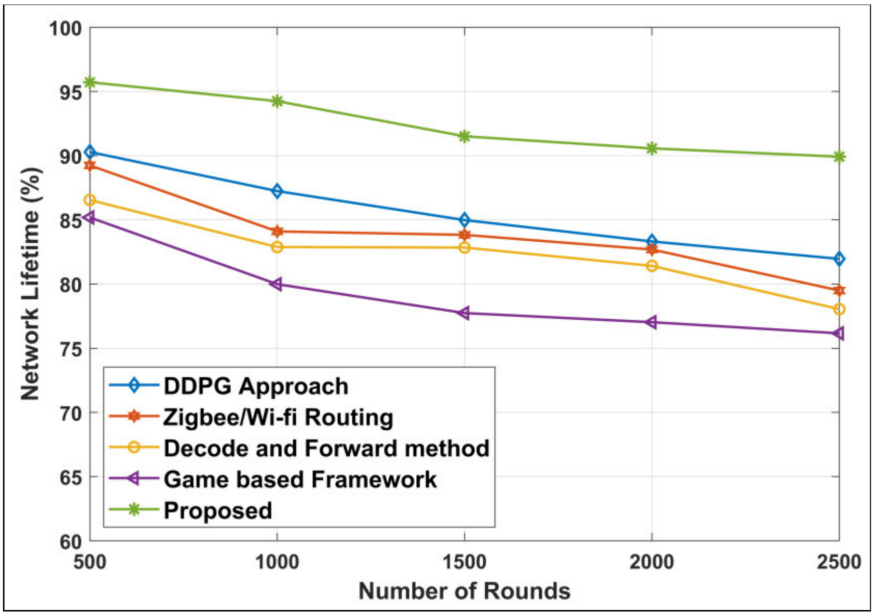


Figure 4.32: Network Life Time with 100 Nodes and 5 Relays

Table 4.28: Network Life Time with 100 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	95.5598	93.0434	91.3457	90.3181	97.3561
1000	93.9258	91.3379	88.9753	88.4894	95.8592
1500	91.1016	88.3035	87.0861	85.8486	94.0952
2000	87.9435	86.2365	85.207	84.7813	92.0501
2500	84.7531	84.0249	83.2525	82.8952	90.6763

Packet Delivery Ratio: The reception amount of information depicts the measure of packet deliver ratio; thus the higher value indicates the better outcome. The analysis of the packet delivery ratio with 100 Nodes and 5 Relays is depicted in Figure 4.33, wherein the newly devised protocol acquired the superior outcome. For example, the newly devised protocol acquired the packet delivery ratio of 0.9973 with 500 rounds; but the conventional methods Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach acquired the 17.45%, 8.59%, 7.92%, and 4.57% degraded outcome. Here, the newly devised protocol acquired the packet delivery ratio of 0.9431, which is 48.51%, 35.76%, 33.78%, and 28.25% enhanced outcome concerning the conventional Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is presented in Table 4.29.

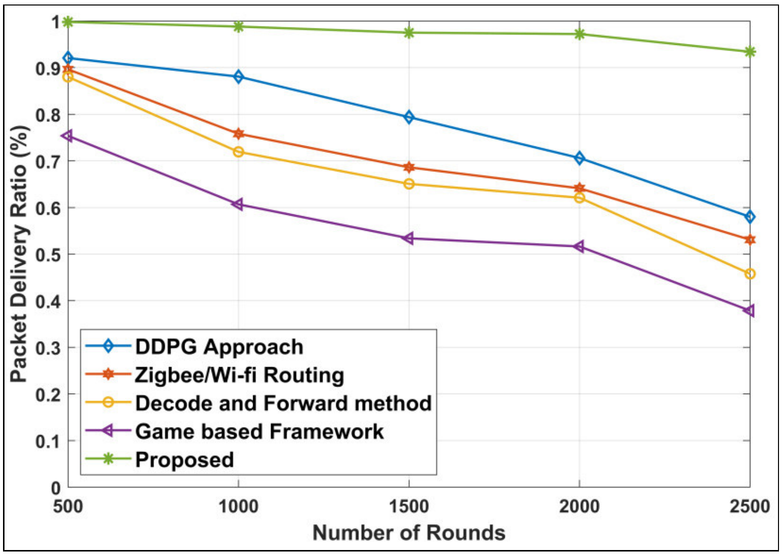


Figure 4.33: Packet Delivery Ratio with 100 Nodes and 5 Relays

Table 4.29: Packet Delivery Ratio with 100 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.9517	0.9183	0.9116	0.8233	0.9973
1000	0.9065	0.8355	0.7897	0.683	0.9908
1500	0.8885	0.7475	0.6817	0.6357	0.9847
2000	0.8463	0.7247	0.6298	0.6128	0.9812
2500	0.6767	0.6245	0.6059	0.4856	0.9431

Throughput: The throughput based interpretation with 100 Nodes and 5 Relays is portrayed in Figure 4.34. The throughput evaluated by the newly devised protocol is 8843 with 500 rounds, which is 12.18%, 32.98%, 34.58%, and 65.02% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the throughput evaluated by the newly devised protocol is 21363, which is 13.11%, 33.75%, 36.71%, and 37.09% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.30.

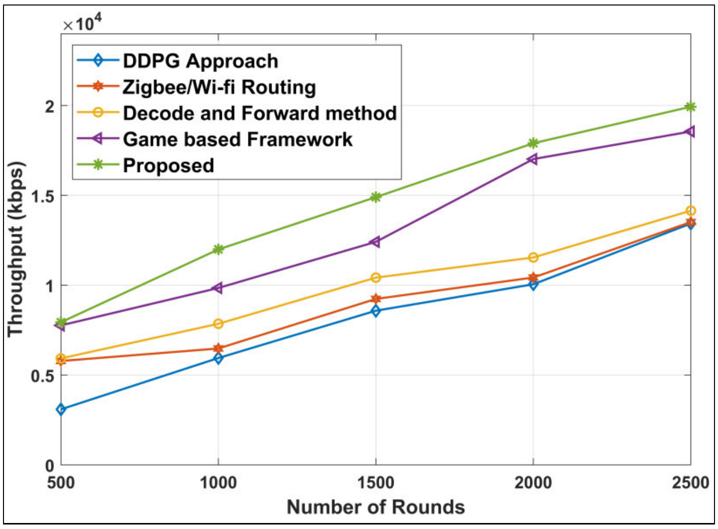


Figure 4.34: Throughput with 100 Nodes and 5 Relays

Table 4.30: Throughput with 100 Nodes and 5 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	3093	5785	5927	7766	8843
1000	5950	6481	7856	9850	12275
1500	8585	9241	10426	12418	16143
2000	10056	10431	11547	17026	18903
2500	13439	13521	14154	18562	21363

(iii) Using 50 Nodes and 10 Relays

Average Residual Energy: The assessment based on the average residual energy is depicted in Figure 4.35 with Using 50 Nodes and 10 Relays. The average residual energy evaluated by the newly devised protocol is 0.9819 with 500 rounds, which is 7.93%, 5.06%, 4.99%, and 4.86% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the average residual energy evaluated by the newly devised protocol is 0.7979, which is 17.67%, 14.70%, 7.38%, and 6.27% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.31.

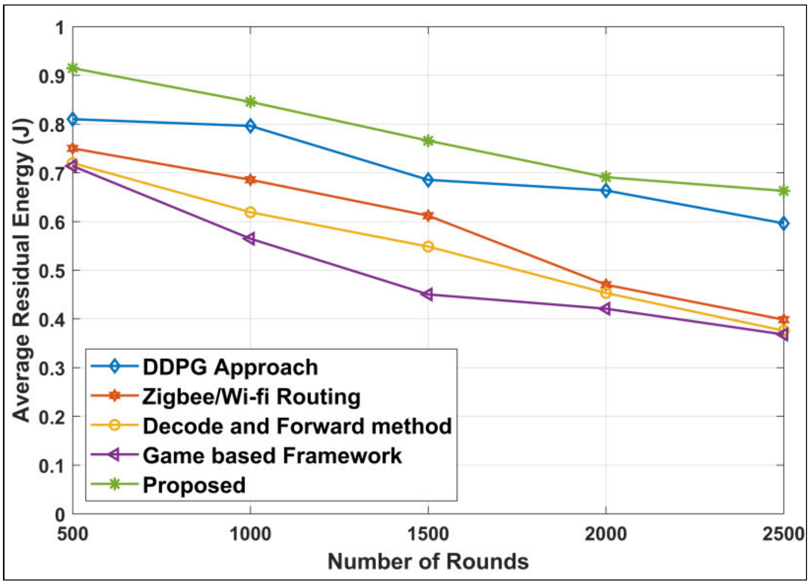


Figure 4.35: Average Residual Energy with 50 Nodes and 10 Relays

Table 4.31: Average Residual Energy with 50 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.9342	0.9329	0.9322	0.904	0.9819
1000	0.8919	0.8802	0.8661	0.8415	0.9529
1500	0.8237	0.8062	0.7745	0.7743	0.8789
2000	0.7738	0.7683	0.7232	0.7146	0.8344
2500	0.7479	0.739	0.6806	0.6569	0.7979

Latency: Figure 4.36 depicts the latency analysis of the proposed method by considering 50 Nodes and 10 Relays. While considering the 500 rounds, the latency evaluated by the newly devised protocol is 2.8663 that is 50.39%, 40.01%, 33.38%, and 27.95% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. Also, the latency estimated by the newly devised protocol is 4.7563 with 2500 rounds that is 50.30%, 48.53%, 43.61%, and 28.84% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.32.

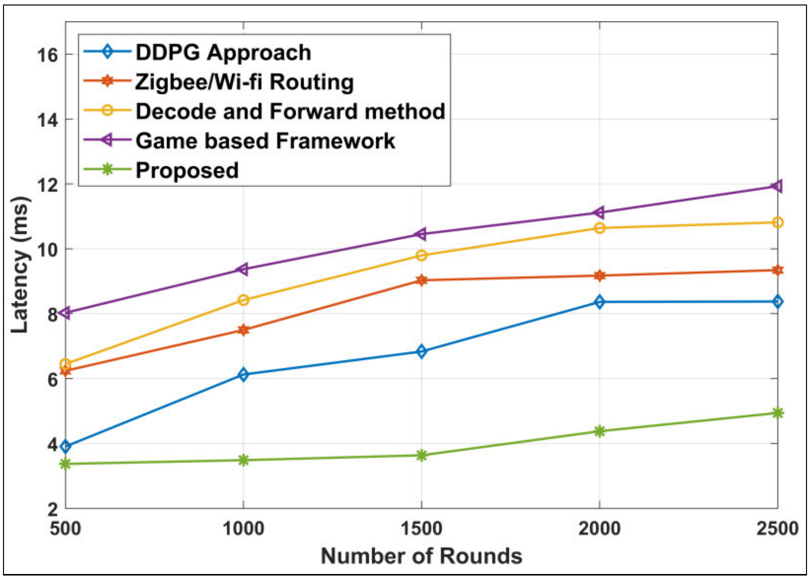


Figure 4.36: Latency with 50 Nodes and 10 Relays

Table 4.32: Latency with 50 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	3.978	4.3025	4.7779	5.7771	2.8663
1000	4.7018	5.0849	5.9417	6.7119	3.0672
1500	5.521	5.9668	6.8569	7.2727	3.1874
2000	5.9921	6.6605	8.213	8.7616	4.0808
2500	6.6839	8.4346	9.2414	9.5705	4.7563

Network Life Time: The network lifetime analysis is portrayed in Figure 4.37 and its detailed analysis is presented in Table 4.33. In this, the newly devised protocol accomplished the higher network life time of 98.8817; but 9.67%, 7.26%, 4.51%, and 0.55% degraded outcome is accomplished by the conventional methods like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach with 500 rounds. Here, the newly devised protocol accomplished the higher network life time of 91.3525, which is 9.28%, 6.46%, 5.57%, and 3.26% elevated outcome as compared to the existing like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach with 2500 rounds.

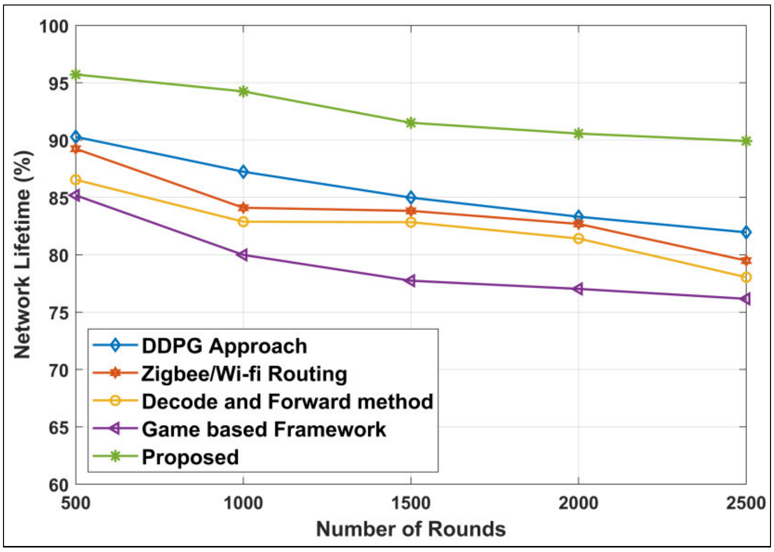


Figure 4.37: Network Life Time with 50 Nodes and 10 Relays

Table 4.33: Network Life Time with 50 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	98.3384	94.4185	91.7076	89.3176	98.8817
1000	92.5049	90.703	89.5894	88.6218	97.5573
1500	91.4707	88.8	88.3979	87.1463	95.6793
2000	90.4793	88.3374	87.0163	85.6733	92.7156
2500	88.3726	86.2596	85.455	82.8747	91.3525

Packet Delivery Ratio: The reception amount of information depicts the measure of packet deliver ratio; thus the higher value indicates the better outcome. The analysis of the packet delivery ratio with 50 Nodes and 10 Relays is depicted in Figure 4.38, wherein the newly devised protocol acquired the superior outcome. For example, the newly devised protocol acquired the packet delivery ratio of 0.9994 with 500 rounds; but 3.29%, 2.26%, 4.23%, and 1.72% superior compared to the conventional methods like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. Here, newly devised protocol acquired the packet delivery ratio of 0.9476 with 2500 rounds that accomplished the performance enhancement of 34.90%, 30.86%, 27.26%, and 12.47% concerning the Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is presented in Table 4.34.

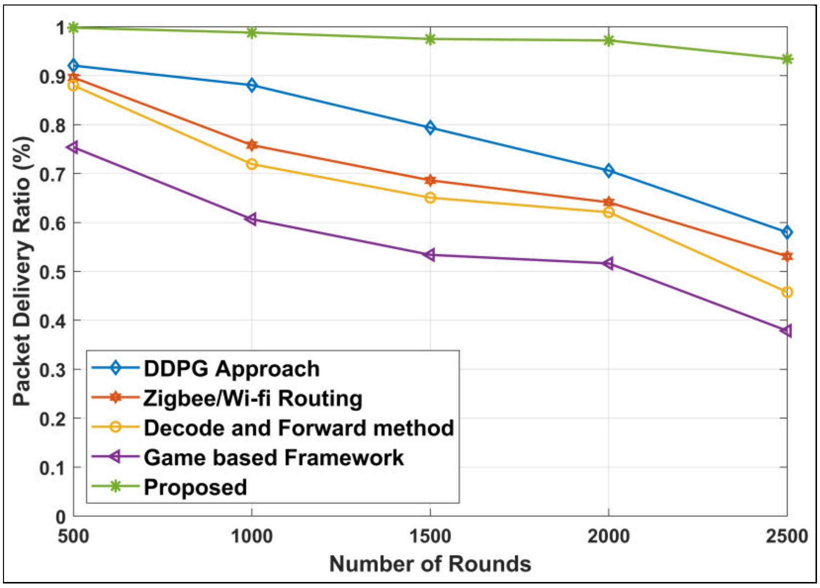


Figure 4.38: Packet Delivery Ratio with 50 Nodes and 10 Relays

Table 4.34: Packet Delivery Ratio with 50 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.9822	0.9571	0.9768	0.9665	0.9994
1000	0.9328	0.8703	0.8451	0.7581	0.9952
1500	0.8826	0.8283	0.7587	0.732	0.9878
2000	0.8699	0.8213	0.7319	0.6445	0.984
2500	0.8294	0.6893	0.6552	0.6169	0.9476

Throughput: The throughput based interpretation with 50 Nodes and 10 Relays is portrayed in Figure 4.39. The throughput evaluated by the newly devised protocol is 9516 with 500 rounds, which is 1.54%, 9.52%, 16.49%, and 23.67% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the throughput evaluated by the newly devised protocol is 22335, which is 9.42%, 20.56%, 26.06%, and 28.95% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.35.

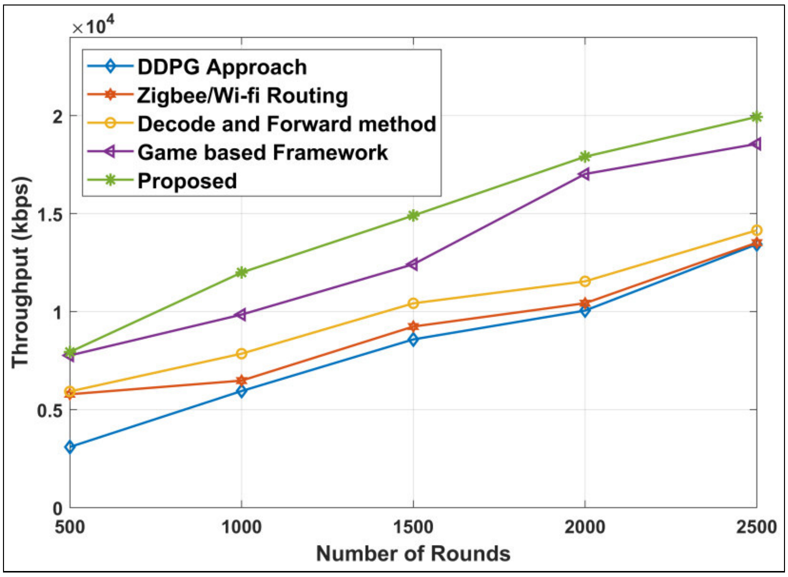


Figure 4.39: Throughput with 50 Nodes and 10 Relays

Table 4.35: Throughput with 50 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	7264	7947	8610	9369	9516
1000	8428	10234	11498	11551	12811
1500	10053	11406	14450	14567	16687
2000	13427	14646	16097	18263	19802
2500	15868	16515	17744	20231	22335

(iii) Using 100 Nodes and 10 Relays

Average Residual Energy: The assessment based on the average residual energy is depicted in Figure 4.40 with 100 Nodes and 10 Relays. The average residual energy evaluated by the newly devised protocol is 0.9980 with 500 rounds, which is 8.51%, 7.86%, 5.74%, and 3.73% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the average residual energy evaluated by the newly devised protocol is 0.8142, which is 15.97%, 13.56%, 9.10%, and 7.04% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.36.

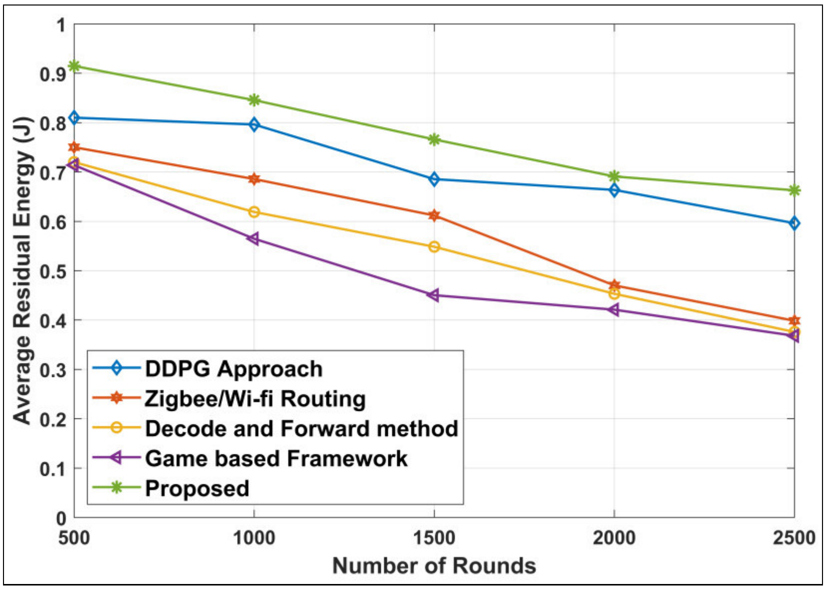


Figure 4.40: Average Residual Energy with 100 Nodes and 10 Relays

Table 4.36: Average Residual Energy with 100 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.9608	0.9407	0.9196	0.9130	0.9980
1000	0.9145	0.8926	0.8718	0.8565	0.9504
1500	0.8396	0.8233	0.8068	0.7805	0.9058
2000	0.7977	0.7881	0.7444	0.7175	0.8520
2500	0.7569	0.7401	0.7038	0.6842	0.8142

Latency: Figure 4.41 depicts the latency analysis of the proposed method by considering 100 Nodes and 10 Relays. While considering the 500 rounds, the latency evaluated by the newly devised protocol is 2.7094 that is 41.02%, 35.55%, 40.35%, and 33.73% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. Also, the latency estimated by the newly devised protocol is 4.4243 with 2500 rounds that is 52.72%, 48.01%, 42.87%, and 28.62% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.37.

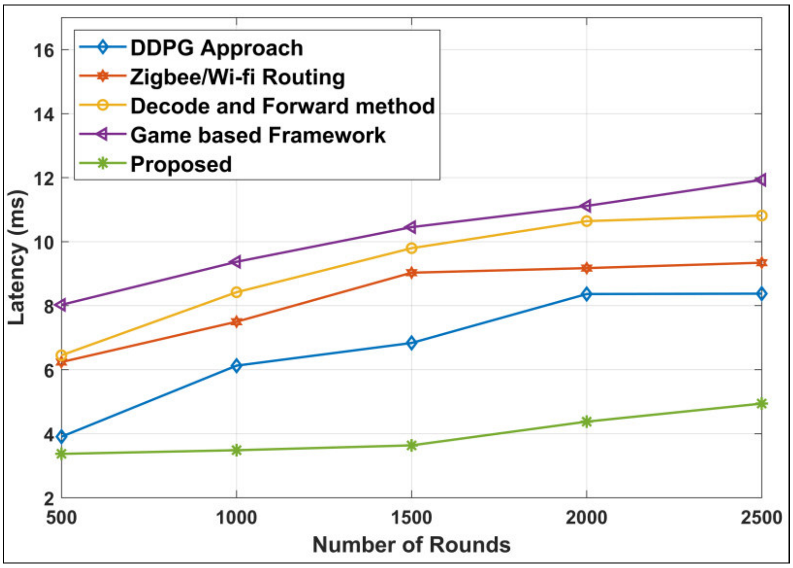


Figure 4.41: Latency with 100 Nodes and 10 Relays

Table 4.37: Latency with 100 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	4.0885	4.5424	4.2042	4.5938	2.7094
1000	4.5363	4.8508	5.6339	5.5944	2.9649
1500	5.2472	6.4409	6.7365	7.5583	3.461
2000	5.941	7.6243	8.2066	8.5718	3.7147
2500	6.198	7.7445	8.5104	9.35791	4.4243

Network Life Time: The network lifetime analysis is portrayed in Figure 4.42 and its detailed analysis is presented in Table 4.38. In this, the newly devised protocol accomplished the higher network life time of 99.5921; it is 6.62%, 4.66%, 2.67%, and 2.37% superior compared to the conventional methods like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach with 500 rounds. Here, the newly devised protocol accomplished the higher network life time of 92.2384; it is 22.88%, 13.24%, 12.59%, and 11.16% superior compared to the conventional methods like Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach with 2500 rounds.

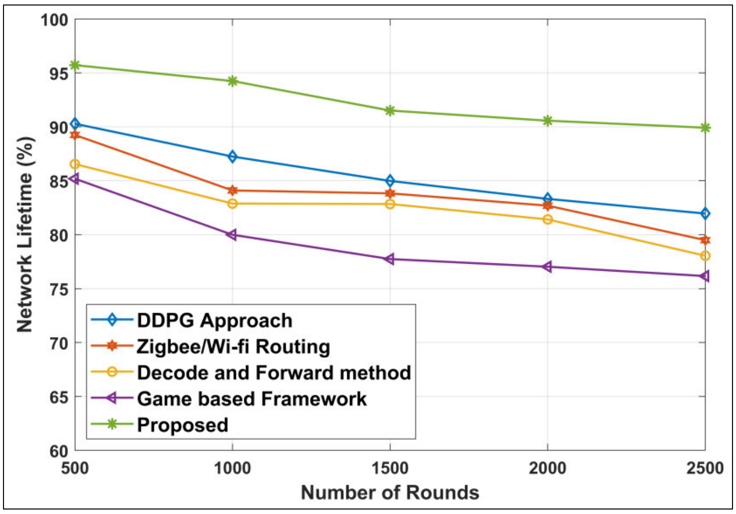


Figure 4.42: Network Life Time with 100 Nodes and 10 Relays

Table 4.38: Network Life Time with 100 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	97.2319	96.9377	94.9471	92.9992	99.5921
1000	94.2967	90.7627	89.3988	83.1402	98.4475
1500	87.2829	85.7078	83.6951	80.0235	96.3095
2000	83.7207	81.8668	80.7718	76.8964	93.8597
2500	81.9402	80.6293	80.0269	71.1314	92.2384

Packet Delivery Ratio: The reception amount of information depicts the measure of packet deliver ratio; thus the higher value indicates the better outcome. The analysis of the packet delivery ratio with 100 Nodes and 10 Relays is depicted in Figure 4.43, wherein the newly devised protocol acquired the superior outcome. For example, the newly devised protocol acquired the packet delivery ratio of 0.9989 with 500 rounds, which is 8.04%, 6.16%, 6.04%, and 1.09% better than the conventional methods Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. Here, newly devised protocol acquired the packet delivery ratio of 0.9714, which is 23.40%, 21.41%, 13.37%, and 9.87% better than the conventional methods Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach with 2500 rounds. The detailed analysis is presented in Table 4.39.

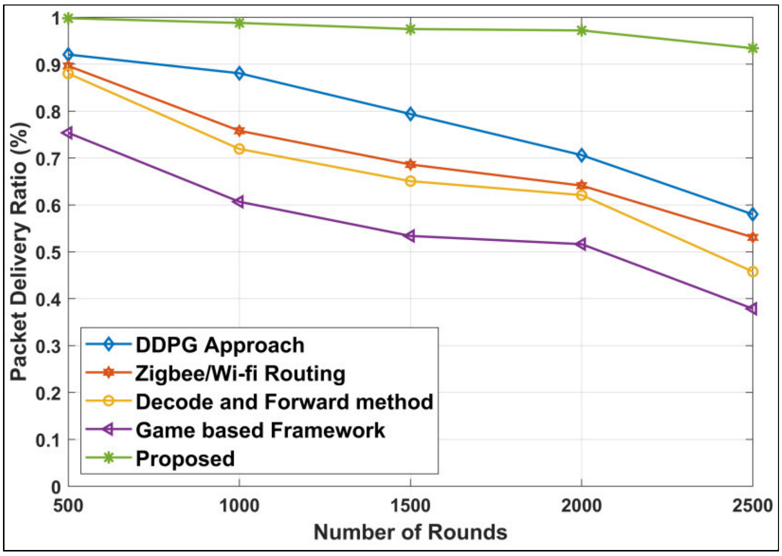


Figure 4.43: Packet Delivery Ratio with 100 Nodes and 10 Relays

Table 4.39: Packet Delivery Ratio with 100 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	0.988	0.9386	0.9374	0.9186	0.9989
1000	0.9338	0.9191	0.9054	0.852	0.999
1500	0.8989	0.8878	0.8524	0.8065	0.9926
2000	0.8783	0.8684	0.804	0.7646	0.9881
2500	0.8755	0.8415	0.7634	0.7441	0.9714

Throughput: The throughput based interpretation with 100 Nodes and 10 Relays is portrayed in Figure 4.44. The throughput evaluated by the newly devised protocol is 10303 with 500 rounds, which is 34.29%, 42.01%, 42.77%, and 64.37% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. For 2500 rounds, the throughput evaluated by the newly devised protocol is 23015, which is 8.00%, 29.98%, 41.63%, and 54.73% improved outcome compared to the existing Game based Framework, Decode and Forward method, Zigbee/WiFi Routing, and DDPG Approach. The detailed analysis is depicted in Table 4.40.

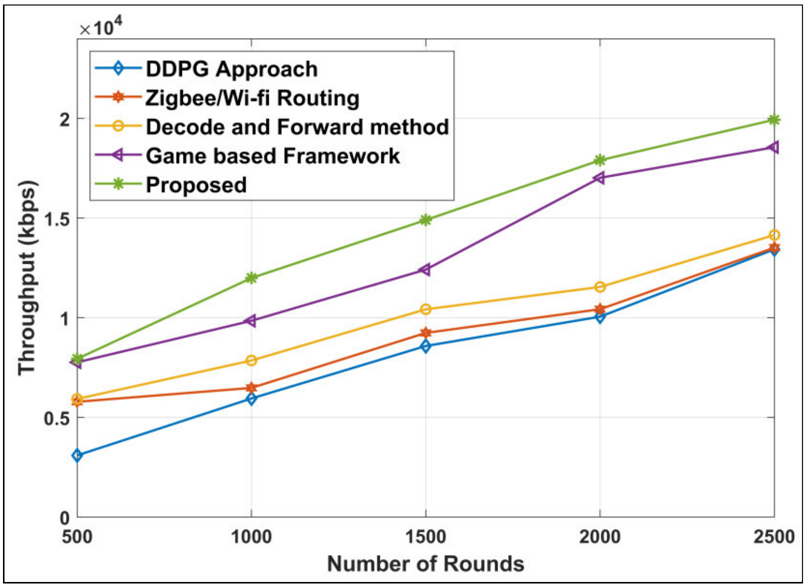


Figure 4.44: Throughput with 100 Nodes and 10 Relays

Table 4.40: Throughput with 100 Nodes and 10 Relays

Rounds/ Methods	DDPG Approach	Zigbee/Wi-fi Routing	Decode and Forward method	Game based Framework	Proposed
500	3671	5896	5975	6770	10303
1000	3719	7713	9545	9824	13728
1500	5437	9171	11098	13863	17389
2000	7002	11275	13986	17986	20497
2500	10418	13433	16114	21173	23015

4.4.4 Discussion

The assessment based on several evaluation criteria illustrates the superiority of the suggested approach. The introduction of a combined channel allocation and relay selection mechanism is what makes the performance better. By taking into account the priority, bandwidth, and transmission rate, the suggested optimum channel allocation approach selects the best channel. In addition, the model's aptitude for balanced local and global search assures the fastest convergence rate and the best overall solution. Utilizing deep reinforcement learning criteria, the relay is chosen once the best channel has been found. Here, the relay selection approach is used with a minimally computationally intensive channel increase based on bit error rate. As a result, the analysis shows the better result.

4.5 Summary

With the use of deep reinforcement learning, this study presented a deep learning technique for joint channel allocation and relay selection. Using the suggested EnHpo algorithm and many fitness functions, including priority, bandwidth, and transmission rate, the channel allocation is originally determined like this. The adaptive weight method is combined with the traditional hunter-prey optimization in the proposed EnHpo to increase convergence and the acquisition of the optimal global solution. Then, using deep reinforcement learning, the channel gain based on bit error rate is taken into consideration while choosing the relay. So, in comparison to the traditional cooperative routing strategies, the suggested strategy achieved greater results. The evaluation using Average Residual Energy, Latency, Network Life Time, Packet Delivery Ratio, and Throughput obtained values of 0.998, 2.709, 99.592, 0.999, and 23015, respectively.

MULTI-OBJECTIVE HYBRID OPTIMIZATION BASED ENERGY EFFICIENT D2D COMMUNICATION WITH DEEP REINFORCEMENT LEARNING ROUTING PROTOCOL

CHAPTER - 5

MULTI-OBJECTIVE HYBRID OPTIMIZATION BASED ENERGY EFFICIENT D2D COMMUNICATION WITH DEEP REINFORCEMENT LEARNING ROUTING PROTOCOL

5.1 Introduction

Device-to-device (D2D) communication represents the B5G wireless network protocols with highest capability by offering spectrum efficiency, energy efficiency, low latency, ubiquity, and high data rates for peer-to-peer users. The advantages of D2D protocol makes it capable of being fully utilized in multi-hop interaction scenarios. Although it is a difficult functioning, energy-efficient multi-hop networking is widely utilized for efficient communication. As a result, a multi-hop routing system based on deep reinforcement learning is presented. The suggested double deep Q learning technique for discovering the potential paths in this takes into account the energy consumption. Here, the Gannet Chimp optimization (GCO) algorithm is introduced for the selection of optimal path by considering the fitness function based on multi-objective factors for enhancing the performance of the model.

5.2. Problem Statement

Through an effective communication approach, D2D communication can take advantage of possibilities created by mobile users frequently moving from one location to other. During these unplanned conversations among people, motion is intimately related to the data flow that occurs. Through the utilization of customer activity, D2D-compatible applications and services can visualize very ad hoc and unpredictable activities. It is challenging to meet all of the demands of the consumer because their requirements are complicated. The key concern is effectively anticipating the growth of communication relationships between D2D consumers. Movement has an effect on all aspects of the D2D system, particularly operating area, strength of the signal, and bandwidth requirements.D2D communication using 5G wireless technologies is widely employed in a variety of application industries, such as the emergency communications, auto industry, and many others. Despite the existence of a number of fascinating researches on conversations between devices which have contributed significantly to and boosted awareness of D2D interactions, the essential discipline of activity study keeps on growing. For instance, reduction of interference, capacity and offload, efficacy in terms of energy, delay, and many other concerns are now being addressed by routing protocols; nevertheless, the creation of an energy-efficient routing is a more crucial task.

5.3. Proposed Energy Efficient D2D Communication for 5G Networks

In this research, a multi-hop routing technique for energy-efficient D2D communication between 5G users of the network is proposed. The suggested double deep Q learning first identify the potential routes for D2D interaction over several hops. In order to prevent overly optimistic problems within the framework of the double deep Q learning, two distinct DeepCNN are used while estimating the reward function and Q-value. In this instance, the suggested double deep Q learning algorithm is used to assess the node's consumption of energy in order to accomplish energy-efficient routing. The newly devised Gannet Chimp Optimization (GCO) algorithm finds the best betting route based on the discovered routes. In order to successfully capture the prey, the GCO combines the gannet's hunting behavior with a chimpanzee's fighting behavior. To increase the rate of convergence with the best global solution, hybridization is devised. The selection of the best path is made here by considering the multi-objective fitness function. In order to develop a multi-objective fitness function that improves the effectiveness of path selection, degree of connectedness, hop count, packet latency, residual energy, and bandwidth are taken into account. Figure 5.1 shows the workflow for the newly devised D2D communication system.

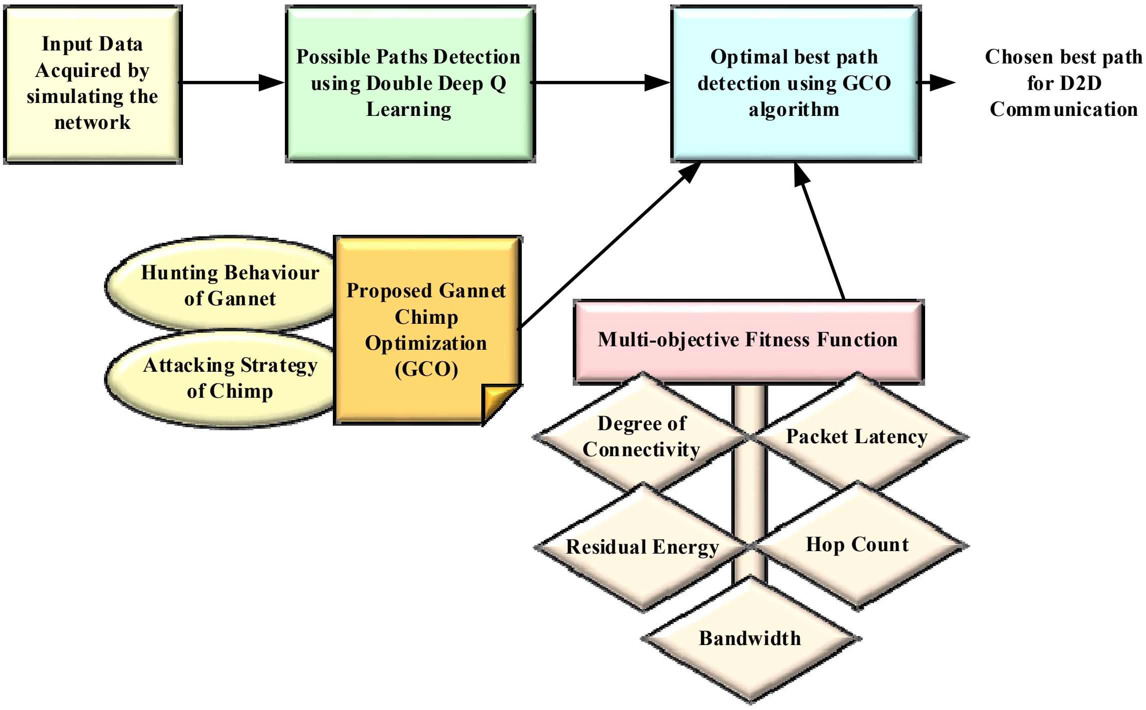


Figure 5.1: Newly devised Energy Efficient D2D communication protocol

5.3.1 Data Acquisition

Network simulation is used to gather the data needed for the suggested D2D communication through multi-hop energy-efficient routing. The collected information is processed in the suggested approach.

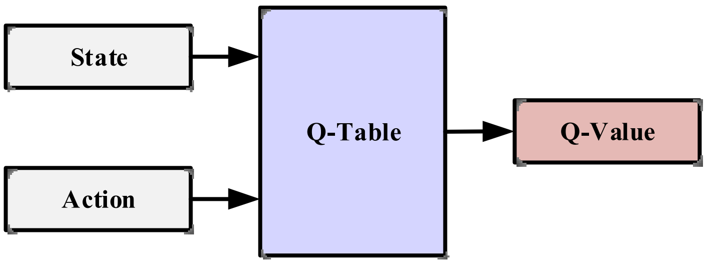
5.3.2 Double Deep Q learning for path detection

By taking energy consumption into consideration, double deep Q learning is able to identify the potential routes for D2D communication utilizing multi-hop routing. However, it is unable to handle complicated parameters because the classical Q learning approach employs the Markov decision-making approach to address problems in learning through reinforcement. Additionally, problems caused by the curse of dimensionality increase the level of difficulty residing in computations and slow down convergence. The deep neural network (DNN) is used in the newly devised method for assessing the Q-value and reward in the deep-Q-learning strategy for solving these problems.The discrete value function of Q-learning has been replaced by the DNN, however deep-Q-learning remains susceptible to overly optimistic problems because only one DNN is used to estimate both the reward and Q-value. By using two distinct

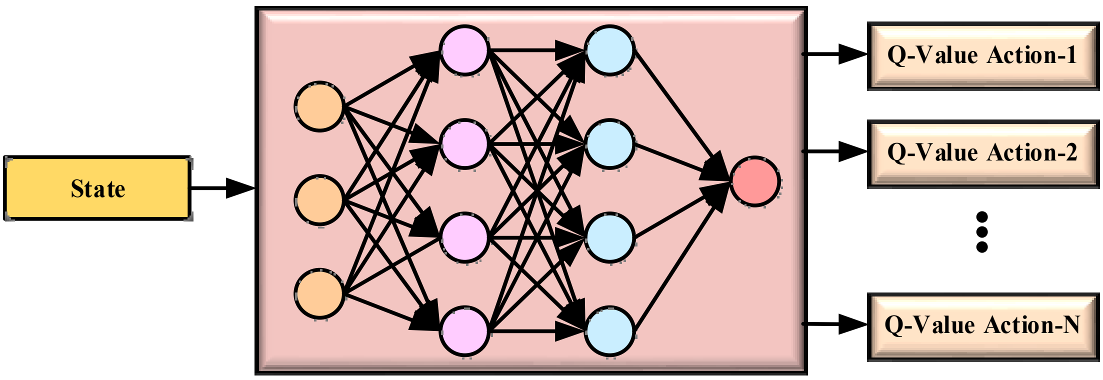
DNN to estimate the reward and Q-value, the double deep Q learning effectively addresses the overly optimistic problem.

5.3.2.1 Deep Q-Learning

The traditional Q learning method acquires state and action as the data inputs and produces the result as a Q-value. Yet, using the state value, a variety of actions are generated by deep Q learning generates as its output. Figure 5.2, which is provided below, structured the deep-Q-learning and Q-learning processes.



(a)



(b)

Figure 5.2: System Model of: (a) Q-learning and (b) Deep Q Learning

Here, for the state X, the rewards are evaluated as $Y^{f}_{X,X'}$, wherein the action is defined as F. The term β defines the discount factor and $E^{f}_{X,X'}$ refers to the action-state pair probability. The routing of multiple hops between the nodes that arrives at the target is described as action, whereas D2D communication between individuals of 5G networks is expressed as state.

5.3.2.2 Reward and Q value Evaluation

The action of an agent in deep Q-learning is determined by the reward determined based on the state, determines the users communicate with one another. Here, the energy consumption is taken into consideration to provide the energy-efficient D2D interaction between individuals.Let us consider the user m_c, who is considered as source node and the receiver node is defined as m_b . The evaluation of the reward function is defined as,

$$Y^{n_c}_{m_c,m_b} = -p - \alpha_1 [l(m_c) + l(m_b)] + \alpha_2 [n(m_c) + n(m_b)] \tag{5.1}$$

where, the action-state pair is defined as $(m \ , f_s)$ and α_1 *and* α_2 refers to the weighting parameter. The reward function is defined as $Y^{n_c}_{m_c,m_b}$; then the cost function enunciated as the punishment factor is defined as p.

If the communication among the nodes succeeds, the reward value is calculated by considering the expression (5.1); otherwise, it is determined as,

$$Y^{n_c}_{m_c,m_b} = -p \times \eta - \gamma_1 l(m_c) + \gamma_2 n(m_c) \tag{5.2}$$

where, η refers the drop case of communication and the energy evaluation for the communication is defined as $l(m_c)$ and is formulated as,

$$l(m_c) = 1 - \frac{E_{resi}(m_c)}{E_{ini}(m_c)} \tag{5.3}$$

where, the initial energy varies from $[0,1]$ and is referred as E_{ini}, then, the residual energy is represented as E_{resi}. The normalized form of energy is indicated as $l(m_c)$ that plays a crucial role in communication between the nodes. Because, for the energy efficient routing protocol, E_{resi} is highly essential. The communication between the nodes takes place when the E_{resi} value becomes higher for the avoidance of communication dropping. Next, the group's reward function is stated as follows:

$$n(m_c) = \frac{2}{\pi} \arctan\left(E_{resi}(m_c) - \overline{E}(m_c)\right) \tag{5.4}$$

where, the term $\overline{E}$ defines the residual energy of a group in average. Then, the final reward function is enunciated as,

$$\text{Reward} = E_X \times Y^{f_c}_{m_c,m_b} + E(1-E_X) \times Y^{f_c}_{m_c,m_b} \tag{5.5}$$

Estimation of Q-Value: For the acquisition of the highest reward value, the Q-value is evaluated to make the required action. The Q-value is enunciated as,

$$Q-V(X,f) = \text{Reward} + \beta\left[Q-V(X,f) + Max_{f'}\left(Q-V(X',:)\right)\right] \tag{5.6}$$

where, estimation of the Q-value is defined as $Q-V$ and is highly helpful in choosing the energy efficient node for D2D communication.

5.3.2.3 Double Deep Q Learning based on DeepCNN

The traditional double deep Q learning utilizes the DNN for estimating the Q-value and reward function. In the proposed methodology, the deep convolutional Neural Network (DeepCNN) is utilized for estimating the Q-value and reward function. The detailed description is given below.

5.3.2.3.1 Architecture of DeepCNN

For the algorithms using deep learning to improve their capacity to generalize, which makes the results easier to use via multiple layers, complicated characteristics must be trained. As a result of favorable findings, deep learning techniques are now frequently used to solve numerous application domains' that considers the computer vision-related problems, such as recognition, prediction, classification, and other tasks. Some of deep learning algorithms like recurrent neural networks, deep belief networks, and convolutional neural networks are utilized in various domains. In addition, the requirement of the additional feature extraction is not essential for the deep learning methods' due to the inbuilt automatic feature extraction. So, the estimation of the Q-value and reward function are devised using the deep CNN (DeepCNN) in the suggested path detection model. Figure 5.3 shows the design of the DeepCNN.

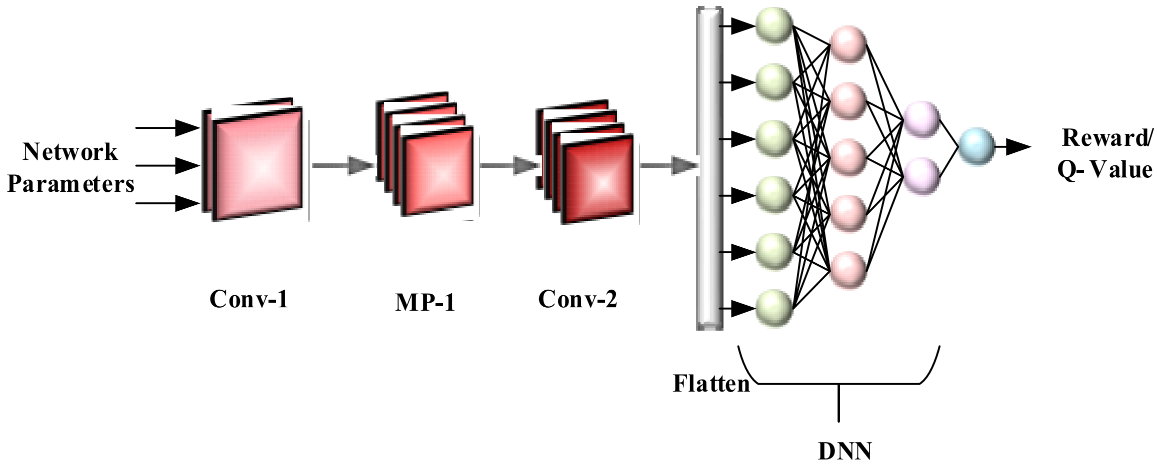


Figure 5.3: Architecture of DeepCNN

Here are comprehensive explanations of the DeepCNN's layer-by-layer operations for determining the Q-value or Reward.

Conv Layer: The Conv layer-1 gathers the network's input parameters for convolving it for the generation of the feature maps using the kernel function. The following is a definition of the formula for the conv layer outcome:

$$R - Q_v = \sum X^w * Y^w + Q^w \tag{5.7}$$

where, the outcome of the conv layer is defined as $R - Q_v$. The input feature is referred as X^w and the weight is represented as Y^w. The bias value is notated as Q^w, wherein the output map corresponding to the w^{th} feature is indicated as w.

Max-Pooling Layer: In order to minimize the attribute duplication during the process of pooling, the relevant attributes have been taken out that lowers the amount of complexity of the processing burden. While retrieving relevant attributes in the newly devised approach, the max-pooling procedure is used. In Figure 5.4, a max-pooling procedure sample is shown.

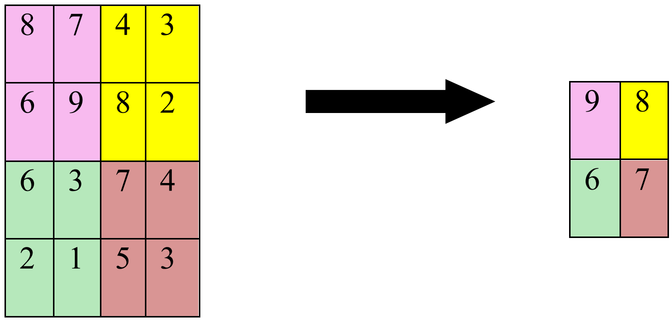


Figure 5.4: Max-pooling operation

Flatten Layer: The flatten layer employs the attribute's conversion into one dimensionality for further processing.

Fully Connected Layer: The fully connected layer's output the employs softmax activation, provides the reward and the Q-value computation. The definition of the assessment of the result is

$$R - Q_{v_{out}} = \frac{e^{z_m}}{\sum_{n=1}^{i} e^{z_n}} \tag{5.8}$$

where, the softmax function is indicated as $R - Q_{v_{out}}$, the element corresponding to the input attribute is indicated as z_m , and i refers to the outcome.

5.3.3 Optimal Path detection using the proposed Gannet Chimp Optimization Algorithm

The suggested Double Deep Q Learning includes a variety of paths throughthe possible paths identification. The suggested GCO method selects the best path from among all those that have been identified by the deep learning technique. Using characteristics including trust factor, hop count, bandwidth, packet latency, and energy consumption, the GCO determines the best path by considering the multi-objective fitness function.

5.3.3.1 Multi-objective Fitness Function

Trust factor, hop count, bandwidth, packet latency, and energy consumption are taken into account while evaluating the best path utilizing the suggested GCO algorithm to compute the multi-objective fitness function. Here is the explanation in more detail.

5.3.3.1.1 Residual Energy: For user-to-user D2D communication to be energy-efficient, residual energy is considered as a critical component. Here, the device with the maximal residual energy is taken for uninterrupted user-to-user communication because sufficient energy is essential for efficient communication. The formulation for the remaining energy measure is defined as:

$$RE = E_c - (E_{txn} + E_{rxn}) \tag{5.9}$$

where, the energy utilized for sender is indicated as E_{txn}, the energy utilized by the receiver is indicated as E_{rxn}, the residual energy is defined as RE, and the present remaining energy of the node is indicated as E_c. The node with higher RE is preferred for D2D communication.

5.3.3.1.2 Packet Latency: The network's time utilized on D2D communication is known as the latency. According to its definition, it is formulated as:

$$PL = a\frac{P + Q(N)}{d} \tag{5.10}$$

where, the packet latency is notated as PL, the count of bits in the packet is notated as a, the number of packet is represented as N, the capacity of the link is indicated as d, the size of data is indicated as Q and the bit size of header is notated as P.

5.3.3.1.3 Bandwidth: For user-to-user communication without any interruptions, higher bandwidth is required. To ensure efficient routing, the resource usage must be in a small portion of its available bandwidth. To ensure effective information routing, the minimum of bandwidth must be taken into account that is denoted as F_{BW}. For communication among devices through node sensing with energy efficient, the minimum bandwidth is utilized.

5.3.3.1.4 Hop Count: For user communication, the suggested routing protocol employs a multi-hop route, but the way with a high number of hops requires enormous energy. Therefore, the fewest hops path is taken into account to save energy usage. F_{HC} denotes the hop count.

5.3.3.1.5 Degree of Connectivity:

The estimation of degree of connectivity is essential for identifying the capability of the node to handle the number of devices within the specified time t. The connectivity is defined as DC_i and the neighbour node is indicated as NN_i. Then, the expression for calculating the degree of connectivity is formulated as,

$$DC_i = \frac{NN_i}{D_{i,j} \leq R_T} \tag{5.11}$$

where, the transmission range is represented as R_T, the distance between the nodes is indicated as $D_{i,j}$.

Thus, the multi-objective fitness function is formulated as,

$$MO_{fitness} = Max(RE, DC_i)Min(PL, F_{HC}, F_{BW}) \tag{5.12}$$

Here, the multi-objective fitness function is indicated as $MO_{fitness}$. The fitness function is normalized within the range of $[0,1]$ for making the computation simpler.

5.3.3.2 Gannet Chimp Optimization

In order to successfully capture the solution more efficiently with fast convergence rate, the Gannet Chimp Optimization (GCO) is introduced, which combines the chimpanzee's fighting style with the gannet's hunting strategy. By using balanced diversification and intensification capabilities, hybridization algorithm aims to achieve the global best solution. Without becoming stuck at a local optimal solution, balanced optimization guarantees the better solution to solve the problems of optimization.

Motivation behind the proposed Gannet Chimp Optimization

A carnivorous bird named Gannet [26] hunts its prey (crabs, amphibians, fish, and other creatures) at the water's edge and in shore areas. With stubby bodies, narrow necks, and strong eyes they live in flocks for hunting. The bird's improved eye sight makes it possible to recognize the target precisely far away, which makes it easier to catch. The prey never has a chance to escape as a result of being in the Gannet’s field of vision. A better surrounding of the target is also ensured by the bird's V- and U-shaped dive behavior. By disregarding water resistance, the bird exhibits a high level of capture ability, making it incredibly easier to obtain the prey.

The chimp's fighting criteria is incorporated in this case to increase the Gannet's capture-ability and produce a fast-convergence. Chimp is a large ape from Africa that is a member of the Hominoid family is the chimpanzee [27]. The attacker, chaser, barrier, and driver categories of chimps are taken into consideration when attempting to solve optimization problems. Every chimpanzee category in this scenario plays a unique part in obtaining the prey. All the chimpanzees combined together to create their assault approach more efficient. Therefore, in order to find the global best solution for resolving the optimization problem, the chimp's attacking approach is hybridized to improve the local search capabilities of the Gannet.

In the suggested approach based on the multi-hop routing strategy the GCO is used to discover the energy-efficient path between users of D2D communication. The solution accomplished by the optimization is nothing but the solution utilized for identifying the best path.

3.3.2.1 Mathematical Modelling

The candidate solutions (Gannets) and the target (prey) are distributed at random manner in the feature space during the initialization phase of the proposed Gannet chimp optimization (GCO) algorithm. To solve the issues concerning the optimization, each candidate's feature space solution is considered. In the feature space, the expression for initialization is written as,

$$A = \begin{bmatrix} a_{1,1} & \cdots & a_{1,y} & \cdots & a_{1,V-1} & a_{1,V} \\ a_{2,1} & \cdots & a_{2,y} & \cdots & a_{2,V-1} & a_{2,V} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \cdots & \cdots & a_{x,y} & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{U-1,1} & \cdots & a_{U-1,y} & \cdots & a_{U-1,V-1} & a_{U-1,V} \\ a_{U,1} & \cdots & a_{U,y} & \cdots & a_{U,V-1} & a_{U,V} \end{bmatrix} \tag{5.13}$$

Here, the x^{th} position of the candidate is defined as a_x. For the dimension y, the x^{th} search agent's solution is written as:

$$a_{x,y} = g_1 \times \left(Q_y - S_y\right) + S, \qquad x = 1,2,....U, \quad y = 1,2,...V \tag{5.14}$$

where, U notates the population and the dimension of the solution is notated as V. The S_y and Q_y are the two boundaries of the feature space concerning the lower and upper limits. $[0,1]$ is the range of randomly chosen variable g_1. Each search agents has the corresponding memory D for updating their solutions.

(i) Diversifying the solution: During the diversification stage, the candidate explores through a variety of diving strategies in an effort to find the solution. The definition of the terms for diving strategies is written as:

$$M = 2 * \cos(2 * \pi * g_2) * t \tag{5.15}$$

$$N = 2 * B(2 * \pi * g_3) * t \tag{5.16}$$

where, V-shaped movement is notated as N and the U-shaped movement is notated as D. The definition of the exploration stage is written as:

$$t = 1 - \frac{\tau}{\tau_{\max}} \tag{5.17}$$

where, $[0,1]$ is the range of randomly chosen variable g_3 and g_2. $\tau_{\max}$ notates the maximal iteration and t indicates the current iteration. The expression for the angle of diving is written as:

$$B(a) = \begin{cases} -\frac{1}{\pi} * a + 1, & a \in (0, \pi) \\ \frac{1}{\pi} * a - 1 & a \in (\pi, 2\pi) \end{cases} \tag{5.18}$$

The solution accomplished in the diversification is stored in D and is written as:

$$D_x(t+1) = \begin{cases} A_x(t) + u_1 + u_2 \ , f \geq 0.5 \\ A_x(t) + v_1 + v_2 \ , f < 0.5 \end{cases} \tag{5.19}$$

where, f notates the equal probability of U and V diving. Then the factors are expressed as,

$$u_2 = K * \left(A_x(t) - A_e(t)\right) \tag{5.20}$$

$$v_2 = L * \left(A_x(t) - A_c(t)\right) \tag{5.21}$$

$$K = \left(2 * g_4 - 1\right) * M \tag{5.22}$$

$$L = \left(2 * g_5 - 1\right) * N \tag{5.23}$$

where, $A_e(t)$notates the randomly selected search agent. The average solution $A_c(t)$ accomplished by the search agents in the written as:

$$A_c(t) = \frac{1}{U} \sum_{x=1}^{U} A_x(t) \tag{5.24}$$

The range of u_1 is $[-M, M]$and the range of v_1 is$[-N, N]$.

(ii) Intensifying Solution: As a result of the candidates' global solution identification during the diversification stage, the solution is then exploited during the local search. To capture the prey in this criteria, the candidate employs its behavior of capturability and is outlined as,

$$C = \frac{1}{G * t_2} \tag{5.25}$$

where, t_2 notates the iteration corresponding to the intensification and is written as:

$$t_2 = 1 + \frac{\tau}{\tau_{\max}} \tag{5.26}$$

The factors like velocity and mass are considered by the algorithm for estimating the search agent's energy G and is written as:

$$G = \frac{H * s^2}{P} \tag{5.27}$$

where,1.5m/svelocity s is assigned for the candidate with 2.5kgmass. The parameters P is defined as:

$$P = 0.2 + (2 - 0.2) * g_6 \tag{5.28}$$

where, $[0,1]$ is the range of randomly chosen variable g_6. The position updation for the search agent is written as:

$$D_m(t+1)_{Gannet} = \begin{cases} t * \gamma * (A_x(t) - A_{better}(t)) + A_x(t), & C \geq d \\ A_{better}(t) - (A_x(t) - A_{better}(t)) * R * t & C < d \end{cases} \tag{5.29}$$

where, $A_{better}(t)$ notates the best agent and the factors $\gamma\ and\ R$ are estimated as,

$$\gamma = C * |A_x(t) - A_{better}(t)| \tag{5.30}$$

$$R = Levy(V) \tag{5.31}$$

Here, R is the parameter considered for performing the levy flight and is written as:

$$Levy(V) = 0.01 \times \frac{\alpha \times \beta}{|v|^{1/\mu}} \tag{5.32}$$

where,

$$\beta = \left(\frac{\Gamma(1+\mu) \times \sin\left(\frac{\pi\mu}{2}\right)}{\Gamma\left(\frac{1+\mu}{2}\right) \times \mu \times 2^{\left(\frac{\mu-1}{2}\right)}} \right)^{1/\mu} \tag{5.33}$$

The values of the random variables $\gamma\ and\ \beta$ has the range of $[0,1]$ and the predefined constant μ has the value of 1.5. As a result of the smart target's quick turn and escape from the search agent in this case, the gannet is unable to capture the solution and must instead look for another fish. As a result, the suggested GCO algorithm incorporates the chimpanzee's fighting conduct to reduce the ability of fish to escape. The chimp updates the solution, which is developed using the solution from all four varieties of chimps. Its updated solution is written as,

$$D_x(t+1) = \frac{D_A + D_B + D_D + D_C}{4} \tag{5.34}$$

where, $D_x(t+1)$ notates the solution updation, D_A refers the attacker, D_B notated as the barrier, D_D refers the driver, D_C refers the carrier. The individual chimp's position is stated as follows:

$$D_A = D_1 - k_1(q_A) \tag{5.35}$$

$$D_B = D_2 - k_2(q_B) \tag{5.36}$$

$$D_C = D_3 - k_3(q_C) \tag{5.37}$$

$$D_D = D_4 - k_4(q_D) \tag{5.38}$$

where, q_A notates the distance among the attacker and prey, q_B notates the distance among the barrier and prey, q_C notates the distance among the carrier and prey, and q_D notates the distance among the driver and prey. The coefficient $k_1, k_2, k_3, and\ k_4$ ranges between $[0,1]$ that forces the candidates to capture the target. $D_1, D_2, D_3, and\ D_4$ refers to the best solutions acquired by the attacker, barrier, carrier and driver. The hybridized solution updating utilizing the suggested GCO is then written as,

$$D_x(t+1) = 0.5D_x(t+1)_{Gannet} + 0.5D_x(t+1)_{Chimp} \tag{5.39}$$

$$W_m(T+1) = \begin{cases} 0.5\left[t * \gamma * (A_x(t) - A_{better}(t)) + A_x(t)\right] + \\ 0.5\left[\dfrac{D_A + D_B + D_D + D_C}{4}\right], & C \geq d \\ 0.5\left[A_{better}(t) - (A_x(t) - A_{better}(t)) * R * t\right] + \\ 0.5\left[\dfrac{D_A + D_B + D_D + D_C}{4}\right], & C < d \end{cases} \tag{5.40}$$

(iii) Feasibility estimation: The multi-objective fitness function established in equation (5.12) is used for the updated solutions from the previous step to assess their viability.

(iv) Stopping Criteria: The attainment of $\tau_{\max}$ or the optimal best solution stop the iteration of the algorithm. The pseudo-code for the proposed GCO algorithm is depicted in Algorithm 5.1.

Algorithm 5.1: Pseudo-code for proposed GCO algorithm

Pseudo-code for proposed GCO algorithm
Initialize the $\tau_{\max}$, U and V
Locate the population (candidate) of Gannet in the search space
Create the memory matrix D
Estimate the fitness for all the updated solutions
while
If $f \geq 0.5$
Update the solution using equation (5.18) based on first condition
else
Update the solution using equation (5.18) based on second condition
End if
If $d \geq 0.2$
Update the solution using equation (5.40) based on first condition
Else
Update the solution using equation (5.40) based on second condition
End if
Recheck the feasibility of the solution
Replace the memory matrix D with best solution
End while
$t = t + 1$
end

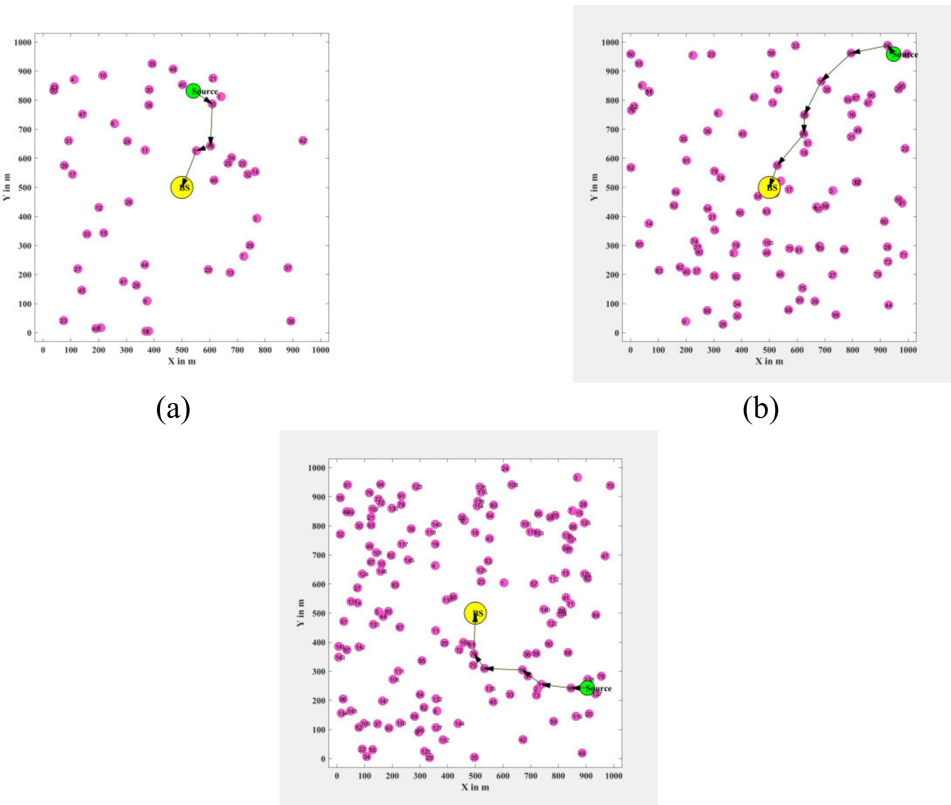
In the 5G networks, the ideal path for D2D communication between users is thus selected using the GCO algorithm, which also provides energy efficient routing with multi-hop.

5.4. Results and Discussion

MATLAB, Windows 10, and 8GB RAM PC configuration system is used to develop the suggested multi hop routing with energy-efficient approach. To demonstrate the superiority of the developed model, the experimental results are assessed using a variety of metrics. To compare the suggested approach to existing energy-efficient D2D routing protocols, such as DRL [24], 5G-EECC [22], Modified Derivative Algorithm [21], and MBLCR [25] are compared with the newly devised approach.

5.4.1 Simulation Outcome

Figure 5.5 shows the simulation results of the suggested protocol among devises by changing the number of rounds. In this case, a multi-objective fitness function is taken into account while designing a multi-hop path for user communication in the 5G network. The path detection using the deep learning approach and optimal path selection technique are utilized for the energy efficiency of the suggested protocol.



(a) (b)

(c)

Figure 5.5: Simulation outcome of the proposed routing protocol based on (a) 50 nodes, (b) 100 nodes and (c) 150 nodes

5.4.2 Performance Evaluation

The performance of the newly devised D2D deep reinforcement learning based routing protocol by varying the iteration size and population are detailed in this section. Besides, the number of users in network varied to depict the robustness of the model.

1. **Analysis by varying Iteration**

The analysis by varying the iteration of the newly introduced GCO algorithm based on the various assessment measures with 50, 100 and 150 users are elaborated in this section.

(a) Using 50 users

Average Residual Energy: The average residual energy by varying the number of communication rounds and iteration size of the newly devised GCO algorithm in the deep learning based multi hop routing protocol is depicted in Figure 5.6. The average residual energy acquired with 500 round is 0.95 for 20 iterations, which is further reduced when the round increases to 2500 with the average residual energy of 0.70. Hence, the elevation in the number of rounds consumes more energy. Still, the increase in iteration elevates the performance of the model by enhancing the amount of residual energy. For example, the average residual energy estimated with 20 iterations and 1000 round is 0.84, which is 0.89 when the iteration increased to 100. The detailed analysis is depicted in Table 5.1.

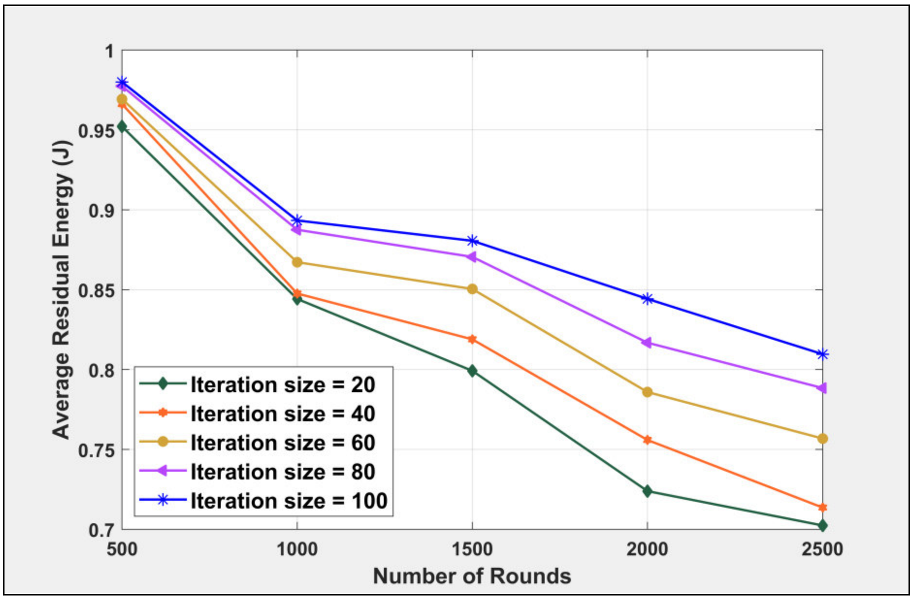


Figure 5.6: Average Residual Energy based on Iteration with 50 users

Table 5.1: Average Residual Energy based on Iteration with 50 users

Iteration / Rounds	500	1000	1500	2000	2500
20	0.95	0.84	0.80	0.72	0.70
40	0.97	0.85	0.82	0.76	0.71
60	0.97	0.87	0.85	0.79	0.76
80	0.98	0.89	0.87	0.82	0.79
100	0.98	0.89	0.88	0.84	0.81

Latency: The latency of the D2D communication depicts the time take for the information to reach the destination from the source. The analysis based on latency by varying the iteration with 50 users is portrayed in Figure 5.7. While considering the 20 iterations of GCO algorithm with 500 rounds, the latency estimated by the proposed method is 1.85, which is increased to 3.56, when the round is increased to 2500. In contrast, the latency gets minimized with increase in the number of iterations of the algorithm. For example, with 1500 round and 20 iterations, the latency estimated by the newly devised method is 2.57, which is further minimized to 2.13 with 100 iterations. Thus, the increase in iteration elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 5.2.

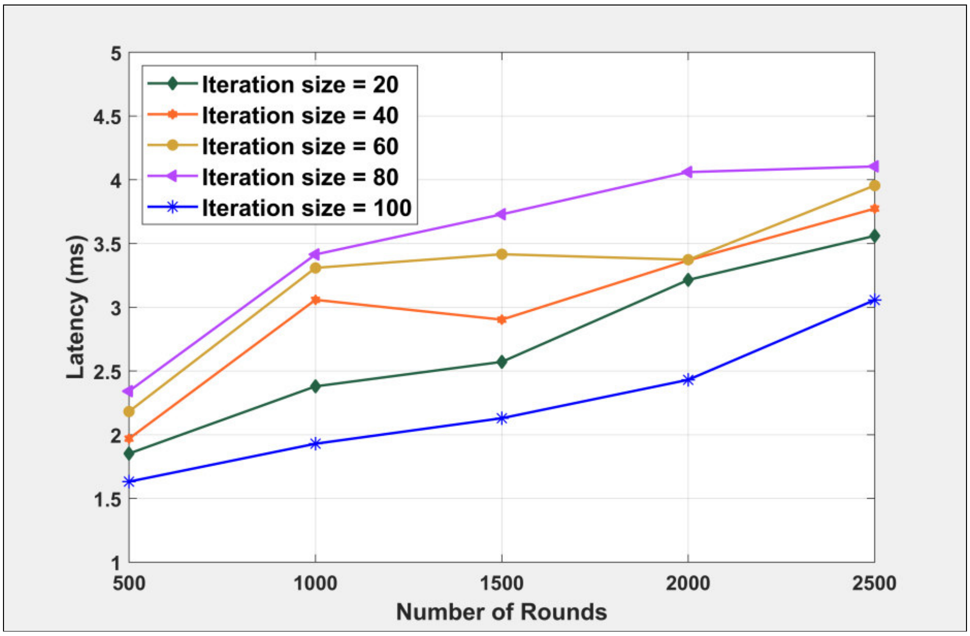


Figure 5.7: Latency based on Iteration with 50 users

Table 5.2: Latency based on Iteration with 50 users

Iteration / Rounds	500	1000	1500	2000	2500
20	1.85	2.38	2.57	3.21	3.56
40	1.97	3.06	2.90	3.37	3.77
60	2.18	3.31	3.42	3.37	3.96
80	2.34	3.41	3.73	4.06	4.10
100	1.63	1.93	2.13	2.43	3.06

Network Life Time: The network lifetime based analysis with 50 users by varying the iteration size is depicted in Figure 5.8. The network lifetime estimated by the newly devised D2D communication protocol with multi hop routing is 98.17 with 20 iteration and 500 rounds. The same is 89.76 with 2500 rounds and 20 iterations, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 91.82 with 1500 rounds and 20 iterations, which elevates with 96.31 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 5.3.

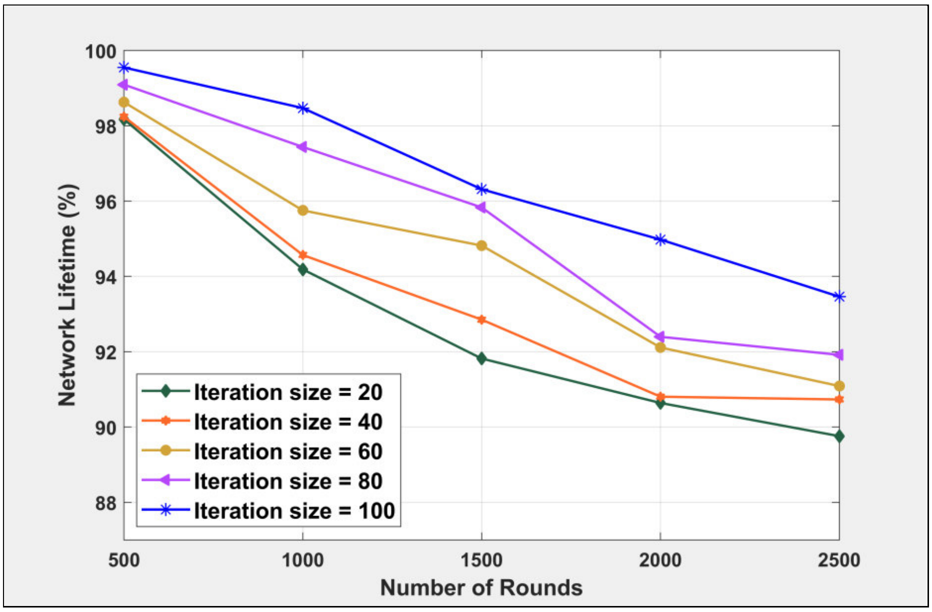


Figure 5.8: Network Life Time based on Iteration with 50 users

Table 5.3: Network Life Time based on Iteration with 50 users

Iteration / Rounds	500	1000	1500	2000	2500
20	98.17	94.18	91.82	90.64	89.76
40	98.24	94.57	92.85	90.80	90.73
60	98.63	95.75	94.82	92.11	91.09
80	99.09	97.44	95.83	92.39	91.92
100	99.55	98.47	96.31	94.98	93.46

Packet Delivery Ratio: The interpretation of the packet delivery ratio for various iteration sizes of the newly devised GCO algorithm of the introduced D2D multi-hop routing with 50 users is depicted in Figure 5.9. For 20 iterations, the packet delivery ration accomplished by the newly devised protocol is 99.54 with 500 rounds, which is 91.29 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 95.18 with 20 iterations and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 iterations is 98.07 with 100 rounds. The detailed analysis is presented in Table 5.4.

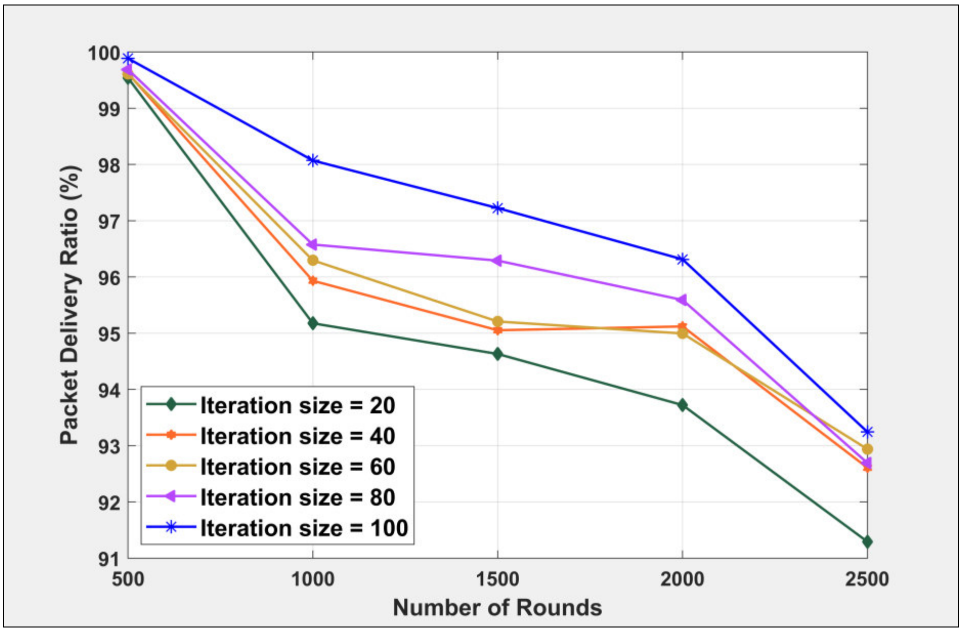


Figure 5.9: Packet Delivery Ratio based on Iteration with 50 users

Table 5.4: Packet Delivery Ratio based on Iteration with 50 users

Iteration / Rounds	500	1000	1500	2000	2500
20	99.54	95.18	94.63	93.72	91.29
40	99.62	95.93	95.05	95.12	92.61
60	99.61	96.30	95.21	95.00	92.94
80	99.69	96.58	96.29	95.59	92.69
100	99.89	98.07	97.22	96.31	93.24

Throughput: The throughput based analysis of the D2D protocol by varying the iteration of the GCO algorithm is depicted in Figure 5.10 with 50 users. The throughput estimated by the newly devised protocol with 20 iterations and 500 communications round is 6, which is 12 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 iterations, the throughput estimated by the proposed protocol is 12. When the iteration increased to 100, the throughput estimated is 18 that depict the better outcome of the model with increase in iteration. The detailed analysis is presented in Table 5.5.

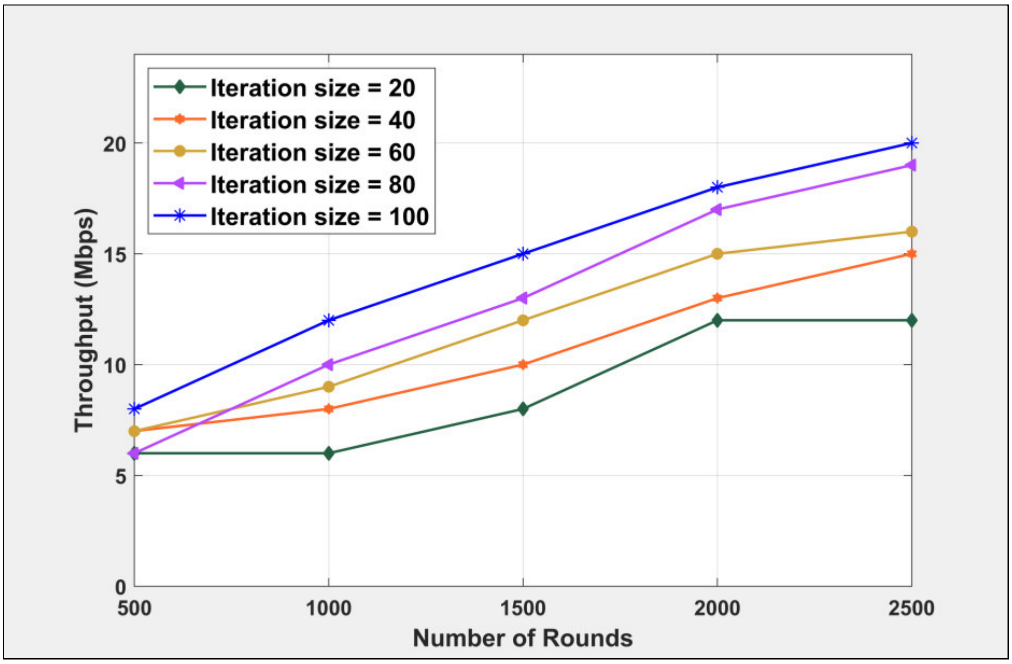


Figure 5.10: Throughput based on Iteration with 50 users

Table 5.5: Throughput based on Iteration with 50 users

Iteration / Rounds	500	1000	1500	2000	2500
20	6	6	8	12	12
40	7	8	10	13	15
60	7	9	12	15	16
80	6	10	13	17	19
100	8	12	15	18	20

(b) Using 100 Users

Average Residual Energy: The average residual energy by varying the number of communication rounds and iteration size with 100 users is depicted in Figure 5.11. The average residual energy acquired with 500 round is 0.94 for 20 iterations, which is further reduced when the round increases to 2500 with the average residual energy of 0.63. Hence, the elevation in the number of rounds consumes more energy. Still, the increase in iteration elevates the performance of the model by enhancing the amount of residual energy. For example, the average residual energy estimated with 20 iterations and 1000 round is 0.80, which is 0.93 when the iteration increased to 100. The detailed analysis is depicted in Table 5.6.

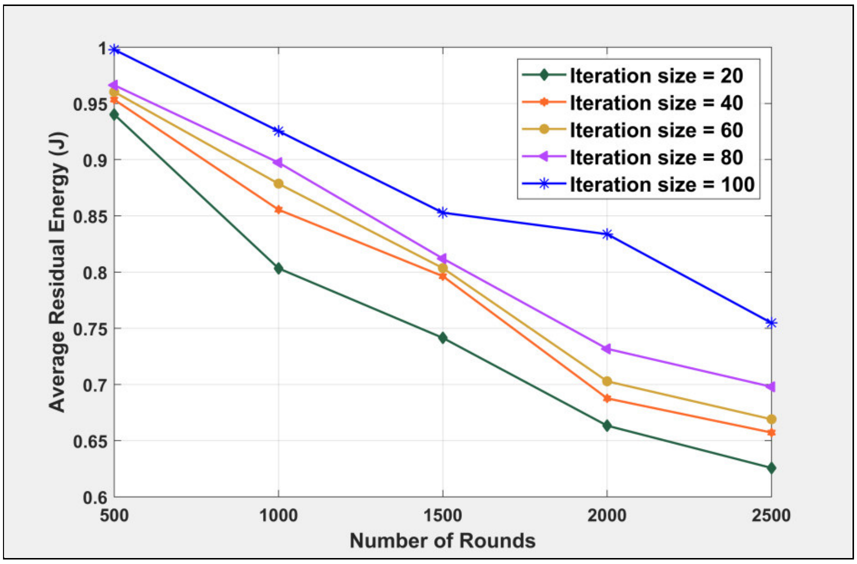


Figure 5.11: Average Residual Energy based on Iteration with 100 users

Table 5.6: Average Residual Energy based on Iteration with 100 users

Iteration / Rounds	500	1000	1500	2000	2500
20	0.94	0.80	0.74	0.66	0.63
40	0.95	0.86	0.80	0.69	0.66
60	0.96	0.88	0.80	0.70	0.67
80	0.97	0.90	0.81	0.73	0.70
100	1.00	0.93	0.85	0.83	0.75

Latency: The analysis based on latency by varying the iteration with 100 users is portrayed in Figure 5.12. While considering the 20 iterations of GCO algorithm with 500 rounds, the latency estimated by the proposed method is 4.76, which is increased to 11.64, when the round is increased to 2500. In contrast, the latency gets minimized with increase in the number of iterations of the algorithm. For example, with 1500 round and 20 iterations, the latency estimated by the newly devised method is 9, which is further minimized to 5 with 100 iterations. Thus, the increase in iteration elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 5.7.

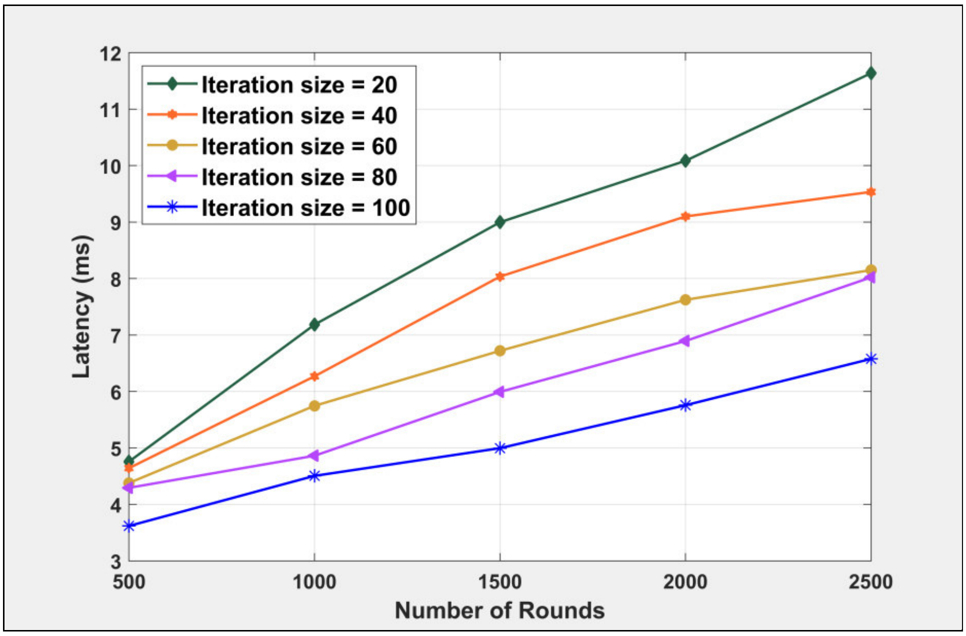


Figure 5.12: Latency based on Iteration with 100 users

Table 5.7: Latency based on Iteration with 100 users

Iteration / Rounds	500	1000	1500	2000	2500
20	4.76	7.18	9.00	10.09	11.64
40	4.64	6.27	8.03	9.10	9.53
60	4.38	5.75	6.72	7.62	8.15
80	4.29	4.86	5.99	6.89	8.02
100	3.62	4.51	5.00	5.76	6.58

Network Life Time: The network lifetime based analysis with 100 users by varying the iteration size is depicted in Figure 5.13. The network lifetime estimated by the newly devised D2D communication protocol with multi hop routing is 97.17 with 20 iteration and 500 rounds. The same is 75.11 with 2500 rounds and 20 iterations, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 86.23 with 1500 rounds and 20 iterations, which elevates with 97.03 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 5.8.

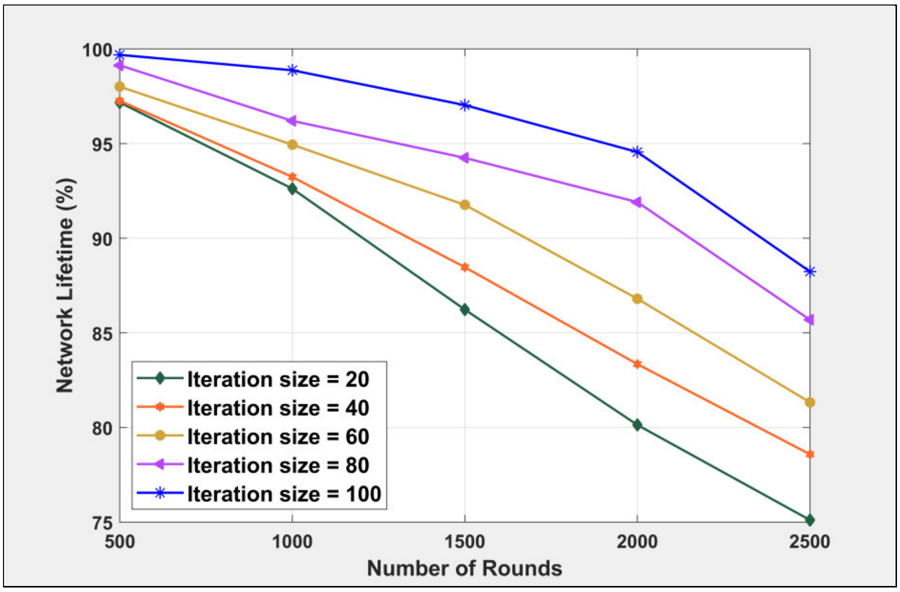


Figure 5.13: Network Life Time based on Iteration with 100 users

Table 5.8: Network Life Time based on Iteration with 100 users

Iteration / Rounds	500	1000	1500	2000	2500
20	97.17	92.62	86.23	80.13	75.11
40	97.26	93.24	88.47	83.35	78.58
60	98.01	94.94	91.76	86.80	81.33
80	99.14	96.20	94.25	91.91	85.69
100	99.69	98.87	97.03	94.55	88.24

Packet Delivery Ratio: The interpretation of the packet delivery ratio for various iteration sizes of the newly devised GCO algorithm of the introduced D2D multi-hop routing with 100 users is depicted in Figure 5.14. For 20 iterations, the packet delivery ration accomplished by the newly devised protocol is 97.25 with 500 rounds, which is 58.80 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 88.38 with 20 iterations and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 iterations is 97.94 with 100 rounds. The detailed analysis is presented in Table 5.9.

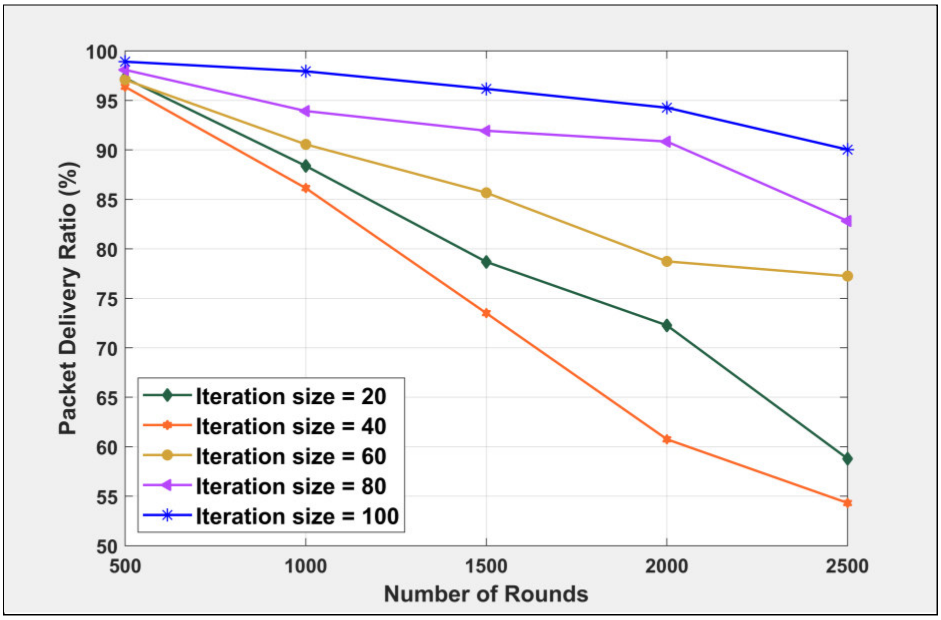


Figure 5.14: Packet Delivery Ratio based on Iteration with 100 users

Table 5.9: Packet Delivery Ratio based on Iteration with 100 users

Iteration / Rounds	500	1000	1500	2000	2500
20	97.25	88.38	78.68	72.27	58.80
40	96.38	86.14	73.50	60.76	54.32
60	97.09	90.56	85.67	78.73	77.24
80	98.09	93.93	91.93	90.84	82.82
100	98.91	97.94	96.16	94.26	90.03

Throughput: The throughput based analysis of the D2D protocol by varying the iteration of the GCO algorithm is depicted in Figure 5.15 with 100 users. The throughput estimated by the newly devised protocol with 20 iterations and 500 communications round is 20, which is 28 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 iterations, the throughput estimated by the proposed protocol is 21. When the iteration increased to 100, the throughput estimated is 34 that depict the better outcome of the model with increase in iteration. The detailed analysis is presented in Table 5.10.

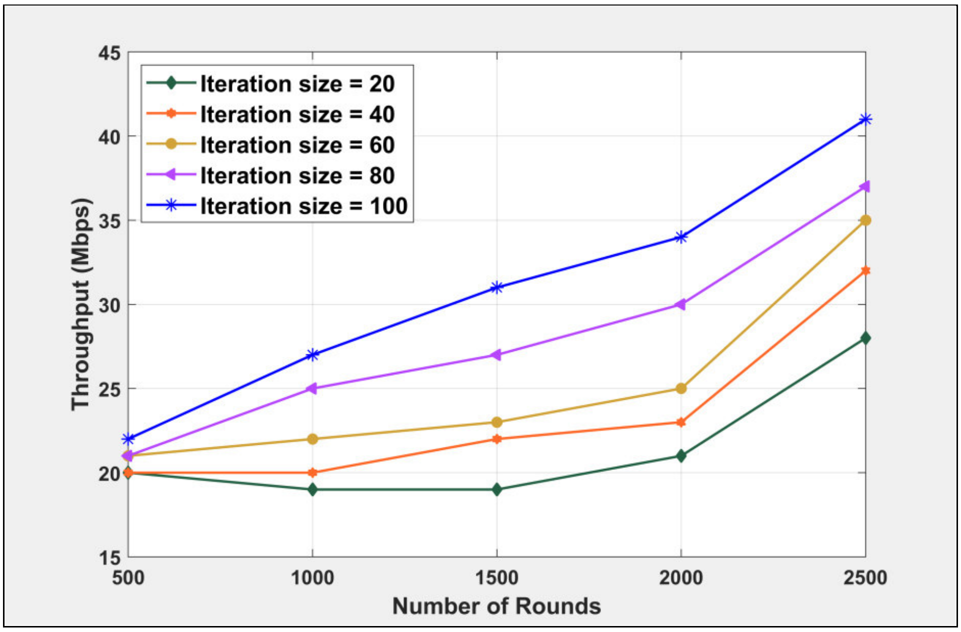


Figure 5.15: Throughput based on Iteration with 100 users

Table 5.10: Throughput based on Iteration with 100 users

Iteration / Rounds	500	1000	1500	2000	2500
20	20	19	19	21	28
40	20	20	22	23	32
60	21	22	23	25	35
80	21	25	27	30	37
100	22	27	31	34	41

(c) Using 150 Users

Average Residual Energy: The analysis by varying the iteration size and average residual energy with 150 users is depicted in Figure 5.16. The average residual energy acquired with 500 round is 0.90 for 20 iterations, which is further reduced when the round increases to 2500 with the average residual energy of 0.60. As a result, increasing the number of rounds uses more energy. Even still, increasing the number of iterations improves the model's performance by raising the quantity of residual energy. For example, the average residual energy estimated with 20 iterations and 1500 round is 0.75, which is 0.88 when the iteration increased to 100. The detailed analysis is depicted in Table 5.11.

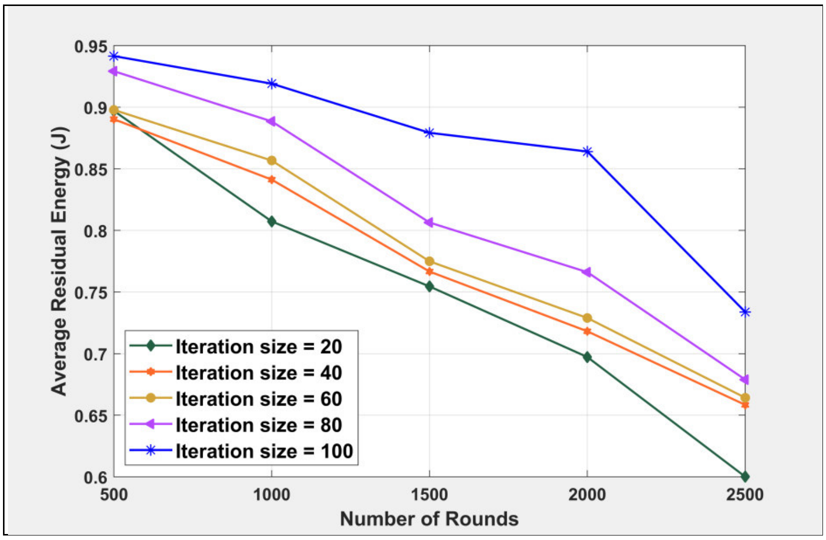


Figure 5.16: Average Residual Energy based on Iteration with 150 users

Table 5.11: Average Residual Energy based on Iteration with 150 users

Iteration / Rounds	500	1000	1500	2000	2500
20	0.90	0.81	0.75	0.70	0.60
40	0.89	0.84	0.77	0.72	0.66
60	0.90	0.86	0.77	0.73	0.66
80	0.93	0.89	0.81	0.77	0.68
100	0.94	0.92	0.88	0.86	0.73

Latency: The analysis based on latency by varying the iteration with 150 users is portrayed in Figure 5.17. While considering the 20 iterations of GCO algorithm with 500 rounds, the latency estimated by the proposed method is 7.87, which is increased to 17.52, when the round is increased to 2500. In contrast, the latency gets minimized with increase in the number of iterations of the algorithm. For example, with 1500 round and 20 iterations, the latency estimated by the newly devised method is 13.99, which is further minimized to 8.06 with 100 iterations. Thus, the increase in iteration elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 5.12.

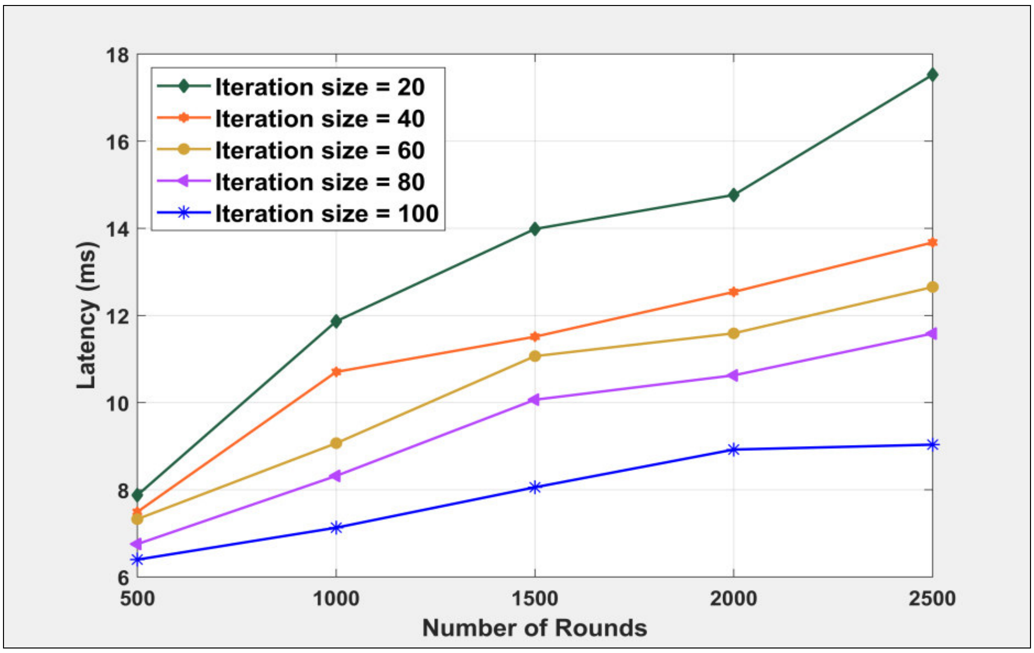


Figure 5.17: Latency based on Iteration with 150 users

Table 5.12: Latency based on Iteration with 150 users

Iteration / Rounds	500	1000	1500	2000	2500
20	7.87	11.87	13.99	14.77	17.52
40	7.49	10.70	11.51	12.54	13.68
60	7.33	9.07	11.07	11.59	12.65
80	6.75	8.32	10.07	10.63	11.59
100	6.40	7.13	8.06	8.92	9.04

Network Life Time: The network lifetime based analysis with 150 users by varying the iteration size is depicted in Figure 5.18. The network lifetime estimated by the newly devised D2D communication protocol with multi hop routing is 94.30 with 20 iteration and 500 rounds. The same is 69.55 with 2500 rounds and 20 iterations, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 80.43 with 1500 rounds and 20 iterations, which elevates with 90.16 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 5.13.

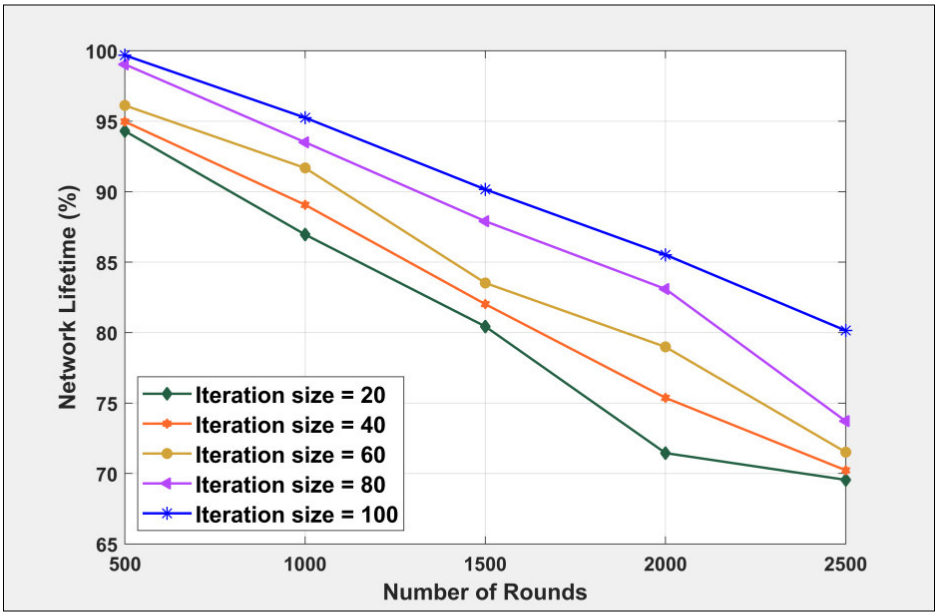


Figure 5.18: Network Life Time based on Iteration with 150 users

Table 5.13: Network Life Time based on Iteration with 150 users

Iteration / Rounds	500	1000	1500	2000	2500
20	94.30	86.96	80.43	71.45	69.55
40	94.97	89.07	82.02	75.37	70.23
60	96.12	91.68	83.52	78.98	71.51
80	99.04	93.51	87.90	83.09	73.71
100	99.68	95.25	90.16	85.52	80.14

Packet Delivery Ratio: The interpretation of the packet delivery ratio for various iteration sizes of the newly devised GCO algorithm of the introduced D2D multi-hop routing with 150 users is depicted in Figure 5.19. For 20 iterations, the packet delivery ratio accomplished by the newly devised protocol is 94.90 with 500 rounds, which is 72.98 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 86.33 with 20 iterations and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 iterations is 93.38 with 100 rounds. The detailed analysis is presented in Table 5.14.

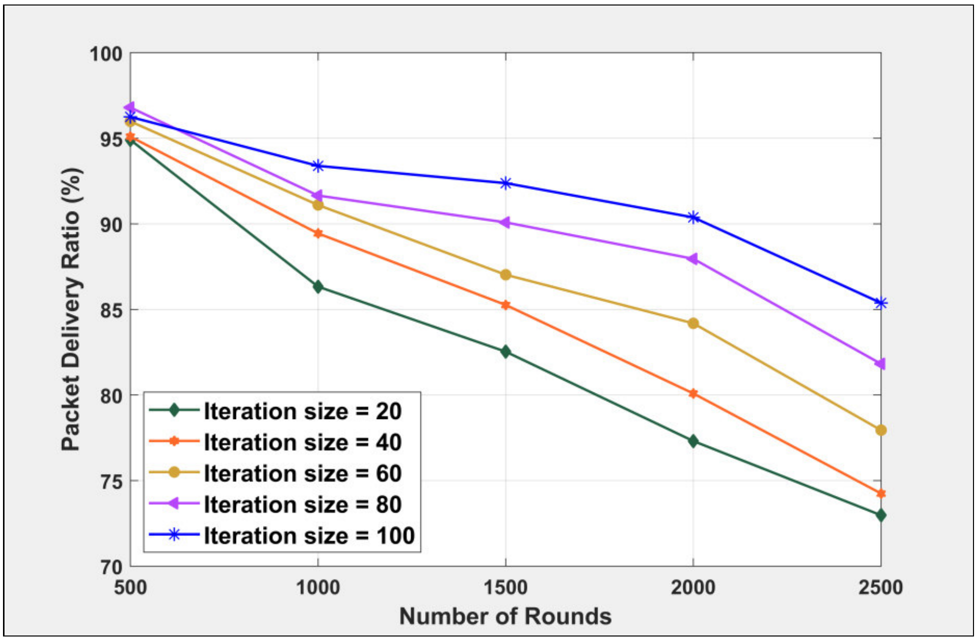


Figure 5.19: Packet Delivery Ratio based on Iteration with 150 users

Table 5.14: Packet Delivery Ratio based on Iteration with 150 users

Iteration / Rounds	500	1000	1500	2000	2500
20	94.90	86.33	82.53	77.31	72.98
40	95.09	89.44	85.26	80.09	74.25
60	95.99	91.10	87.03	84.19	77.94
80	96.80	91.65	90.08	87.96	81.82
100	96.25	93.38	92.38	90.37	85.38

Throughput: The throughput based analysis of the D2D protocol by varying the iteration of the GCO algorithm is depicted in Figure 5.20 with 150 users. The throughput estimated by the newly devised protocol with 20 iterations and 500 communications round is 22, which is 43 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 iterations, the throughput estimated by the proposed protocol is 38. When the iteration increased to 100, the throughput estimated is 62 that depict the better outcome of the model with increase in iteration. The detailed analysis is presented in Table 5.15.

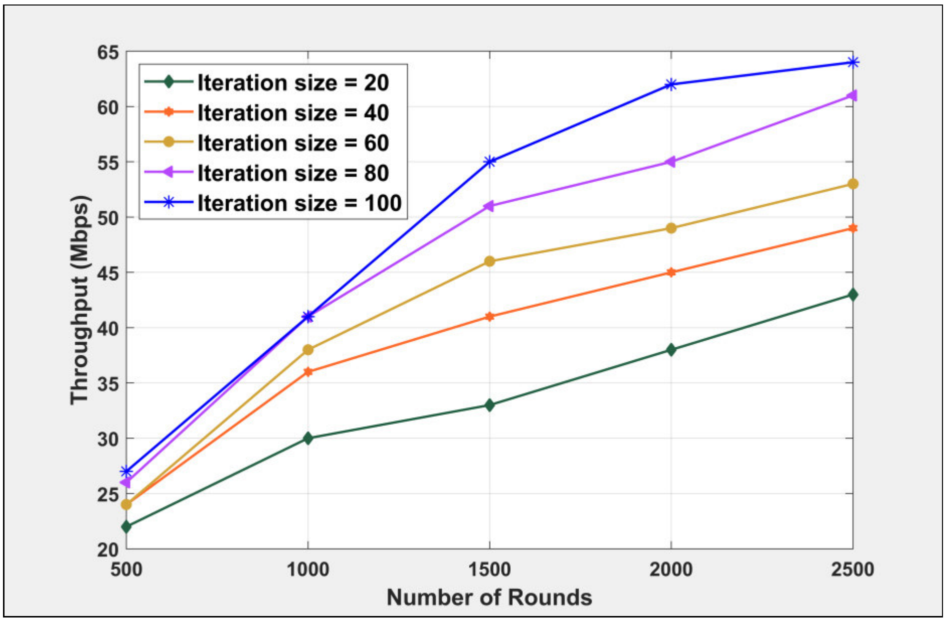


Figure 5.20: Throughput based on Iteration with 150 users

Table 5.15: Throughput based on Iteration with 150 users

Iteration / Rounds	500	1000	1500	2000	2500
20	22	30	33	38	43
40	24	36	41	45	49
60	24	38	46	49	53
80	26	41	51	55	61
100	27	41	55	62	64

2. Analysis by varying the Population

The analysis by varying the population size of the algorithm is detailed in this section by varying the number of users in the network.

(a) Using 50 users

Average Residual Energy: The analysis by varying the population size and average residual energy with 50 users is depicted in Figure 5.21. The average residual energy acquired with 500 round is 0.95 concerning to the population size 20, which is further reduced when the round increases to 2500 with the average residual energy of 0.74. As a result, increasing the number of rounds uses more energy. Even still, increasing the population size improves the model's performance by raising the amount of residual energy. For example, the average residual energy estimated with the population size 20 and 1500 round is 0.82, which is 0.88 when the population size increased to 100. The detailed analysis is depicted in Table 5.16.

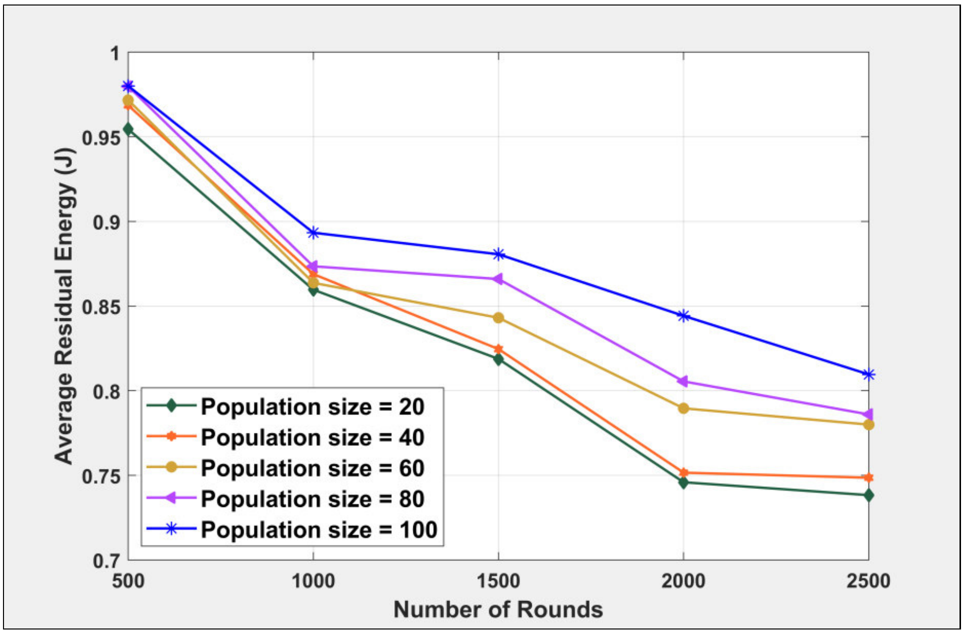


Figure 5.21: Average Residual Energy based on Population size with 50 users

Table 5.16: Average Residual Energy based on Population size with 50 users

Population / Rounds	**500**	**1000**	**1500**	**2000**	**2500**
20	0.95	0.86	0.82	0.75	0.74
40	0.97	0.87	0.82	0.75	0.75
60	0.97	0.86	0.84	0.79	0.78
80	0.98	0.87	0.87	0.81	0.79
100	0.98	0.89	0.88	0.84	0.81

Latency: The analysis based on latency by varying the population size with 50 users is portrayed in Figure 5.22. While considering the population size 20 with 500 rounds, the latency estimated by the proposed method is 2.30, which is increased to 3.60, when the round is increased to 2500. In contrast, the latency gets minimized with increase in population size of the algorithm. For example, with 2000 round and population size of 20, the latency estimated by the newly devised method is 3.26, which is further minimized to 2.43 with 100 populations. Thus, the increase in population size elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 5.17.

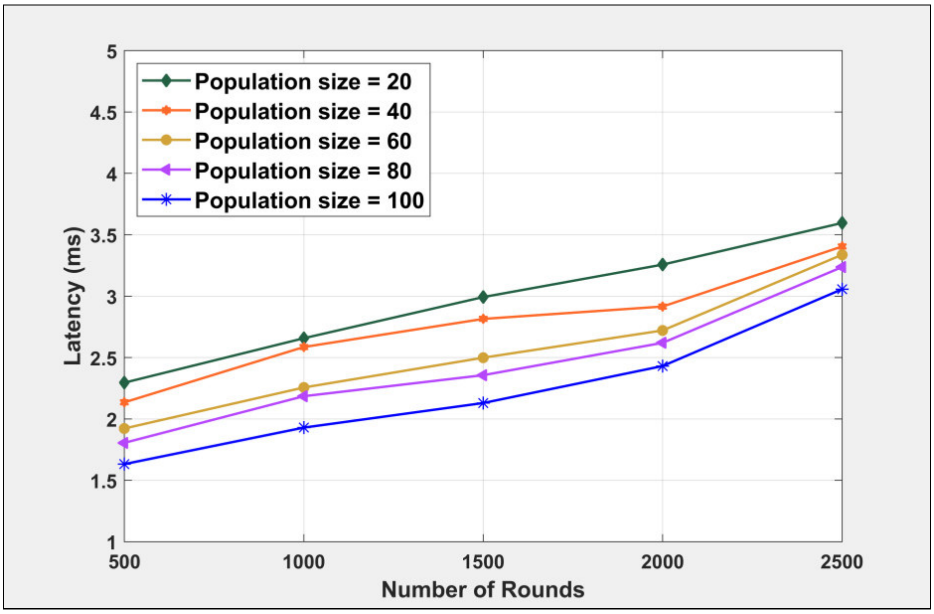


Figure 5.22: Latency based on Population size with 50 users

Table 5.17: Latency based on Population size with 50 users

Population / Rounds	**500**	**1000**	**1500**	**2000**	**2500**
20	2.30	2.66	2.99	3.26	3.60
40	2.14	2.59	2.81	2.92	3.40
60	1.92	2.26	2.50	2.72	3.34
80	1.81	2.19	2.36	2.62	3.24
100	1.63	1.93	2.13	2.43	3.06

Network Life Time: The network lifetime based analysis with 50 users by varying the population size is depicted in Figure 5.23. The network lifetime estimated by the newly devised D2D communication protocol with multi hop routing is 98.63 with 20 population and 500 rounds. The same is 90.84 with 2500 rounds and population size of 20, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 92.06 with 1500 rounds and 20 populations, which elevates with 96.31 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 5.18.

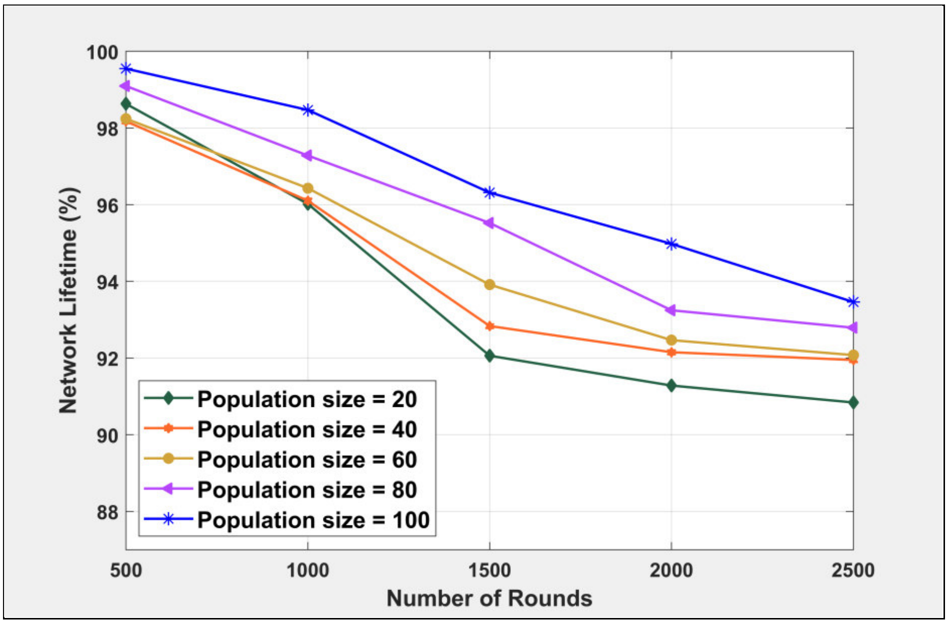


Figure 5.23: Network Life Time based on Population size with 50 users

Table 5.18: Network Life Time based on Population size with 50 users

Population / Rounds	500	1000	1500	2000	2500
20	98.63	96.02	92.06	91.28	90.84
40	98.17	96.10	92.83	92.15	91.95
60	98.24	96.43	93.91	92.47	92.08
80	99.09	97.28	95.52	93.24	92.79
100	99.55	98.47	96.31	94.98	93.46

Packet Delivery Ratio: The outcome based on the packet delivery ratio for various population sizes of the newly devised GCO algorithm of the introduced D2D multi-hop routing with 50 users is depicted in Figure 5.24. For the population size of 20, the packet delivery ratio accomplished by the newly devised protocol is 99.59 with 500 rounds, which is 92.14 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 96.09 with 20 population and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 populations is 98.07 with 100 rounds. The detailed analysis is presented in Table 5.19.

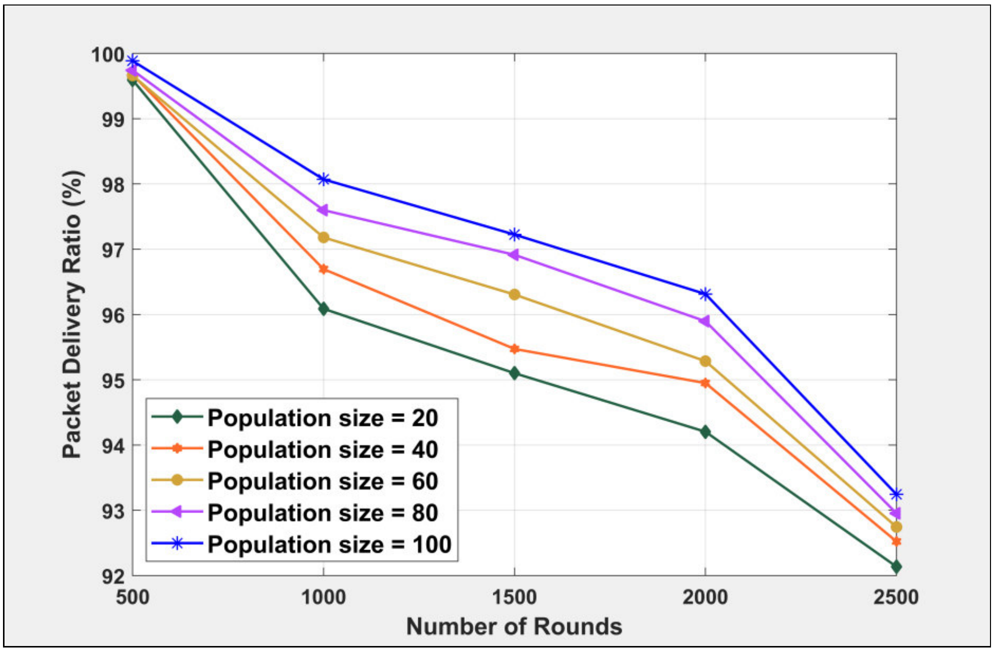


Figure 5.24: Packet Delivery Ratio based on Population size with 50 users

Table 5.19: Packet Delivery Ratio based on Population size with 50 users

Population / Rounds	500	1000	1500	2000	2500
20	99.59	96.09	95.10	94.20	92.14
40	99.67	96.70	95.47	94.95	92.52
60	99.66	97.18	96.31	95.28	92.75
80	99.74	97.60	96.91	95.90	92.95
100	99.89	98.07	97.22	96.31	93.24

Throughput: The throughput based analysis of the D2D protocol by varying the population size of the GCO algorithm is depicted in Figure 5.25 with 100 users. The throughput estimated by the newly devised protocol with 20 population size and 500 communications round is 6, which is 14 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 population size, the throughput estimated by the proposed protocol is 13. When the population size increased to 100, the throughput estimated is 18 that depict the better outcome of the model with increase in population size. The detailed analysis is presented in Table 5.20.

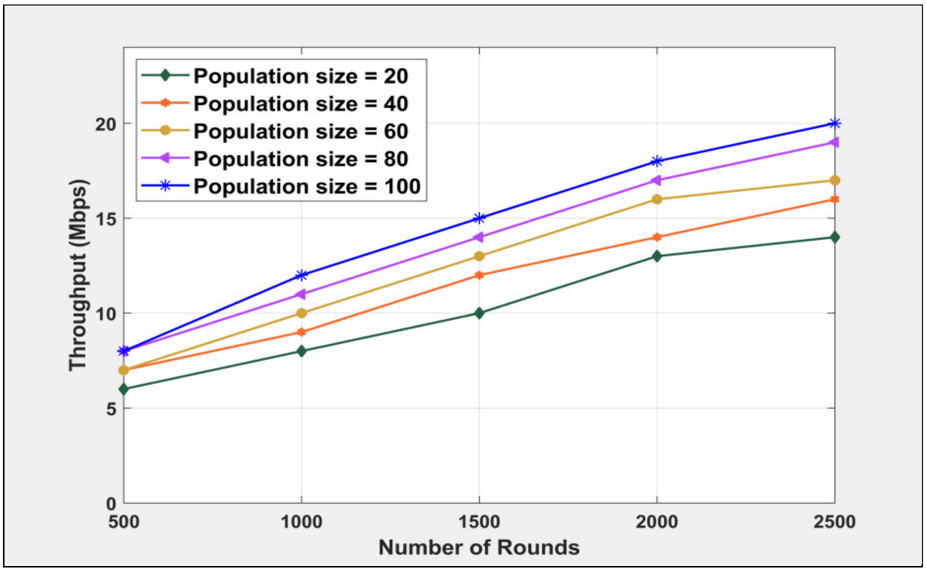


Figure 5.25: Throughput based on Population size with 50 users

Table 5.20: Throughput based on Population size with 50 users

Population / Rounds	500	1000	1500	2000	2500
20	6.00	8.00	10.00	13.00	14.00
40	7.00	9.00	12.00	14.00	16.00
60	7.00	10.00	13.00	16.00	17.00
80	8.00	11.00	14.00	17.00	19.00
100	8.00	12.00	15.00	18.00	20.00

(b) Using 100 Users

Average Residual Energy: The analysis by varying the population size and average residual energy with 100 users is depicted in Figure 5.26. The average residual energy acquired with 1000 round is 0.84 concerning to the population size 20, which is further reduced when the round increases to 2500 with the average residual energy of 0.69. Consequently, the interpretation depicts that the increasing the rounds uses more energy. The model's performance is still enhanced by expanding the population by increasing the amount of residual energy. For example, the average residual energy estimated with the population size 20 and 1500 round is 0.78, which is 0.85 when the population size increased to 100. The detailed analysis is depicted in Table 5.21.

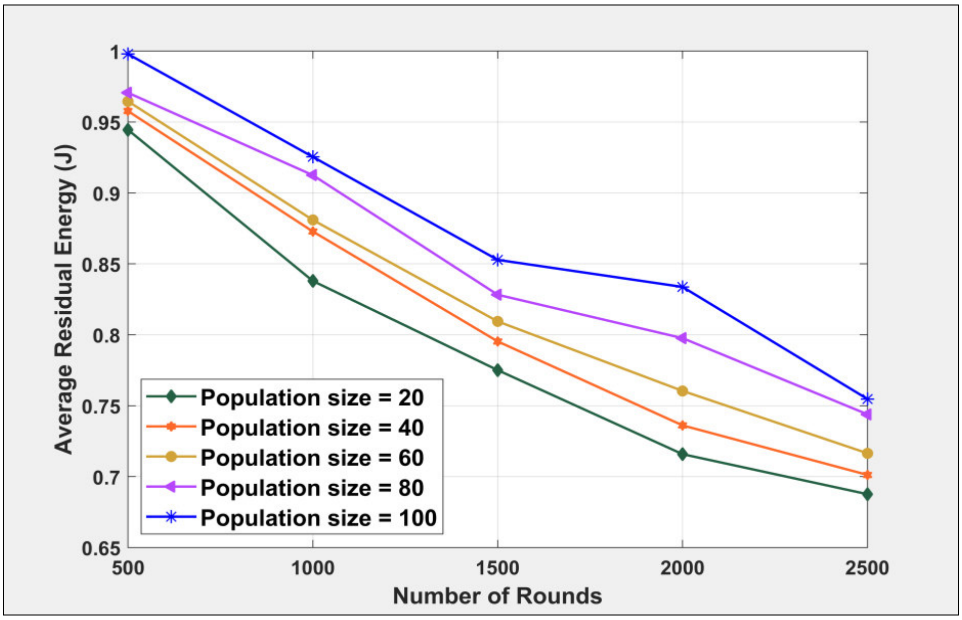


Figure 5.26: Average Residual Energy based on Population size with 100 users

Table 5.21: Average Residual Energy based on Population size with 100 users

Population / Rounds	500	1000	1500	2000	2500
20	0.94	0.84	0.78	0.72	0.69
40	0.96	0.87	0.80	0.74	0.70
60	0.96	0.88	0.81	0.76	0.72
80	0.97	0.91	0.83	0.80	0.74
100	1.00	0.93	0.85	0.83	0.75

Latency: The analysis based on latency by varying the population size with 100 users is portrayed in Figure 5.27. While considering the population size 20 with 500 rounds, the latency estimated by the proposed method is 4.33, which is increased to 9.94, when the round is increased to 2500. In contrast, the latency gets minimized with increase in population size of the algorithm. For example, with 2000 round and population size of 20, the latency estimated by the newly devised method is 9.36, which is further minimized to 5.76 with 100 populations. Thus, the increase in population size elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 5.22.

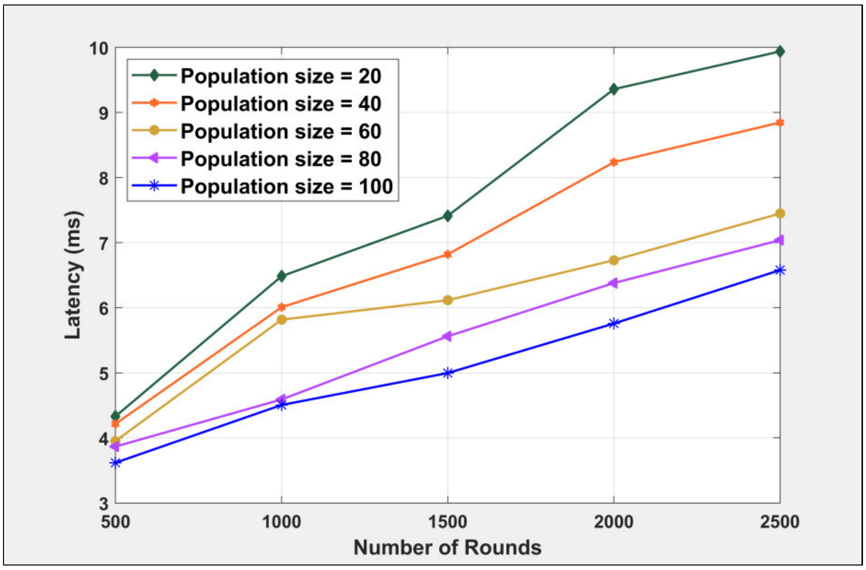


Figure 5.27: Latency based on Population size with 100 users

Table 5.22: Latency based on Population size with 100 users

Population / Rounds	**500**	**1000**	**1500**	**2000**	**2500**
20	4.33	6.48	7.41	9.36	9.94
40	4.22	6.01	6.82	8.24	8.85
60	3.95	5.82	6.12	6.73	7.45
80	3.87	4.59	5.56	6.38	7.04
100	3.62	4.51	5.00	5.76	6.58

Network Life Time: The network lifetime based analysis with 100 users by varying the population size is depicted in Figure 5.28. The network lifetime estimated by the newly devised D2D communication protocol with multi hop routing is 97.17 with 20 population and 500 rounds. The network lifetime is 75.11 with 2500 rounds and population size of 20, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 86.23 with 1500 rounds and 20 populations, which elevates with 97.03 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 5.23.

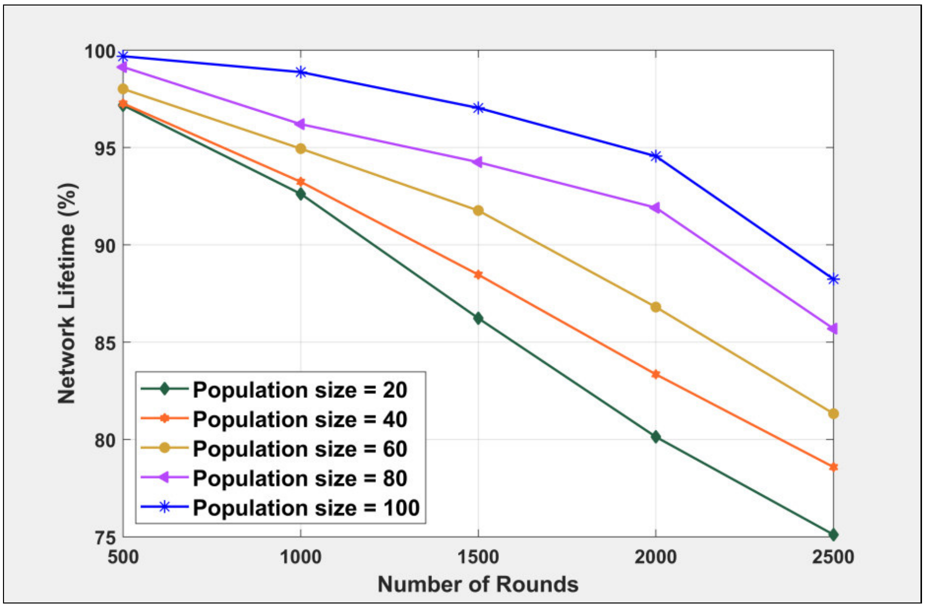


Figure 5.28: Network Life Time based on Population size with 100 users

Table 5.23: Network Life Time based on Population size with 100 users

Population / Rounds	**500**	**1000**	**1500**	**2000**	**2500**
20	97.17	92.62	86.23	80.13	75.11
40	97.26	93.24	88.47	83.35	78.58
60	98.01	94.94	91.76	86.80	81.33
80	99.14	96.20	94.25	91.91	85.69
100	99.69	98.87	97.03	94.55	88.24

Packet Delivery Ratio: The outcome based on the packet delivery ratio for various population sizes of the newly devised GCO algorithm of the introduced D2D multi-hop routing with 100 users is depicted in Figure 5.29. For the population size of 20, the packet delivery ratio accomplished by the newly devised protocol is 97.78 with 500 rounds, which is 80.92 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 92.50 with 20 population and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 populations is 97.94 with 100 rounds. The detailed analysis is presented in Table 5.24.

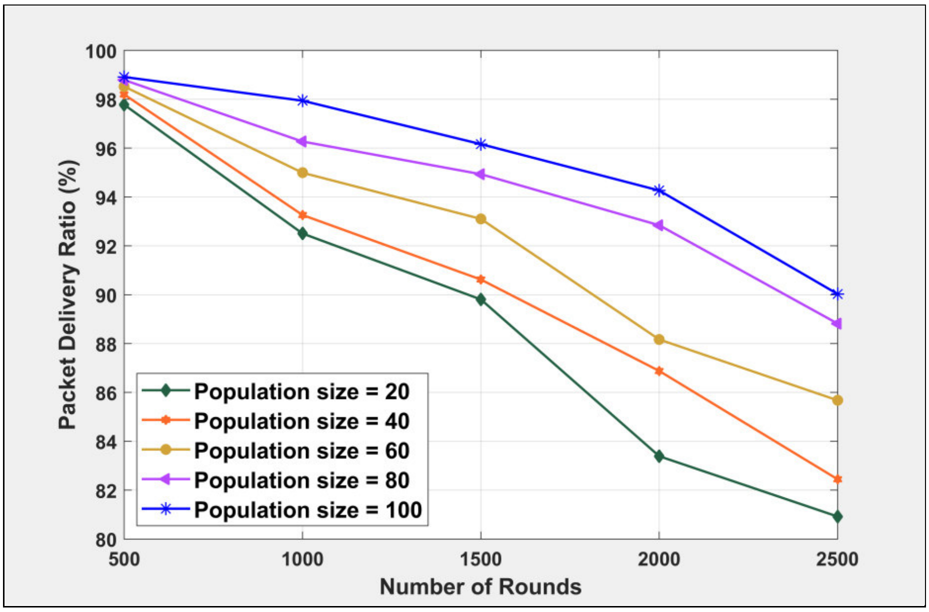


Figure 5.29: Packet Delivery Ratio based on Population size with 100 users

Table 5.24: Packet Delivery Ratio based on Population size with 100 users

Population / Rounds	500	1000	1500	2000	2500
20	97.78	92.50	89.81	83.39	80.92
40	98.20	93.26	90.62	86.88	82.45
60	98.52	94.99	93.10	88.17	85.68
80	98.79	96.27	94.93	92.84	88.82
100	98.91	97.94	96.16	94.26	90.03

Throughput: The throughput based analysis of the D2D protocol by varying the population size of the GCO algorithm is depicted in Figure 5.30 with 100 users. The throughput estimated by the newly devised protocol with 20 population size and 500 communications round is 18, which is 30 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 population size, the throughput estimated by the proposed protocol is 24. When the population size increased to 100, the throughput estimated is 34 that depict the better outcome of the model with increase in population size. The detailed analysis is presented in Table 5.25.

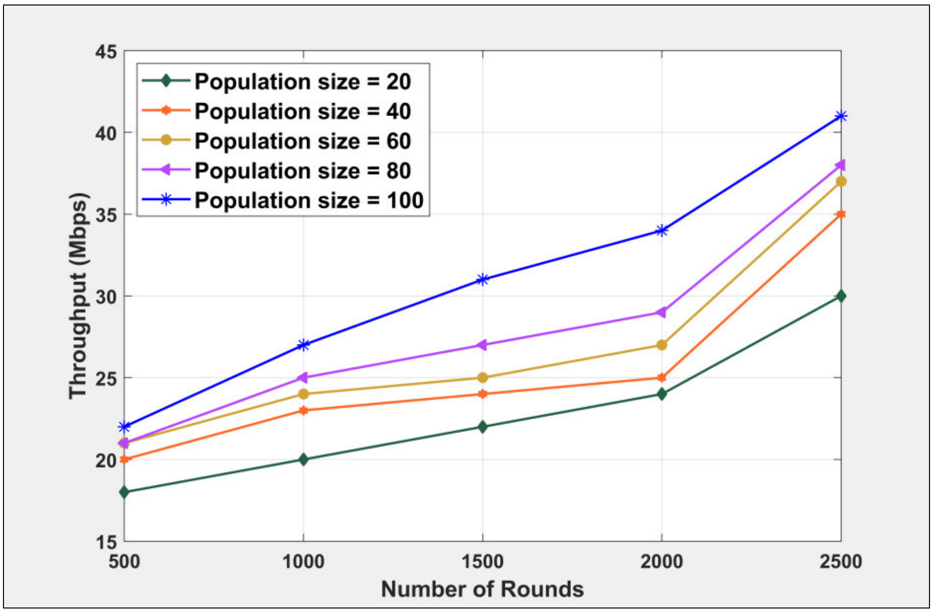


Figure 5.30: Throughput based on Population size with 100 users

Table 5.25: Throughput based on Population size with 100 users

Population / Rounds	500	1000	1500	2000	2500
20	18.00	20.00	22.00	24.00	30.00
40	20.00	23.00	24.00	25.00	35.00
60	21.00	24.00	25.00	27.00	37.00
80	21.00	25.00	27.00	29.00	38.00
100	22.00	27.00	31.00	34.00	41.00

(c) Using 150 Users

Average Residual Energy: The analysis by varying the population size and average residual energy with 150 users is depicted in Figure 5.31. The average residual energy acquired with 1000 round is 0.85 concerning to the population size 20, which is further reduced when the round increases to 2500 with the average residual energy of 0.63. Consequently, the interpretation depicts that the increasing the rounds uses more energy. The model's performance is still enhanced by expanding the population by increasing the amount of residual energy. For example, the average residual energy estimated with the population size 20 and 2000 round is 0.73, which is 0.86 when the population size increased to 100. The detailed analysis is depicted in Table 5.26.

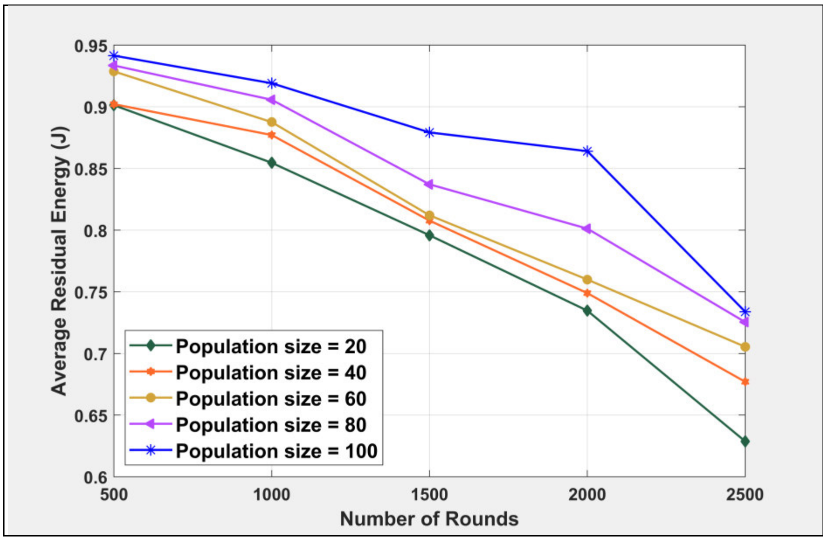


Figure 5.31: Average Residual Energy based on Population size with 150 users

Table 5.26: Average Residual Energy based on Population size with 150 users

Population / Rounds	**500**	**1000**	**1500**	**2000**	**2500**
20	0.90	0.85	0.80	0.73	0.63
40	0.90	0.88	0.81	0.75	0.68
60	0.93	0.89	0.81	0.76	0.71
80	0.93	0.91	0.84	0.80	0.73
100	0.94	0.92	0.88	0.86	0.73

Latency: The analysis based on latency by varying the population size with 150 users is portrayed in Figure 5.32. While considering the population size 20 with 500 rounds, the latency estimated by the proposed method is 7.88, which is increased to 16.83, when the round is increased to 2500. In contrast, the latency gets minimized with increase in population size of the algorithm. For example, with 2000 round and population size of 20, the latency estimated by the newly devised method is 14.61, which is further minimized to 8.92 with 100 populations. Thus, the increase in population size elevates the performance and increase in number of rounds limits the performance. The detailed analysis is presented in Table 5.27.

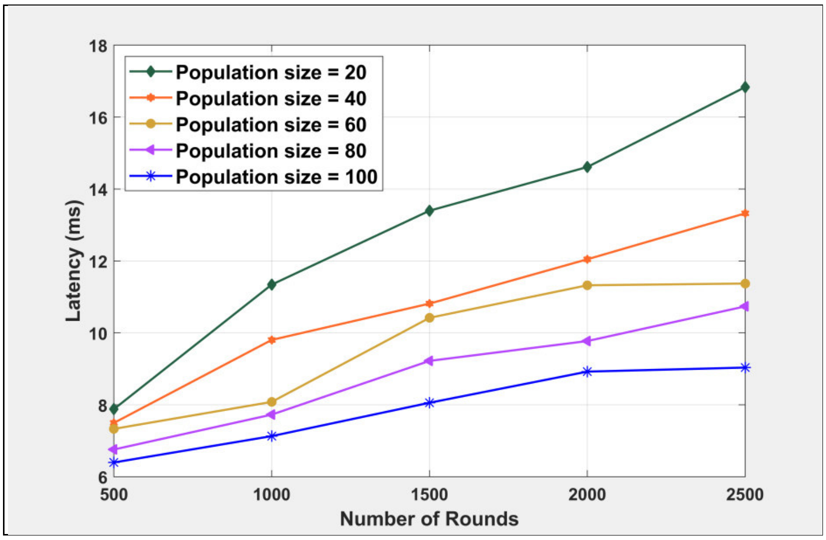


Figure 5.32: Latency based on Population size with 150 users

Table 5.27: Latency based on Population size with 150 users

Population / Rounds	**500**	**1000**	**1500**	**2000**	**2500**
20	7.88	11.34	13.40	14.61	16.83
40	7.50	9.80	10.81	12.05	13.32
60	7.33	8.08	10.42	11.32	11.37
80	6.76	7.73	9.22	9.77	10.74
100	6.40	7.13	8.06	8.92	9.04

Network Life Time: The network lifetime based analysis with 150 users by varying the population size is depicted in Figure 5.33. The network lifetime estimated by the newly devised D2D communication protocol with multi hop routing is 94.31 with 20 population and 500 rounds. The network lifetime is 71.73 with 2500 rounds and population size of 20, which indicates that the minimal rounds provides the better network lifetime. Also, the network lifetime estimated is 81.51 with 1500 rounds and 20 populations, which elevates with 90.16 with 100 iterations and 1500 rounds. Here, the analysis indicates the enhanced performance with minimal communication round and higher iteration. The detailed analysis is presented in Table 5.28.

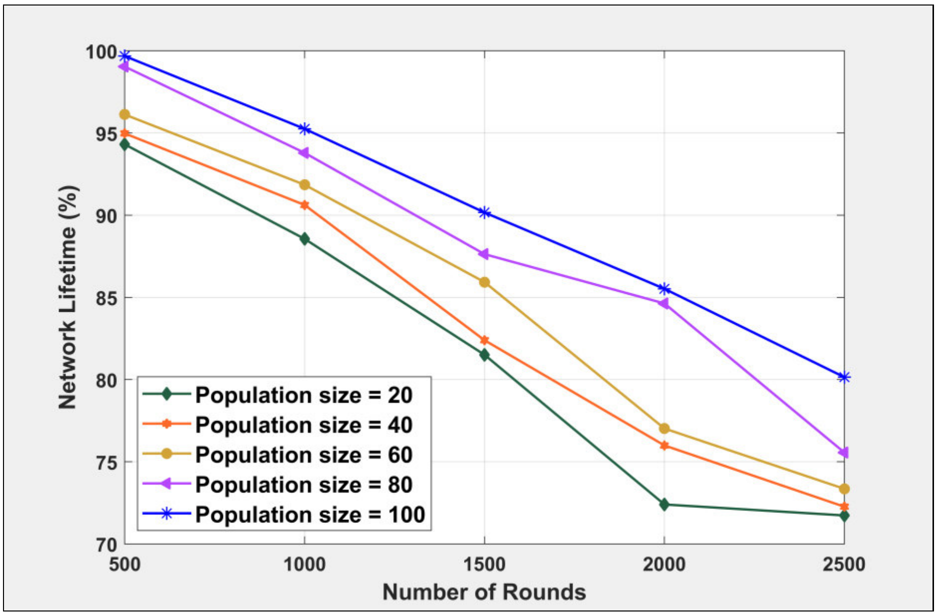


Figure 5.33: Network Life Time based on Population size with 150 users

Table 5.28: Network Life Time based on Population size with 150 users

Population / Rounds	500	1000	1500	2000	2500
20	94.31	88.56	81.51	72.40	71.73
40	94.97	90.62	82.39	75.99	72.26
60	96.12	91.85	85.93	77.02	73.35
80	99.04	93.79	87.63	84.63	75.56
100	99.68	95.25	90.16	85.52	80.14

Packet Delivery Ratio: The outcome based on the packet delivery ratio for various population sizes of the newly devised GCO algorithm of the introduced D2D multi-hop routing with 150 users is depicted in Figure 5.34. For the population size of 20, the packet delivery ratio accomplished by the newly devised protocol is 94.91 with 500 rounds, which is 71.88 when the round is increased to 2500. In contrast, the packet delivery ratio acquired by the proposed model is 85.32 with 20 population and 1000 rounds. Besides, the packet delivery ratio measured by the proposed protocol with 100 populations is 93.38 with 100 rounds. The detailed analysis is presented in Table 5.29.

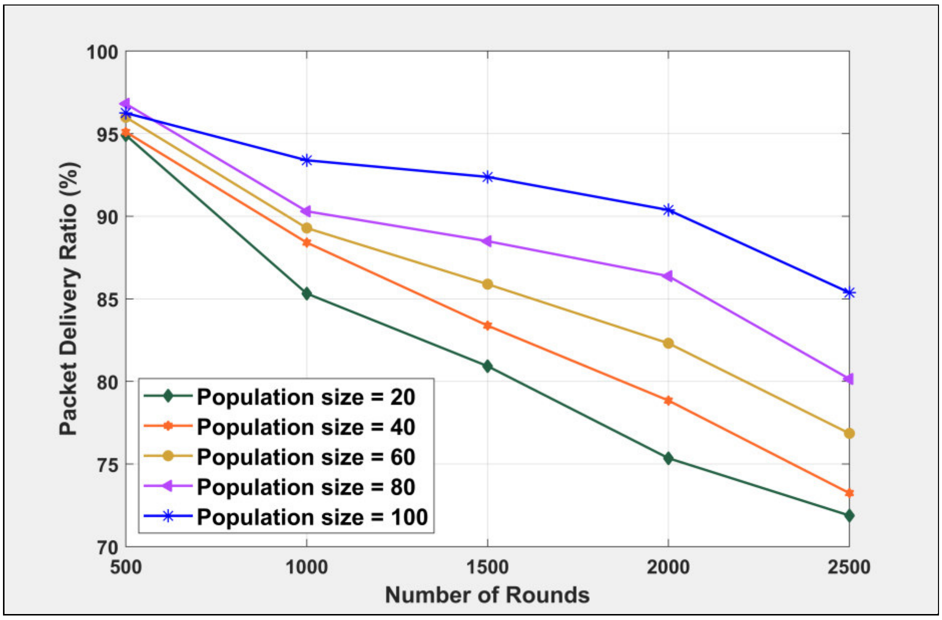


Figure 5.34: Packet Delivery Ratio based on Population size with 150 users

Table 5.29: Packet Delivery Ratio based on Population size with 150 users

Population / Rounds	**500**	**1000**	**1500**	**2000**	**2500**
20	94.91	85.32	80.92	75.35	71.88
40	95.10	88.40	83.38	78.84	73.24
60	95.99	89.28	85.89	82.31	76.85
80	96.80	90.30	88.49	86.37	80.15
100	96.25	93.38	92.38	90.37	85.38

Throughput: The throughput based analysis of the D2D protocol by varying the population size of the GCO algorithm is depicted in Figure 5.35 with 150 users. The throughput estimated by the newly devised protocol with 20 population size and 500 communications round is 20, which is 41 with 2500 rounds. While analyzing the performance with 2000 rounds and 20 population size, the throughput estimated by the proposed protocol is 37. When the population size increased to 100, the throughput estimated is 62 that depict the better outcome of the model with increase in population size. The detailed analysis is presented in Table 5.30.

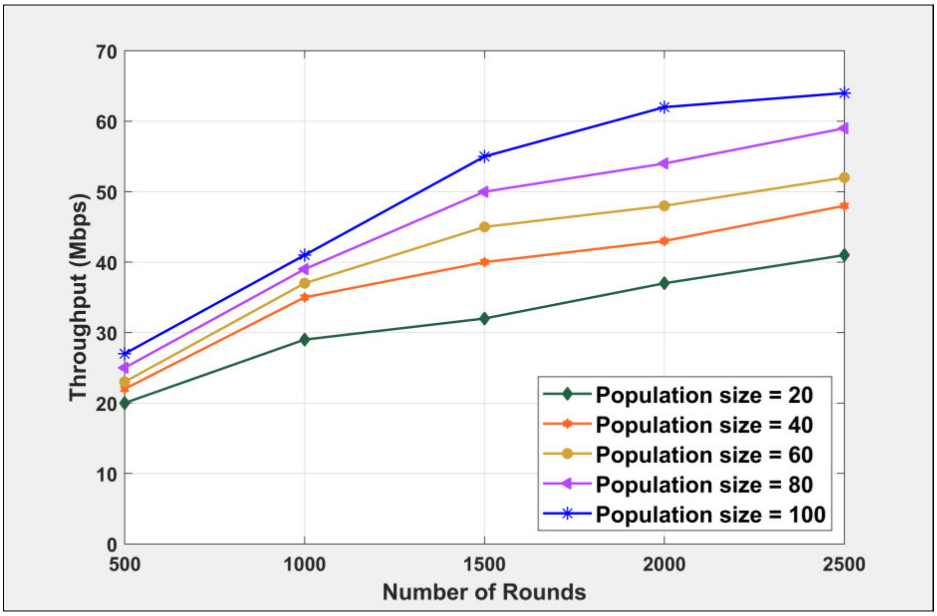


Figure 5.35: Throughput based on Population size with 150 users

Table 5.30: Throughput based on Population size with 150 users

Population / Rounds	500	1000	1500	2000	2500
20	20.00	29.00	32.00	37.00	41.00
40	22.00	35.00	40.00	43.00	48.00
60	23.00	37.00	45.00	48.00	52.00
80	25.00	39.00	50.00	54.00	59.00
100	27.00	41.00	55.00	62.00	64.00

5.4.3 Comparative Methods

The comparative analysis of the newly devised D2D communication protocols with the conventional methods to depict the superiority of the proposed model. To compare the suggested approach to existing energy-efficient D2D routing protocols, such as DRL [182], 5G-EECC [183], Modified Derivative Algorithm [184], and MBLCR [185] are compared with the newly devised approach. The comparative analysis of the D2D communication by varying the number of users in the network is detailed in this section.

(a) Using 50 users

Average Residual Energy: The assessment based on the average residual energy is depicted in Figure 5.36 with 50 users. The average residual energy evaluated by the newly devised protocol is 0.98 with 500 rounds, which is 0.90%, 2.18%, 8.37%, and 9.81% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. For 2500 rounds, the average residual energy evaluated by the newly devised protocol is 0.81, which is 11.68%, 33.41%, 40.99%, and 52.80% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.31.

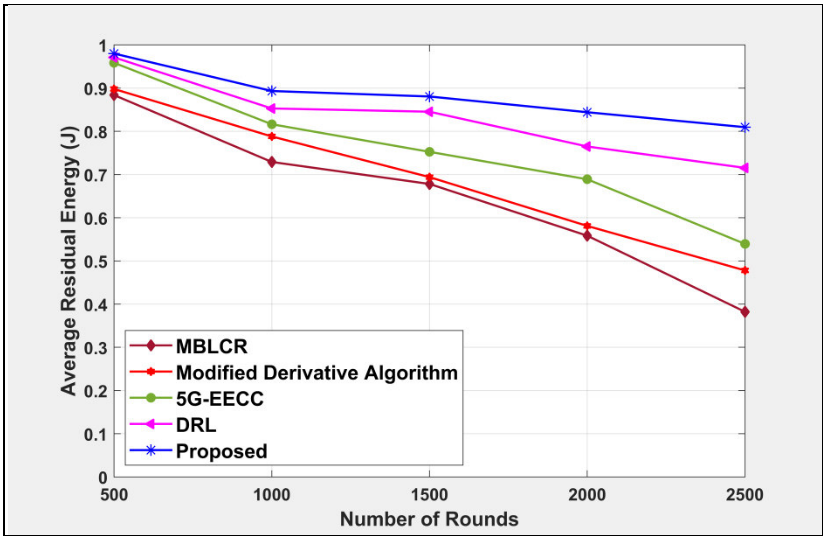


Figure 5.36: Average Residual Energy with 50 users

Table 5.31: Average Residual Energy with 50 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	0.88	0.73	0.68	0.56	0.38
Modified Derivative Algorithm	0.90	0.79	0.69	0.58	0.48
5G-EECC	0.96	0.82	0.75	0.69	0.54
DRL	0.97	0.85	0.85	0.76	0.72
Proposed	0.98	0.89	0.88	0.84	0.81

Latency: Figure 5.37 depicts the latency analysis of the proposed method by considering the number of users as 50. While considering the 500 rounds, the latency evaluated by the newly devised protocol is 1.63 that is 9.36%, 14.89%, 23.39%, and 39.34% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. Also, the latency estimated by the newly devised protocol is 3.06 with 2500 rounds that is 22.27%, 35.41%, 36.32%, and 42.23% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.32.

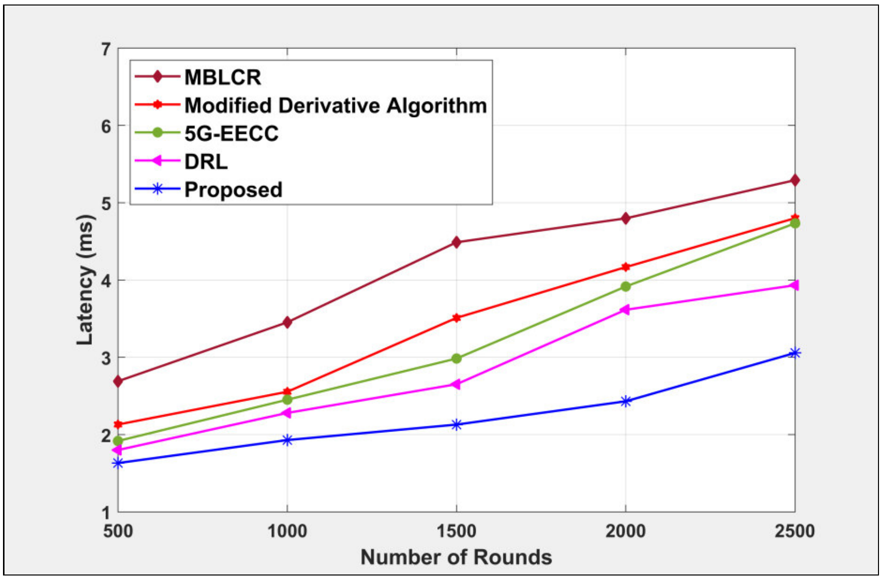


Figure 5.37: Latency with 50 users

Table 5.32: Latency with 50 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	2.69	3.45	4.49	4.80	5.29
Modified Derivative Algorithm	2.13	2.55	3.51	4.17	4.80
5G-EECC	1.92	2.45	2.98	3.92	4.73
DRL	1.80	2.28	2.65	3.62	3.93
Proposed	1.63	1.93	2.13	2.43	3.06

Network Life Time: The network lifetime analysis is portrayed in Figure 5.38 and its detailed analysis is presented in Table 5.33. In this, the newly devised protocol accomplished the higher network life time of 96.31; still the conventional methods like DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR accomplished the network life time of 92.52, 88.91, 85.13 and 74.05 respectively. Here, the newly devised protocol is 3.94%, 7.69%, 11.61%, and 23.11% elevated outcome as compared to the existing like DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods.

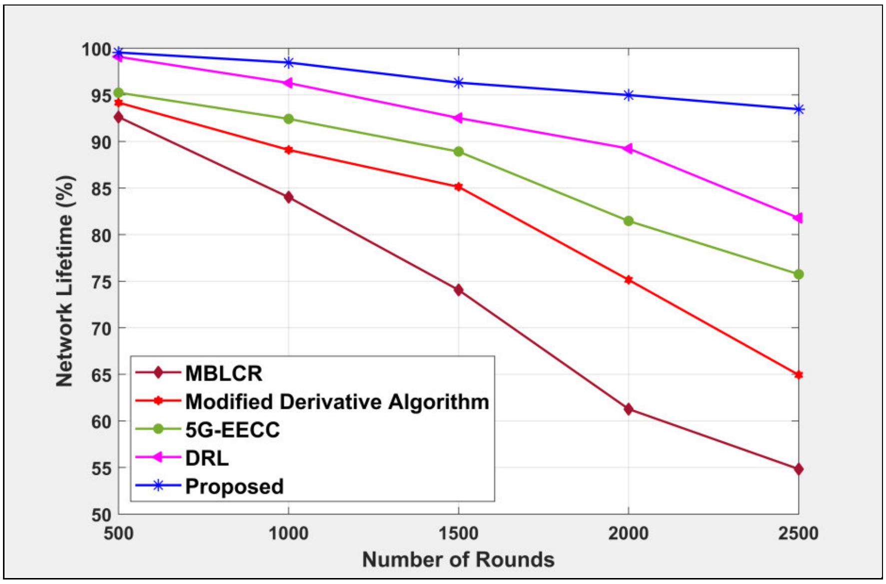


Figure 5.38: Network Life Time with 50 users

Table 5.33: Network Life Time with 50 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	92.62	84.02	74.05	61.28	54.84
Modified Derivative Algorithm	94.17	89.10	85.13	75.15	64.94
5G-EECC	95.24	92.42	88.91	81.46	75.75
DRL	99.09	96.28	92.52	89.24	81.78
Proposed	99.55	98.47	96.31	94.98	93.46

Packet Delivery Ratio: The reception amount of information depicts the measure of packet deliver ratio; thus the higher value indicates the better outcome. The analysis of the packet delivery ratio with 50 users is depicted in Figure 5.39, wherein the newly devised protocol acquired the superior outcome. For example, the newly devised protocol acquired the packet delivery ratio of 96.31 with 2000 rounds; still the conventional methods DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR acquired the minimal packet delivery ratio of 89.05, 85.84, 82.10, and 75.25 respectively. Here, the performance enhancement of 7.54%, 10.88%, 14.75%, and 21.87% concerning the DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is presented in Table 5.34.

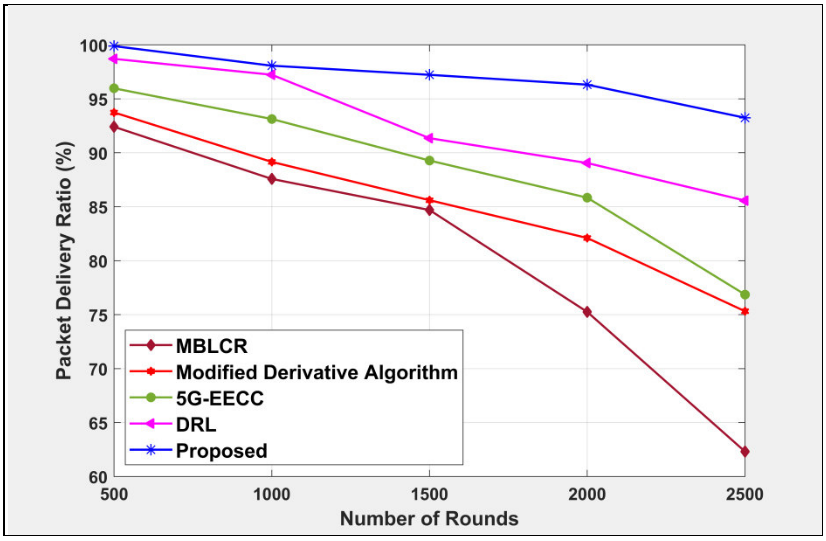


Figure 5.39: Packet Delivery Ratio with 50 users

Table 5.34: Packet Delivery Ratio with 50 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	92.41	87.58	84.69	75.25	62.32
Modified Derivative Algorithm	93.74	89.16	85.61	82.10	75.32
5G-EECC	95.97	93.13	89.28	85.84	76.86
DRL	98.70	97.23	91.35	89.05	85.57
Proposed	99.89	98.07	97.22	96.31	93.24

Throughput: The throughput based interpretation with 50 users is portrayed in Figure 5.40. The throughput evaluated by the newly devised protocol is 8 with 500 rounds, which is 25.00%, 37.50%, 37.50%, and 62.50% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. For 2500 rounds, the throughput evaluated by the newly devised protocol is 20, which is 15.00%, 20.00%, 40.00%, and 50.00% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.35.

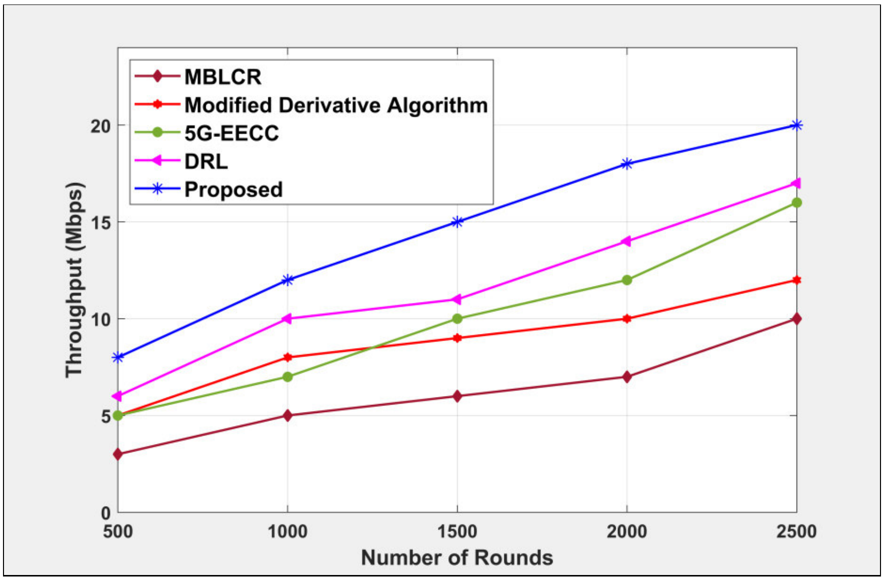


Figure 5.40: Throughput with 50 users

Table 5.35: Throughput with 50 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	3	5	6	7	10
Modified Derivative Algorithm	5	8	9	10	12
5G-EECC	5	7	10	12	16
DRL	6	10	11	14	17
Proposed	8	12	15	18	20

(b) Using 100 Users

Average Residual Energy: The assessment based on the average residual energy is depicted in Figure 5.41 with 100 users. The average residual energy evaluated by the newly devised protocol is 0.98 with 500 rounds, which is 6.59%, 8.23%, 9.43%, and 10.75% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. For 2500 rounds, the average residual energy evaluated by the newly devised protocol is 0.81, which is 6.54%, 18.43%, 31.46%, and 42.53% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.36.

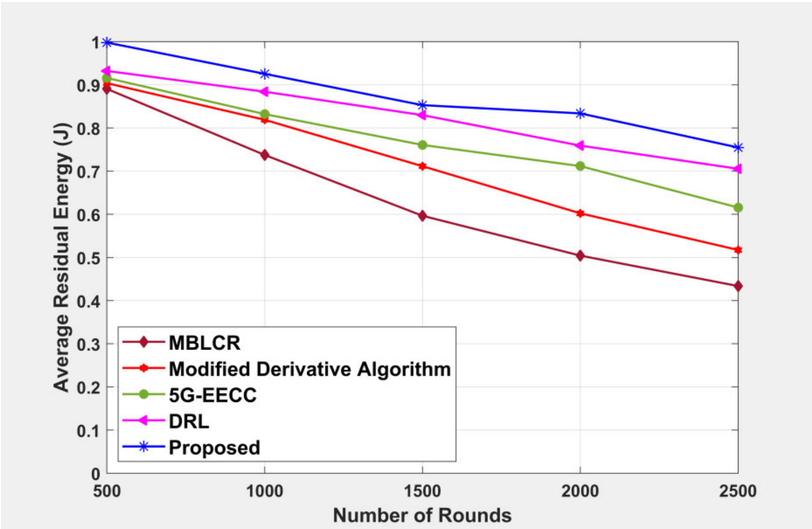


Figure 5.41: Average Residual Energy with 100 users

Table 5.36: Average Residual Energy with 100 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	0.89	0.74	0.60	0.50	0.43
Modified Derivative Algorithm	0.90	0.82	0.71	0.60	0.52
5G-EECC	0.92	0.83	0.76	0.71	0.62
DRL	0.93	0.88	0.83	0.76	0.71
Proposed	1.00	0.93	0.85	0.83	0.75

Latency: Figure 5.42 depicts the latency analysis of the proposed method by considering the number of users as 50. While considering the 500 rounds, the latency evaluated by the newly devised protocol is 3.62 that is 10.06%, 14.01%, 22.02%, and 48.13% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. Also, the latency estimated by the newly devised protocol is 6.58 with 2500 rounds that is 8.57%, 14.62%, 24.14%, and 42.72% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.37.

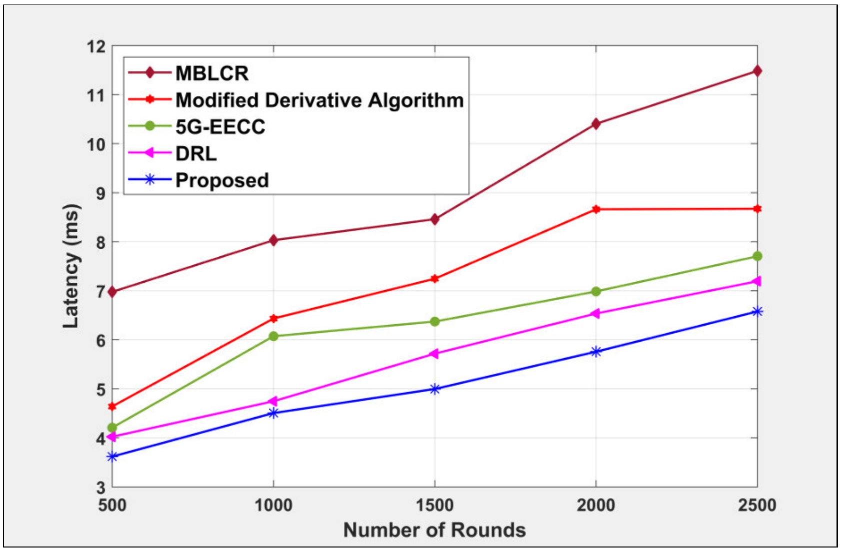


Figure 5.42: Latency with 100 users

Table 5.37: Latency with 100 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	6.98	8.03	8.46	10.40	11.48
Modified Derivative Algorithm	4.64	6.43	7.25	8.66	8.67
5G-EECC	4.21	6.07	6.37	6.99	7.70
DRL	4.02	4.75	5.72	6.54	7.19
Proposed	3.62	4.51	5.00	5.76	6.58

Network Life Time: The network lifetime analysis is portrayed in Figure 5.43 and its detailed analysis is presented in Table 5.38. In this, the newly devised protocol accomplished the higher network life time of 97.03; still the conventional methods like DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR accomplished the network life time of 89.51, 86.03, 78.73 and 63.49 respectively with 1500 rounds. Here, the newly devised protocol is 7.75%, 11.34%, 18.86%, and 34.57% elevated outcome as compared to the existing like DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods.

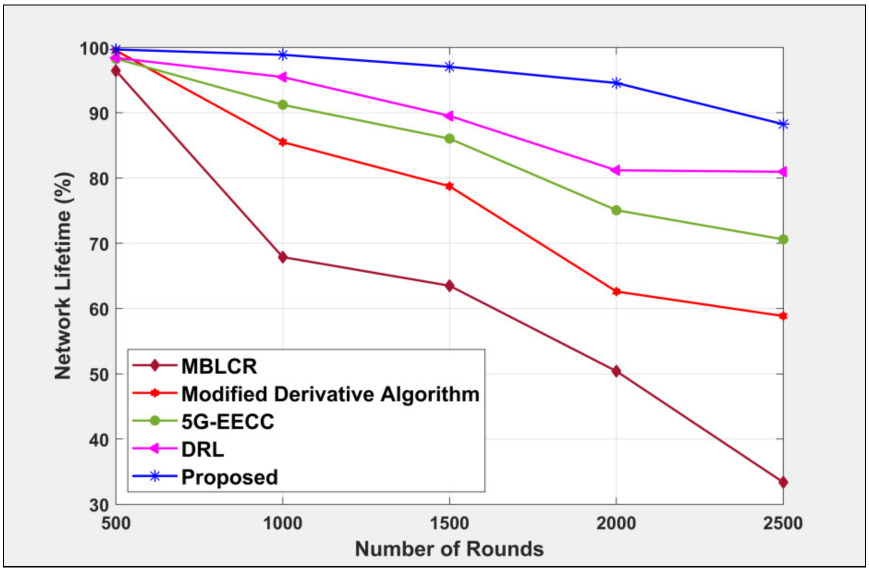


Figure 5.43: Network Life Time with 100 users

Table 5.38: Network Life Time with 100 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	96.44	67.88	63.49	50.40	33.38
Modified Derivative Algorithm	99.53	85.50	78.73	62.61	58.85
5G-EECC	98.27	91.21	86.03	75.07	70.59
DRL	98.40	95.46	89.51	81.17	80.95
Proposed	99.69	98.87	97.03	94.55	88.24

Packet Delivery Ratio: The analysis of the packet delivery ratio with 100 users is depicted in Figure 5.44, wherein the newly devised protocol acquired the superior outcome. For example, the newly devised protocol acquired the packet delivery ratio of 94.26 with 2000 rounds; still the conventional methods DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR acquired the minimal packet delivery ratio of 90.83, 77.16, 57.87, and 69.38 respectively. Here, the performance enhancement of 3.64%, 18.15%, 38.61%, and 26.40% concerning the DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is presented in Table 5.39.

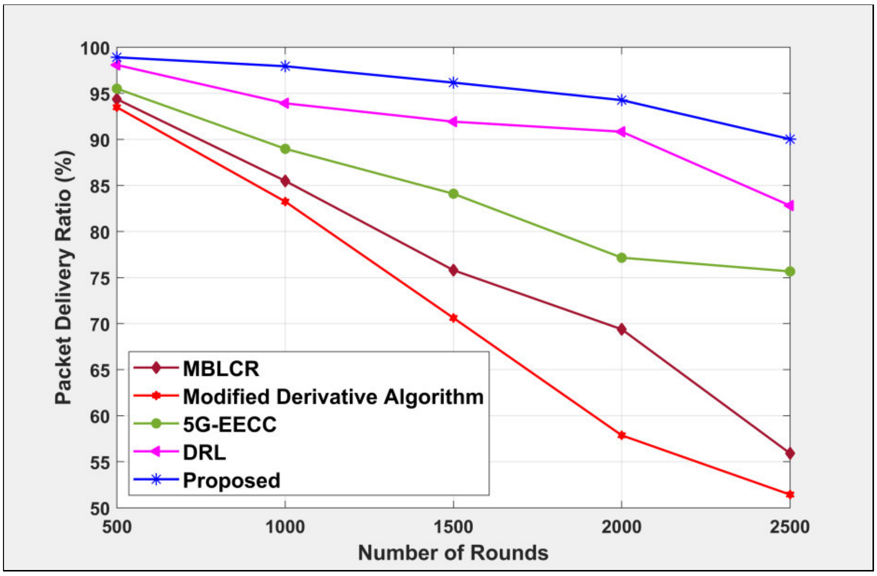


Figure 5.44: Packet Delivery Ratio with 100 users

Table 5.39: Packet Delivery Ratio with 100 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	94.37	85.50	75.80	69.38	55.91
Modified Derivative Algorithm	93.49	83.25	70.61	57.87	51.44
5G-EECC	95.51	88.98	84.09	77.16	75.67
DRL	98.08	93.92	91.92	90.83	82.81
Proposed	98.91	97.94	96.16	94.26	90.03

Throughput: The throughput based interpretation with 100 users is portrayed in Figure 5.45. The throughput evaluated by the newly devised protocol is 22 with 500 rounds, which is 22.73%, 40.91%, 54.55%, and 59.09% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. For 2500 rounds, the throughput evaluated by the newly devised protocol is 41, which is 7.32%, 21.95%, 39.02%, and 43.90% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.40.

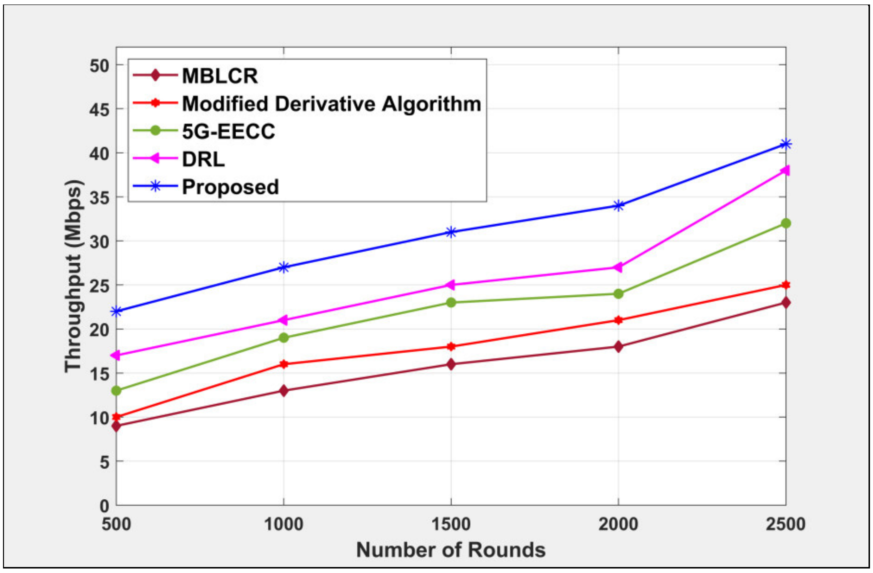


Figure 5.45: Throughput with 100 users

Table 5.40: Throughput with 100 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	9	13	16	18	23
Modified Derivative Algorithm	10	16	18	21	25
5G-EECC	13	19	23	24	32
DRL	17	21	25	27	38
Proposed	22	27	31	34	41

(c) Using 150 Users

Average Residual Energy: The assessment based on the average residual energy is depicted in Figure 5.46 with 150 users. The average residual energy evaluated by the newly devised protocol is 0.98 with 500 rounds, which is 3.66%, 9.12%, 10.89%, and 22.66% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. For 2500 rounds, the average residual energy evaluated by the newly devised protocol is 0.81, which is 21.11%, 43.81%, 54.40%, and 78.99% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.41.

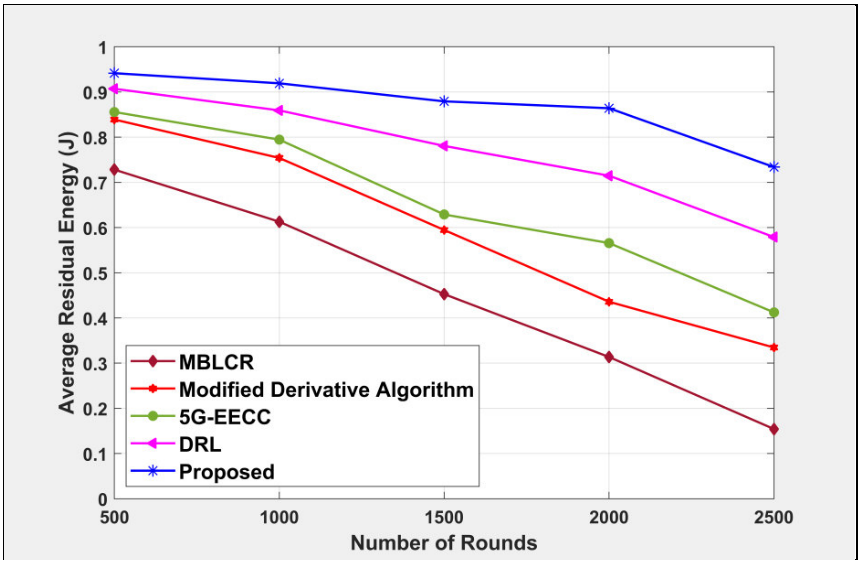


Figure 5.46: Average Residual Energy with 150 users

Table 5.41: Average Residual Energy with 150 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	0.73	0.61	0.45	0.31	0.15
Modified Derivative Algorithm	0.84	0.75	0.59	0.44	0.33
5G-EECC	0.86	0.79	0.63	0.57	0.41
DRL	0.91	0.86	0.78	0.71	0.58
Proposed	0.94	0.92	0.88	0.86	0.73

Latency: Figure 5.47 depicts the latency analysis of the proposed method by considering the number of users as 50. While considering the 500 rounds, the latency evaluated by the newly devised protocol is 6.40 that is 4.59%, 12.10%, 14.05%, and 18.26% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. Also, the latency estimated by the newly devised protocol is 9.04 with 2500 rounds that is 15.42%, 26.65%, 36.68%, and 49.18% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.42.

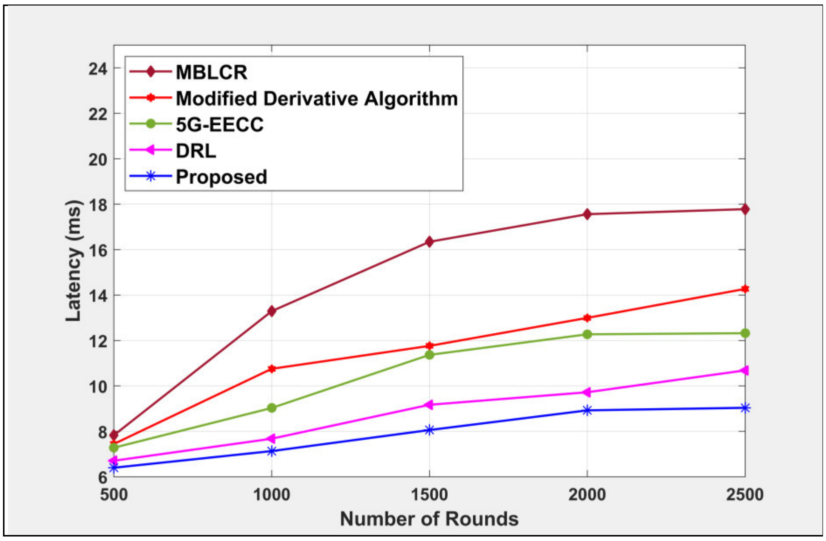


Figure 5.47: Latency based on Iteration with 150 users

Table 5.42: Latency based on Iteration with 150 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	7.83	13.29	16.34	17.56	17.78
Modified Derivative Algorithm	7.44	10.75	11.76	12.99	14.27
5G-EECC	7.28	9.03	11.37	12.27	12.32
DRL	6.70	7.67	9.17	9.72	10.68
Proposed	6.40	7.13	8.06	8.92	9.04

Network Life Time: The network lifetime analysis is portrayed in Figure 5.48 and its detailed analysis is presented in Table 5.43 for 150 users. In this, the newly devised protocol accomplished the higher network life time of 90.16; still the conventional methods like DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR accomplished the network life time of 85.06, 74.10, 61.43 and 71.60 respectively with 1500 rounds. Here, the newly devised protocol is 6.00%, 21.68%, 46.77%, and 25.92% elevated outcome as compared to the existing like DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods.

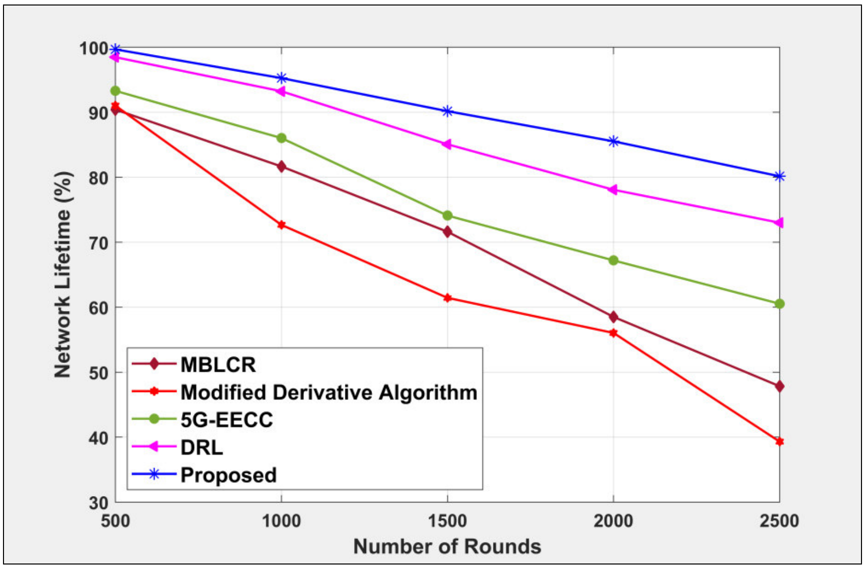


Figure 5.48: Network Life Time with 150 users

Table 5.43: Network Life Time with 150 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	90.41	81.66	71.60	58.50	47.83
Modified Derivative Algorithm	91.02	72.66	61.43	56.03	39.31
5G-EECC	93.30	86.02	74.10	67.19	60.52
DRL	98.47	93.23	85.06	78.06	73.00
Proposed	99.68	95.25	90.16	85.52	80.14

Packet Delivery Ratio: The analysis of the packet delivery ratio with 150 users is depicted in Figure 5.49, wherein the newly devised protocol acquired the superior outcome. For example, the newly devised protocol acquired the packet delivery ratio of 90.37 with 2000 rounds; still the conventional methods DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR acquired the minimal packet delivery ratio of 80.39, 69.32, 61.86, and 44.37 respectively. Here, the performance enhancement of 11.05%, 23.29%, 31.55%, and 50.91% concerning the DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is presented in Table 5.44.

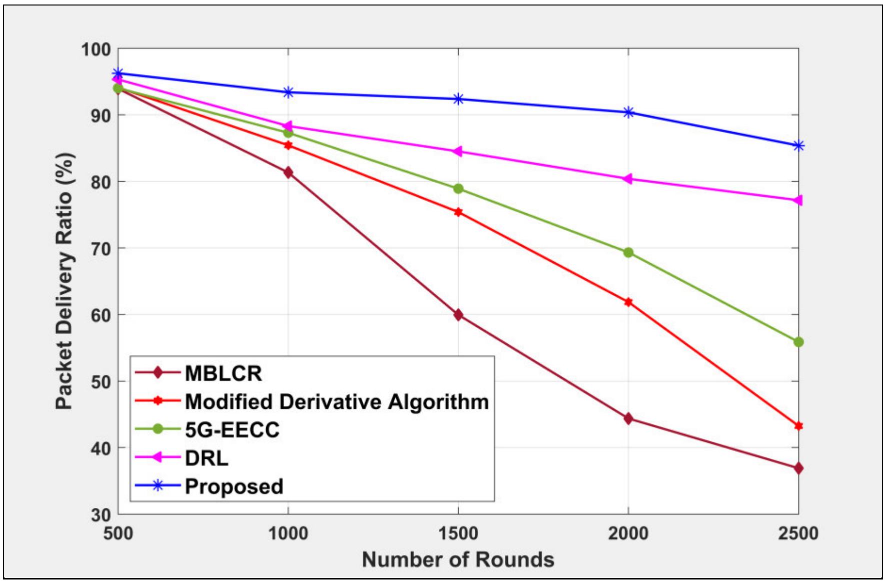


Figure 5.49: Packet Delivery Ratio with 150 users

Table 5.44: Packet Delivery Ratio with 150 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	93.92	81.34	59.94	44.37	36.90
Modified Derivative Algorithm	94.11	85.42	75.39	61.86	43.25
5G-EECC	94.01	87.30	78.90	69.32	55.86
DRL	95.32	88.31	84.51	80.39	77.17
Proposed	96.25	93.38	92.38	90.37	85.38

Throughput: The throughput based interpretation with 150 users is portrayed in Figure 5.51. The throughput evaluated by the newly devised protocol is 27 with 500 rounds, which is 7.41%, 22.22%, 29.63%, and 44.44% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. For 2500 rounds, the throughput evaluated by the newly devised protocol is 64, which is 14.06%, 25.00%, 35.94%, and 46.88% improved outcome compared to the existing DRL, 5G-EECC, Modified Derivative Algorithm, and MBLCR methods. The detailed analysis is depicted in Table 5.46.

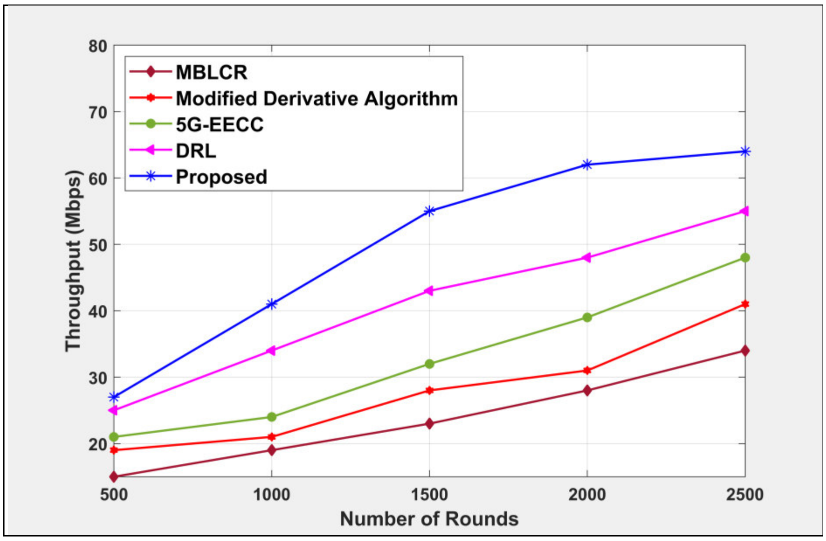


Figure 5.50: Throughput with 150 users

Table 5.45: Throughput with 150 users

Methods/ Rounds	500	1000	1500	2000	2500
MBLCR	15	19	23	28	34
Modified Derivative Algorithm	19	21	28	31	41
5G-EECC	21	24	32	39	48
DRL	25	34	43	48	55
Proposed	27	41	55	62	64

5.4.4 Discussion

The suggested energy efficient routing protocol with multi hop for D2D communication between the user in the 5G network attained enhanced performance while analysing the performance based on several measures like packet delivery ratio, latency, residual energy, throughput and network lifetime. The suggested method uses the multi-hop possible path detection using the suggested double deep Q learning technique. Here, the considing energy consumption between the nodes for selecting the next hop node identifies the best energy efficient node for communication. Besides, the consideration of DeepCNN to estimate the Q-value and reward function enhances the detection accuracy of finding the possible paths which solves the over optimistic issues. Also, the suggested GCO algorithm uses the multi-objective fitness function for finding the optimal best path for communication among the identified path. Thus, the considering of the combined behavior of the double deep Q learning along with the GCO algorithm helps in identifying the optimal best energy efficient path for D2D communication and is shown based on several assessment measures.

5.5 Summary

An energy efficient multi hop routing protocol was introduced in the research for D2D communication between the 5G network users. Here, a deep reinforcement learning method named double deep Q learning is suggested for the identification of multi hop paths for D2D communication. In this, the DeepCNN is introduced for the estimation of the Q-value and reward function of the double deep Q learning for improving the path detection accuracy and solving the problem concerning the over optimization. Also, a hybrid optimization named GCO is introduced by hybridizing the hunting behavior of the Gannet with the chimp in obtaining the global best solution to choose the optimal best path. The balanced exploration and exploitation capability of the suggested GCO algorithm with multi-objective fitness function opts for the best path for D2D communication. The assessment of the suggested method based on various measures like packet delivery ratio, latency, residual energy, throughput and network lifetime accomplished the values of 99.89, 1.63, 0.98, 64 and 99.69 respectively.

CONCLUSION

CHAPTER - 6

CONCLUSION

6.1 Conclusion

The 5G Networks based D2D communication protocols along with the types utilized for the communicating among the devices for reducing the burden of the base station (BS). Also, the D2D routing mechanisms and the generalized deep learning framework are outlined. Then the challenges faced by the D2D communication protocols and the application domains of D2D communication are elaborated in Chapter 1. Chapter 2 elaborates the conventional communication protocols based on Machine learning based techniques, D2D communication techniques and Cooperative communication techniques along with the research gaps. The architecture of the D2D communication protocols and the general challenges are detailed in Chapter 3.

Chapter 4 presents the joint channel selection and relay selection mechanism for efficient communication between the devices. Using the suggested EnHpo algorithm and many fitness functions, including priority, bandwidth, and transmission rate, the channel allocation is originally determined like this. The adaptive weight method is combined with the traditional hunter-prey optimization in the proposed EnHpo to increase convergence and the acquisition of the optimal global solution. Then, using deep reinforcement learning, the channel gain based on bit error rate is taken into consideration while choosing the relay.

Chapter 4 details the energy-efficient multi-hop routing system based on deep reinforcement learning. Here, a deep reinforcement learning method named double deep Q learning is suggested for the detection of multi hop path for D2D communication. In this, the DeepCNN was introduced for estimating the Q-value and reward function of the double deep Q learning for improving the path detection accuracy and solving the problem concerning the over optimization. Also, a hybrid optimization named GCO is introduced by hybridizing the hunting behavior of the Gannet with the chimp in obtaining the global best solution in choosing the optimal best path. The balanced exploration and exploitation capability of the suggested GCO algorithm with multi-objective fitness function chooses the best path for D2D communications.

6.2 Main Finding

The evaluation of first contribution EnHpo+DRL, Joint channel allocation and relay selection is performed based on the measures like Average Residual Energy, Latency, Network Life Time, Packet Delivery Ratio, and Throughput and obtained the values of 0.998, 2.709, 99.592, 0.999, and 23015, respectively.

The evaluation of second contribution GCO+DDQL, energy efficient multi-hop routing is performed based on the measures like Average Residual Energy, Latency, Network Life Time, Packet Delivery Ratio, and Throughput and obtained the values of 0.998, 2.709, 99.592, 0.999, and 23015, respectively.

6.3 Future Scope

The future scope of the research are:

- Equipment moving around the network causes the structure of the network to change in an unanticipated way, which is challenges, as the proposed research failed to consider the dynamic scenario.
- The resource reuse strategy is not considered for efficient resource allocation among the devices.
- Users of wireless communication systems have allowed roaming about; therefore managing portability becomes an important issue that has to be solved.
- It is crucial to consider privacy and security issues thoroughly while adopting and deploying communication between devices on cellular networks. Hence, during exchange, data has to be secured using an encryption method to prevent attackers.

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ANNEXURES

Annexure 1: Code

<u>Annexure 3</u>

Code for Cooperative Device-to-Device Communication using Joint Relay Assignment and Channel Allocation using deep learning.

```
clc;
clear;
close all;
addpath(genpath(pwd));
warning off;
Node_all=[50,100,150]; % number of nodes

for nn=1:3
    N=Node_all(nn);
min1=0;
max1=1000;
X = min1+(max1-min1)*rand(1,N);
Y = min1+(max1-min1)*rand(1,N);
figure,
plot(X,Y,'o','LineWidth',0.2,'MarkerEdgeColor','k',...
      'MarkerFaceColor',[0.9686    0.3412    0.8000],'MarkerSize',12');
xlabel('X in m')
ylabel('Y in m')
set(gca,'FontSize',12,'FontName', 'Times','FontWeight', 'bold');
set(gcf,'units','centimeters ','position',[5,2,18.15,18.11])
box on;
for i2 = 1:N
      text(X(i2)-12, Y(i2), num2str(i2),'Color','k','FontSize',8);
      hold on;
end
hold on


minVel=-4;
maxVel=4;

minPause=0;
maxPause=1;

rounds=2500;
Rc=150;



Xb =500;
Yb =500;
hold on
plot(Xb,Yb,'o','LineWidth',2,'MarkerEdgeColor','k','MarkerFaceColor','y','MarkerSize'
,30');
xlabel('X in m')
ylabel('Y in m')
text(Xb-10, Yb, 'BS','FontSize',12,'FontName', 'Times','FontWeight', 'bold');
hold on;
```

```
ipp=1;


figure,
slider1_data.val=40;
PauseTime=minPause+(maxPause-minPause).*rand(1,N);
ipppause=zeros(1,N);
set(gca,'FontSize',12,'FontName', 'Times');
set(gcf,'units','centimeters ','position',[5,2,18.15,18.11])
box on;
%%
alpha=0.01;%0.001 energy per distance% 0.001                                  %% node
to CH power Ratio
beta=0.045;%0.0015                                                             %% CH to
sink distance power ratio

Sector1=1;
nodes=N;% Total No. of Nodes

%% Energy
E=50.*ones(1,nodes);  % intial Energy 4W

PackSize=2; % 2Mb/sec
nodesCH=10;% no of cluster head
EexL=E;
while(ipp<rounds+1)

     r=randi([1,N],1,1);
    Xs =X(r);
    Ys =Y(r);
%     X1=[Xs X Xb];
%     Y1=[Ys Y Yb];

    %% Mobility Range
    cla;
    axis([min1-30 max1+30 min1-30 max1+30])
    hold on

    Velocity=minVel+(maxVel-minVel).*rand(2,N);


    [valPause,indexPause]=find(abs(PauseTime-ipppause)>0);
    ipppause(indexPause)=0;

    ipppause=ipppause+1;


      m1=10;%0.01+(slider1_data.val/100);
      aa=-1;ba=1;
      delx=Velocity(1,:);
      dely=Velocity(2,:);


      delx(indexPause) = Velocity(1,indexPause);
      dely(indexPause) = Velocity(2,indexPause);
```

```
        X(indexPause)=X(indexPause)+delx.*m1;
        Y(indexPause)=Y(indexPause)+dely.*m1;
        X(X<min1 | X>max1)=X(X<min1 | X>max1)-delx(X<min1 | X>max1).*m1;
        Y(Y<min1 | Y>max1)=Y(Y<min1 | Y>max1)-dely(Y<min1 | Y>max1).*m1;

    X1=[Xs X Xb];
    Y1=[Ys Y Yb];
    matrizP=pdist2([X1 ;Y1]',[X1; Y1]');

    plot(X,Y,'o','LineWidth',0.2,'MarkerEdgeColor','k',...
          'MarkerFaceColor',[0.9686    0.3412    0.8000],'MarkerSize',12');
    xlabel('X in m')
    ylabel('Y in m')
    set(gca,'FontSize',12,'FontName', 'Times','FontWeight', 'bold');
    set(gcf,'units','centimeters ','position',[5,2,18.15,18.11])
    box on;
    for i2 = 1:N
        text(X(i2)-12, Y(i2), num2str(i2),'Color','k','FontSize',8);
        hold on;
    end
    hold on

plot(Xs,Ys,'o','LineWidth',2,'MarkerEdgeColor','k','MarkerFaceColor','g','MarkerSize'
,20');
    xlabel('X in m')
    ylabel('Y in m')
    text(Xs-5, Ys, 'Source','FontSize',12,'FontName', 'Times','FontWeight', 'bold');
    hold on;

    Xb =500;
    Yb =500;
    hold on

plot(Xb,Yb,'o','LineWidth',2,'MarkerEdgeColor','k','MarkerFaceColor','y','MarkerSize'
,30');
    xlabel('X in m')
    ylabel('Y in m')
    text(Xb-10, Yb, 'BS','FontSize',12,'FontName', 'Times','FontWeight', 'bold');
    hold on;

      EneExL(ipp)=0;

       A1=randperm(N);                                                    %
Randomly select Source node
       ind=A1(3);
       pathL=[];


       %% Custom Adhoc Routing

          Source =1;
          Dest=numel(X1);
          Rc1=Rc;
          matrizP(matrizP>Rc1)=inf;
```

```
            [pathP,cost]=proposed(Source,Dest,matrizP);
            costN=cost.*length(pathP);

            dist1L=costN;
            dist2L=0;
            apL=0;
            if(~isempty(pathP))

              if(pathP(end)~=Dest)
                   pathP=[pathP Dest];
              end

            if(EexL(ind)~=0 )
                pathP(pathP==Source)=-2;
                pathP(pathP==Dest)=-1;
                pathL=pathP;%[ind -1];
                path11=pathP;
                path11(path11==-1)=[];
                path11(path11==-2)=[];
                apL=apL+1;
                path11=path11-1;
                EexL(path11)=EexL(path11)-Energyfun(alpha,beta,dist1L,dist2L);
                EneExL(ipp)=Energyfun(alpha,beta,dist1L,dist2L).*numel(path11);
            end

            end
                        if(EexL(ind)<=0)
                 EexL(ind)=0;
                        end
               % Throughput Calculation
    RxData1L=apL;
    if(ipp>1)
         ThroughputL(ipp)=Throughputfun(ThroughputL,RxData1L,ipp-1);
    else
         ThroughputL(ipp)=RxData1L*PackSize;
    end

   if(~isempty(pathL))
        path1=pathL;
            disp(strcat(['Round ',num2str(ipp),'/',num2str(rounds),'; Hop Count :
',num2str(size(path1,2)-2)] ));
      for p =1:(size(path1,2))-1
          try
              if(path1(p+1)==-1)
                  line([X1(path1(p)) Xb], [Y1(path1(p)) Yb], 'Color',[0.4667    0.6745
0.1882],'LineWidth',1, 'LineStyle','-');
                  arrow([X1(path1(p)) Y1(path1(p)) ], [Xb Yb ]);
              elseif(path1(p)==-2)
                      line([Xs X1(path1(p+1))], [Ys Y1(path1(p+1))], 'Color',[0.4667
0.6745    0.1882],'LineWidth',1, 'LineStyle','-');
                  arrow([Xs Ys ],[X1(path1(p+1)) Y1(path1(p+1)) ])    ;
              else
                  line([X1(path1(p)) X1(path1(p+1))], [Y1(path1(p)) Y1(path1(p+1))],
'Color',[0.4667    0.6745    0.1882],'LineWidth',1, 'LineStyle','-');
                  arrow([X1(path1(p)) Y1(path1(p)) ], [X1(path1(p+1)) Y1(path1(p+1))]);
```

```
            end
        catch
            line([Xs Xb], [Ys Yb], 'Color',[0.4667    0.6745
0.1882],'LineWidth',1, 'LineStyle','-');
            arrow([Xs Ys], [Xb Yb ]);
        end
            hold on
    end
 else
     line([Xs Xb], [Ys Yb], 'Color',[0.4667    0.6745    0.1882],'LineWidth',1,
'LineStyle','-');
     arrow([Xs Ys], [Xb Yb ]);
    disp(strcat(['Round ',num2str(ipp),'/',num2str(rounds),'; Hop Count :
',num2str('0')]));
 end
 pause(0.0001)
 % Energy
 AvgEcL(ipp)=mean(EneExL);

ipp=ipp+1;

end


if nn==1
node50;
elseif nn==2
node100;
else
node150;
end
end
```

Code for Multi-objective hybrid optimization based Energy Efficient D2D communication with deep reinforcement learning routing protocol

```
clc;
clear;
close all;
addpath(genpath(pwd));
warning off;
Node_all=[50,100]; % number of nodes
N_relay=[5,10];
for nn=1:2
N=Node_all(nn);
for re=1:2
Nr=N_relay(re);
min1=0;
max1=1000;
X = min1+(max1-min1)*rand(1,N);
Y = min1+(max1-min1)*rand(1,N);
Rx=min1+(max1-min1)*rand(1,Nr);
Ry=min1+(max1-min1)*rand(1,Nr);
figure,
```

```
plot(X(1:end-Nr),Y(1:end-Nr),'o','LineWidth',1,'MarkerEdgeColor','k',...
      'MarkerFaceColor',[0.9686    0.3412    0.8000],'MarkerSize',10'); hold on
plot(X(end-Nr+1:end),Y((end-Nr+1:end)),'^','LineWidth',1,'MarkerEdgeColor','k',...
      'MarkerFaceColor','g','MarkerSize',10);
xlabel('X in m')
ylabel('Y in m')
set(gca,'FontSize',12,'FontName', 'Times','FontWeight', 'bold');
set(gcf,'units','centimeters ','position',[5,2,22.15,18.11])
box on;

hold on


minVel=-4;
maxVel=4;

minPause=0;
maxPause=1;

rounds=2;
Rc=150;



Xb =500;
Yb =500;
hold on
plot(Xb,Yb,'o','LineWidth',2,'MarkerEdgeColor','k','MarkerFaceColor','c','MarkerSize'
,30');
xlabel('X in m')
ylabel('Y in m')
hold on;
legend('Sensor Nodes','Relay Nodes','Base Station')

ipp=1;


figure,
slider1_data.val=40;
PauseTime=minPause+(maxPause-minPause).*rand(1,N);
ipppause=zeros(1,N);
set(gca,'FontSize',12,'FontName', 'Times');
set(gcf,'units','centimeters ','position',[5,2,22.15,18.11])
box on;
%%
alpha=0.01;%0.001 energy per distance% 0.001                                 %% node
to CH power Ratio
beta=0.045;%0.0015                                                          %% CH to
sink distance power ratio

Sector1=1;
nodes=N;% Total No. of Nodes

%% Energy
E=50.*ones(1,nodes);  % intial Energy 4W
```

```
PackSize=2; % 2Mb/sec
nodesCH=10;% no of cluster head
EexL=E;
while(ipp<rounds+1)

     r=randi([1,N],1,1);
    Xs =X(r);
    Ys =Y(r);

     r=randi([1,N],1,1);
    Xd =X(r);
    Yd =Y(r);


    %% Mobility Range
    cla;
    axis([min1-30 max1+30 min1-30 max1+30])
    hold on

    Velocity=minVel+(maxVel-minVel).*rand(2,N);


    [valPause,indexPause]=find(abs(PauseTime-ipppause)>0);
    ipppause(indexPause)=0;

    ipppause=ipppause+1;


      m1=10;%0.01+(slider1_data.val/100);
      aa=-1;ba=1;
      delx=Velocity(1,:);
      dely=Velocity(2,:);


      delx(indexPause) = Velocity(1,indexPause);
      dely(indexPause) = Velocity(2,indexPause);

        X(indexPause)=X(indexPause)+delx.*m1;
        Y(indexPause)=Y(indexPause)+dely.*m1;
        X(X<min1 | X>max1)=X(X<min1 | X>max1)-delx(X<min1 | X>max1).*m1;
        Y(Y<min1 | Y>max1)=Y(Y<min1 | Y>max1)-dely(Y<min1 | Y>max1).*m1;

    X1=[Xs X Xb];
    Y1=[Ys Y Yb];
    matrizP=pdist2([X1 ;Y1]',[X1; Y1]');

    plot(X(1:end-Nr),Y(1:end-Nr),'o','LineWidth',1,'MarkerEdgeColor','k',...
      'MarkerFaceColor',[0.9686    0.3412    0.8000],'MarkerSize',10'); hold on
    plot(X(end-Nr+1:end),Y((end-
Nr+1:end)),'^','LineWidth',1,'MarkerEdgeColor','k',...
      'MarkerFaceColor','g','MarkerSize',10);
    xlabel('X in m')
    ylabel('Y in m');cg=rand()*(1-0.9)+0.9;
    set(gca,'FontSize',12,'FontName', 'Times','FontWeight', 'bold');
```

```
set(gcf,'units','centimeters ','position',[5,2,22.15,18.11])
    box on;

    hold on

plot(Xs,Ys,'o','LineWidth',2,'MarkerEdgeColor','k','MarkerFaceColor','g','MarkerSize'
,20');
    xlabel('X in m')
    ylabel('Y in m')
    text(Xs-5, Ys, 'Source','FontSize',12,'FontName', 'Times','FontWeight', 'bold');
    hold on;

    Xb =500;
    Yb =500;
    hold on

plot(Xb,Yb,'o','LineWidth',2,'MarkerEdgeColor','k','MarkerFaceColor','c','MarkerSize'
,30');
    xlabel('X in m')
    ylabel('Y in m')
    text(Xb-10, Yb, 'BS','FontSize',12,'FontName', 'Times','FontWeight', 'bold');
    hold on;

      EneExL(ipp)=0;

       A1=randperm(N);                                                   %
Randomly select Source node
       ind=A1(3);
       pathL=[];



          Source =1;
          Dest=numel(X1);
          Rc1=Rc;
          matrizP(matrizP>Rc1)=inf;
          [pathP,cost]=proposed(Source,Dest,matrizP);
          costN=cost.*length(pathP);

          dist1L=costN;
          dist2L=0;
          apL=0;
          if(~isempty(pathP))

            if(pathP(end)~=Dest)
                 pathP=[pathP Dest];
            end

          if(EexL(ind)~=0 )
              pathP(pathP==Source)=-2;
              pathP(pathP==Dest)=-1;
              pathL=pathP;%[ind -1];
              path11=pathP;
              path11(path11==-1)=[];
              path11(path11==-2)=[];
```

```
              apL=apL+1;
              path11=path11-1;
              EexL(path11)=EexL(path11)-Energyfun(alpha,beta,dist1L,dist2L);
              EneExL(ipp)=Energyfun(alpha,beta,dist1L,dist2L).*numel(path11);
          end

          end
                      if(EexL(ind)<=0)
               EexL(ind)=0;
                      end
                      rayChan = comm.RayleighChannel( ...
    SampleRate=1e5, ...
    MaximumDopplerShift=130);
             % Throughput Calculation
  RxData1L=apL;
  if(ipp>1)
      ThroughputL(ipp)=Throughputfun(ThroughputL,RxData1L,ipp-1);
  else
      ThroughputL(ipp)=RxData1L*PackSize;
  end

 if(~isempty(pathL))
     path1=pathL;
    for p =1:(size(path1,2))-1
        try
            if(path1(p+1)==-1)
                line([X1(path1(p)) Xb], [Y1(path1(p)) Yb], 'Color',[0.4667    0.6745
0.1882],'LineWidth',1, 'LineStyle','-');
                arrow([X1(path1(p)) Y1(path1(p)) ], [Xb Yb ]);
            elseif(path1(p)==-2)
                    line([Xs X1(path1(p+1))], [Ys Y1(path1(p+1))], 'Color',[0.4667
0.6745    0.1882],'LineWidth',1, 'LineStyle','-');
                arrow([Xs Ys ],[X1(path1(p+1)) Y1(path1(p+1)) ])    ;
            else
                line([X1(path1(p)) X1(path1(p+1))], [Y1(path1(p)) Y1(path1(p+1))],
'Color',[0.4667    0.6745    0.1882],'LineWidth',1, 'LineStyle','-');
                arrow([X1(path1(p)) Y1(path1(p)) ], [X1(path1(p+1)) Y1(path1(p+1))]);
            end
        catch
            line([Xs Xb], [Ys Yb], 'Color',[0.4667    0.6745
0.1882],'LineWidth',1, 'LineStyle','-');
            arrow([Xs Ys], [Xb Yb ]);
        end
            hold on
    end
      disp(strcat(['Round ',num2str(ipp),'/',num2str(rounds),' : channel gain -
',num2str(cg)]));
      for iii=1:size(path11,2)
             if path11(iii)>N-Nr
                disp('             Relay selection enabled');
             end
     end
 else
     line([Xs Xb], [Ys Yb], 'Color',[0.4667    0.6745    0.1882],'LineWidth',1,
'LineStyle','-');
```

```
     arrow([Xs Ys], [Xb Yb ]);
      disp(strcat(['Round ',num2str(ipp),'/',num2str(rounds),' : channel gain -
',num2str(cg)]));
      end

 pause(0.0001)
 % Energy
 AvgEcL(ipp)=mean(EneExL);

ipp=ipp+1;

end


if nn==1
    if re==1
    Comp_5relay_50node;
    Perf_5relay_50node;
    else
       Comp_5relay_100node;
    Perf_5relay_100node;
    end
elseif nn==2
    if re==1
    Comp_10relay_50node;
    Perf_10relay_50node;
    else
       Comp_10relay_100node;
    Perf_10relay_100node;
    end
end
end
end
```

Annexure 2: Research Papers

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Energy Efficient Multi Hop D2D Communication Using Deep Reinforcement Learning in 5G Networks

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RESEARCH ARTICLE

Energy Efficient Multi Hop D2D Communication Using Deep Reinforcement Learning in 5G Networks

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Abstract – One of the most potential 5G technologies for wireless networks is device-to-device (D2D) communication. It promises peer-to-peer consumers high data speeds, ubiquity, and low latency, energy, and spectrum efficiency. These benefits make it possible for D2D communication to be completely realized in a multi-hop communication scenario. However, the energy efficient multi hop routing is more challenging task. Hence, this research deep reinforcement learning based multi hop routing protocol is introduced. In this, the energy consumption is considered by the proposed double deep Q learning technique for identifying the possible paths. Then, the optimal best path is selected by the proposed Gannet Chimp optimization (GCO) algorithm using multi-objective fitness function. The assessment of the proposed method based on various measures like packet delivery ratio, latency, residual energy, throughput and network lifetime accomplished the values of 99.89, 1.63, 0.98, 64 and 99.69 respectively.

Index Terms – 5G Networks, D2D Communication, Energy Efficient Routing, Multi-Hop Path, Deep Q Learning, Optimal Path Selection.

1. INTRODUCTION

Due to the rising demand for multimedia applications and smart phones over the last few years, mobile data traffic has accomplished an accelerated enhancement. Demand for bandwidth is brought on by this sharp rise in data traffic [1]. Although many conventional approaches, such as employing femto and pico cells to reduce cell size and increase throughput, have been suggested to address this issue, their high deployment costs mean that the issue has not yet been resolved. Due to characteristics like resistance, high energy efficiency, high throughput, and cellular traffic offloading to infrastructure failure, device-to-device (D2D) communication is regarded as the best option [2-4]. According to the definition, it is a kind of communication in which mobile nodes interact with one another without the use of a base station or other centralized structure. Instead, they use their own internal communication channels. The two-tier paradigm used by traditional D2D communication relies on cellular architecture to fetch resources. Due to the fact that the devices are closer together, less power is consumed, which improves battery life. Nevertheless, the communication required for this architecture causes interference problems. In order to combat interference, relay nodes are given dedicated resources for lengthy communication, yet these results in resource waste. The utilization of multimedia information is rising, which uses image, audios, videos and several other information having the highest request factor (78%) and driving the majority of the network traffic through the year 2022. Massive congestion on devices and traffic loads, as well as backhaul issues that impair device battery life, can be caused by high demand for videos [5].

With the dramatic rise in demand for faster data rates, D2D communication has attracted a lot of attention from the business world, standards bodies, and academic institutions [6]. Direct wireless communication between two transceivers is made possible via D2D communication without a base station (BS). It is a crucial method for 5G networks since it helps to boost energy efficiency (EE) and use less power while still transferring data without loss [7, 8]. It immediately links the devices while simultaneously enhancing the network's performance, latency, and throughput, which in turn increases the energy efficiency and spectral efficiency of D2D communication. Moreover, it shares frequencies with cellular networks, which degrades network quality because more interference are generated [9]. Cellular networks that support D2D are taken into account, with an emphasis on maximizing energy efficiency. Only single-cell scenarios are supported by the available technologies. Since the user's requirement needs a lot of power, a single-cell situation received more attention

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than multiple bands; therefore, research is concentrated on how to provide the energy efficiency routing with minimal resource utilization through multi-hop routing strategy [10, 11]. To transmit and receive the information, either an uplink or a downlink is taken into account. Energy efficiency optimization is necessary whenever the demand for optimal energy efficiency arises. The answer to the energy efficiency optimization issue is to obtain the greatest EE (energy efficiency) in D2D communication [12].

Several network issues in 5G have been successfully solved using machine learning. One of the best methods of machine learning for controlling strategy is reinforcement learning (RL) [13]. The intelligent resource management challenge in D2D underlay networks has subsequently been addressed in a number of publications using reinforcement learning. Depending on the policy, an agent supporting D2D combination dynamically chooses an acceptable range that was acquired through RL [14-16]. An efficient routing protocol based on Q-learning utilizes the actor-critic (AC) technique. An AC technique is necessary since Q-learning is inadequate to handle continuous valued state and action spaces [17]. Deep Neural Networks (DNNs) are employed in the Deep Q-Network (DQN) algorithm to estimate the value function of Q-learning, relieving the burden of computing and storing Q-values [18, 19]. As a result, certain RL-based distributed resource efficient routing strategies have been put forth to lessen computing complexity [20].

As the world moves closer to the era of digitization that demands for the internet and hence the use of it is increasing dramatically. The internet is connected to billions of physical objects all around the world, which are gathering and exchanging data. The Internet of Things (IoT) makes transportation, environment, industrial automation, smart grid, smart cities, smart homes, as well as healthcare monitoring over the network for transmitting vast amounts of data without human intervention.

Future 5G networks will manage this data and information by offering better connection, larger data rates, ultra-low latency, more energy efficiency, and improved spectrum efficiency. D2D communication is completely realized in a multi-hop communication environment because to these advantages. A multi-hop network might perform worse than a typical mobile system if the improper routing decisions are made without the right processes; hence in order to construct multi-hop D2D communication networks optimally, the routing component should be designed more efficiently.

As a result, this research introduces routing in multi-hop networks. The major goal of the research is to provide the energy efficient cooperative routing protocol. For this a hybrid approach with deep learning based path detection and optimized path selection is proposed. The major contributions of the research are:

- Double Deep Q-Learning: The double deep Q learning is introduced for the detection of paths from source to destination. In the proposed double deep Q learning, the estimation of Q-value and reward are estimated using two various Deep CNN models to avoid the over optimistic issues.
- Gannet Chimp Optimization: The Gannet chimp optimization (GCO) is designed by hybridizing the hunting behavior of the Gannet with the chimp to identify the optimal best path D2D communication.

The organizations of the introduced D2D communication protocol are: Section 2 details the literature review along with the problem statement and the methodology to overcome the issues is detailed in Section 3. The experimental outcome is elaborated in Section 4 and Section 5 presents the conclusion.

2. LITERATURE REVIEW

Some of the prior methods concerning the D2D communication are detailed in this section. An energy efficient D2D communication was devised by [21], in which modified derivative algorithm was introduced for the energy efficient computation overhead. The goal behind the development of the protocol is to minimize the data traffic through optimal resource allocation strategy. The outcome of the experimentation depicts the ideal performance with enhanced efficiency in terms of energy. The failure in considering the significant parameters limits the performance of the model. The energy efficient information sharing using the clustering based criteria was developed by [22]. In this, a weighted algorithm along with the group mobility criteria was designed for the cluster formation and cluster head selection. The direction and speed of the dynamic users were considered for clustering the devices for efficient information sharing. The major challenging aspect of the devised method was the security concerns that create the information leakage. Also, the failure in considering the energy and delay parameters affects the network's scalability.

Machine learning based D2D was designed by [23] using a single relay hop, wherein the recursive learning was utilized for the updating the agents. Besides, the usage of fuzzy logic was incorporated with the recursive learning to choose the best relay node by considering the local knowledge. The performance of the method in terms of power consumption and spectral efficiency depicted the flexibility and effectiveness of the model. However, the failure in considering the bandwidth for performing the cooperative routing limits the efficiency of the model.

Hybrid routing protocol based on reinforcement learning was designed by [24] using the static learning criteria. In this, the channel capacity and traffic intensity were considered for the selecting the best route for information sharing. The analysis

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based on various measures depicts the enhanced quality of service through the constant learning criteria. The failure in considering the processing delay enhances the latency of the information sharing between the devices.

D2D communication using the multi criteria decision making was designed by [25] by considering the factors like contention window, link quality, battery and mobility. In this, multi hop routing was devised for the information sharing with optimal best path. Besides, the energy cost, delay, energy consumption, packet delivery ratio and throughput were considered for the analysis of the performance of the devised protocol and illustrated the superior performance. However, the optimal routing selection criteria failed to consider the bandwidth for traffic-less information flow. An energy efficient routing protocol using the deep reinforcement learning was designed by [19] for communication between two devices. In this, the delay associated with the routing was minimized through the energy consumption based route selection using the deep reinforcement learning technique. The consideration of power consumption and latency in selecting the route enhances the efficiency of the model. The short description of the literature review along with the advantages, disadvantages and methodology utilized were included in Table 1.

Table 1 Short Description of Literature Review

Reference	Methodology	Advantages	Disadvantages
L. Nagapuri et al., [21]	Modified derivative algorithm for energy efficient routing	The optimal D2D user selection enhances the performance of the network in terms of energy efficiency	The scalability of the network is still a challenging task.
N. Khan et al., [22]	Cluster based energy efficient D2D communication	Energy efficient communication is accomplished for dynamic user assignment.	Insecure communication is the challenging aspect.
I. Ioannou et al., [23]	Distributed artificial intelligence framework	Accomplished minimal delay and enhanced spectral efficiency in flexible D2D communication.	Failed to consider the significant features that enhance the energy efficiency.
M. K. Chamran et al., [24]	Reinforcement learning based route selection	Accomplished minimal delay with better quality of service.	The number of routes utilized for communication was minimal.
V. Tilwari et al., [25]	Optimal path selection using multi-criteria based decision making	Acquired better QoS with the optimal route selection.	Failed to consider the bandwidth for traffic-less information flow.
D Han and J. So [19]	Reinforcement learning based route selection	Acquired enhanced power consumption and latency through the best energy efficient route selection algorithm.	Failed to consider the interference between the devices while allocating the resource.

2.1. Problem Statement

When mobile users randomly moves across one place to another, D2D communication make benefits from the opportunities through an efficient routing strategy. The exchange of information in such chance interactions among individuals is closely tied to physical movement. Services and apps that support D2D visualize highly ad hoc and unexpected movements by taking advantage of user movement. Due to the users' complex requirement, there are difficulties in fully user's requirement. The main focus is on foreseeing the development of communication linkages between D2D users efficiently. The complete D2D network is impacted by mobility, including signal strength, area of operation, and bandwidth demands. In many different application sectors, including the automobile industry, emergency communications, and many other sectors, D2D communication with 5G wireless technologies is extensively used. The vital field of movement research continues to undergo development, despite the existence of a number of

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intriguing investigations on D2D communications that have made significant contributions and greater recognition of D2D communications. For example, the most recent issues in Routing protocol include interference reduction, storage and offload, energy efficiency, delay, and many others; still, the energy efficient routing protocol development is more challenging task. Hence, a novel energy efficient D2D communication protocol is designed using deep learning based path detection and multi-objective function based optimal path selection algorithm. In this, the consideration of residual energy, packet latency, bandwidth, hop count, and degree of connectivity assist to solve the interference, energy efficient communication, and latency issue more effectively.

3. PROPOSED ENERGY EFFICIENT D2D COMMUNICATION FOR 5G NETWORKS

The energy efficient D2D communication between the users of 5G network with multi-hop routing strategy is introduced in this research. Initially, the possible paths for D2D communication with multi-hop is identified using the proposed double deep Q learning. The double deep Q learning utilizes two various Deep CNN for the estimation of the Q-value and reward function to avoid the over optimistic issues. Here, the energy consumption of the node is evaluated by the proposed double deep Q learning method for the acquisition of energy efficient routing. From the detected paths, the optimal bets path is identified by the proposed Gannet Chimp Optimization (GCO) algorithm. The GCO is designed by hybridizing the hunting behavior of the Gannet with the attacking behavior of the chimp in capturing the target. The reason behind the hybridization is to enhance the convergence rate with global best solution. Here, the multi-objective fitness function is considered for the selection of optimal best path. The multi-objective fitness based on residual energy, packet latency, bandwidth, hop count and degree of connectivity are considered for the design of multi-objective fitness function that enhances the efficiency of path selection. The work flow of the proposed energy efficient D2D communication is depicted in Figure 1.

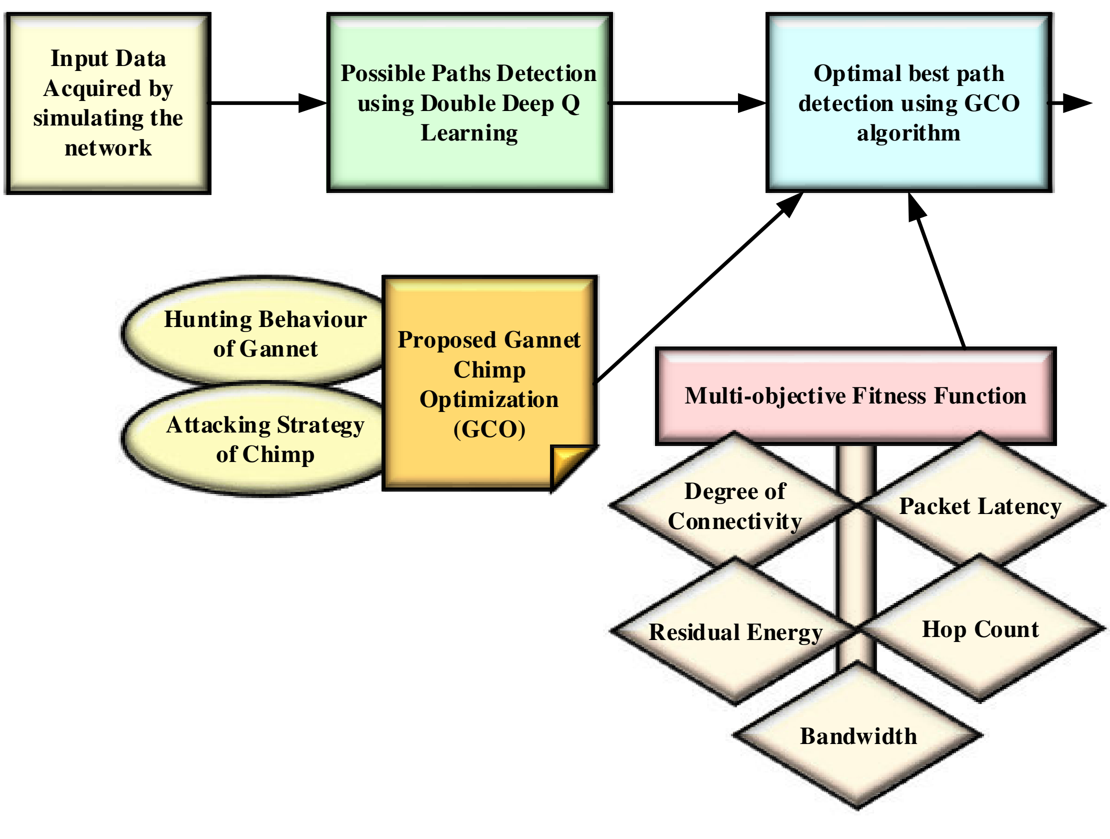

Figure 1 Workflow of Proposed Energy Efficient D2D Communication

3.1. Data Acquisition

The data utilized for the processing of the proposed D2D communication with multi-hop energy efficient routing is acquired by simulating the network. The data acquired is utilized for processing the proposed methodology.

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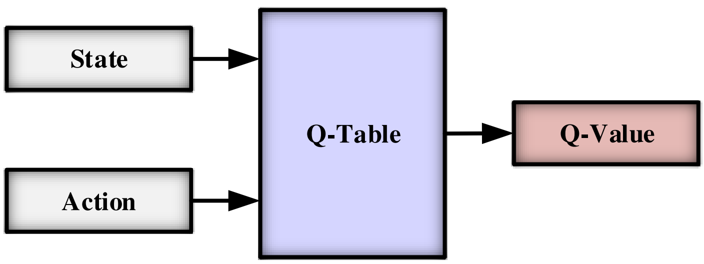
3.2. Double Deep Q Learning for Path Detection

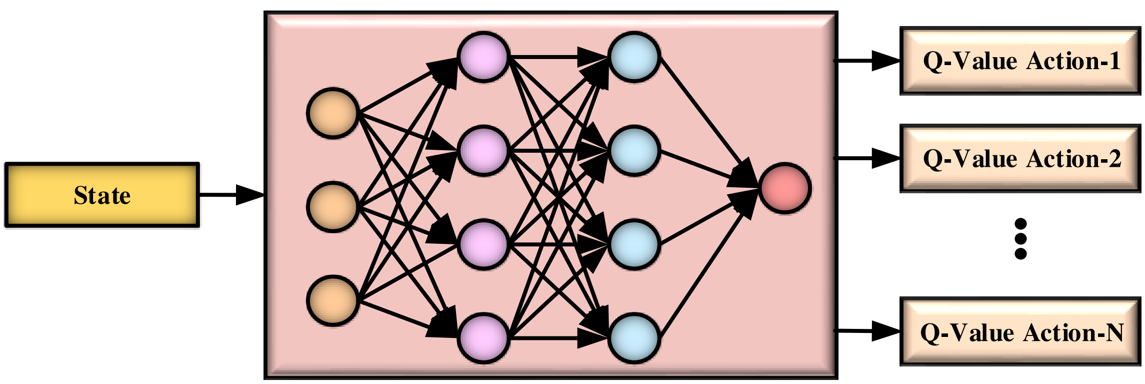
The possible paths for D2D communication using the multi-hop routing is identified by the double deep Q learning by considering the energy efficiency. The conventional Q learning uses the Markov decision making strategy for solving the issues in the reinforcement learning; still it is incapable for solving the complex variables. Besides, the curse of dimensionality issues and elevates the computation complexity and limits the convergence speed. These issues are solved using the deep-Q-learning approach, in which the deep neural network (DNN) is utilized for evaluating the reward and Q-value. The DNN is the replacement of the discrete value function of the Q-learning; still, the deep-Q-learning introduces the over optimistic issues due to the usage of single DNN for estimating the reward and Q-value. Thus, the double deep Q learning efficiently solves the over optimistic issue by introducing two separate DNN for estimating the reward and Q-value.

3.2.1. Deep Q-Learning

The conventional Q learning provides the outcome as Q-value by acquiring the inputs state and action. However, the deep Q learning provides various actions as its outcome utilizing the state value. The architecture of the deep-Q-learning and the Q-learning process is depicted in Figure 2 given below.



(a)



(b)

Figure 2 System Model of: (a) Q-Learning and (b) Deep Q Learning

Here, for the state X, the rewards are evaluated as $Y^{f}_{X,X'}$, wherein the action is defined as F. The term β defines the discount factor and $E^{f}_{X,X'}$ refers to the action-state pair probability. The D2D communication among the users of 5G communication is enunciated as states and the multi-hop routing among the nodes to reach the destination is enunciated as action.

3.2.2. Reward and Q Value Evaluation

The D2D communication among the user depends on the behaviour of the agent in the deep-Q-Learning through the reward estimated from the state. Here, for the energy efficient D2D communication among the users considers the energy consumption for providing the energy efficient communication. Let us consider the user m_c, who is considered as source node and the receiver node is defined as m_b. The evaluation of the reward function is defined in equation (1).

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$$Y^{n_c}_{m_c,m_b} = -p - \alpha_1 \left[l(m_c) + l(m_b) \right] + \alpha_2 \left[n(m_c) + n(m_b) \right] \quad (1)$$

Where, the action-state pair is defined as $(m \, , f_s)$ and α_1 *and* α_2 refers to the weighting parameter. The reward function is defined as $Y^{n_c}_{m_c,m_b}$; then the cost function enunciated as the punishment factor is defined as p. The reward function estimated in equation (2) is utilized for the successful communication between the nodes, if the communication gets dropped; then, the reward is estimated in equation (2).

$$Y^{n_c}_{m_c,m_b} = -p \times \eta - \gamma_1 l(m_c) + \gamma_2 n(m_c) \quad (2)$$

Where, η refers the drop case of communication and the energy evaluation for the communication is defined as $l(m_c)$ and is formulated in equation (3).

$$l(m_c) = 1 - \frac{E_{resi}(m_c)}{E_{ini}(m_c)} \quad (3)$$

Where, the initial energy varies from $[0,1]$ and is referred as E_{ini}, then, the residual energy is represented as E_{resi}. The normalized form of energy is indicated as $l(m_c)$ that plays a crucial role in communication between the nodes. Because, for the energy efficient routing protocol, E_{resi} is highly essential. The communication between the nodes takes place when the E_{resi} value becomes higher for the avoidance of communication dropping. Then, the reward function formulation for the group is enunciated in equation (4).

$$n(m_c) = \frac{2}{\pi} \arctan \left(E_{resi}(m_c) - \bar{E}(m_c) \right) \quad (4)$$

Where, the term $\bar{E}$ defines the residual energy of a group in average. Then, the final reward function is enunciated in equation (5).

$$\mathrm{Re}\,ward = E_X \times Y^{f_c}_{m_c,m_b} + E(1 - E_X) \times Y^{f_c}_{m_c,m_b} \quad (5)$$

Estimation of Q-Value: For the acquisition of the highest reward value, the Q-value is evaluated to make the required action. The Q-value is enunciated in equation (6).

$$Q - V(X, f) = \mathrm{Re}\,ward + \beta \left[Q - V(X, f) + Max_{f'} \left(Q - V(X', :) \right) \right] \quad (6)$$

Where, estimation of the Q-value is defined as $Q - V$ and is highly helpful in choosing the energy efficient node for D2D communication.

3.2.3. Double Deep Q Learning based on Deep CNN

The traditional double deep Q learning utilizes the DNN for estimating the Q-value and reward function. In the proposed methodology, the deep convolutional Neural Network (Deep CNN) is utilized for estimating the Q-value and reward function. The detailed description is given below.

3.2.3.1. Architecture of Deep CNN

The complex features are learned by the deep learning models to enhance the generalization capability that provides the outcome more efficient through various layers. Recent years, the deep learning methods are widely utilized for solving various application domains concerning the computer vision related tasks like classification, prediction, recognition and various other tasks due to the promising outcome of the deep learning models. The convolutional neural network (CNN), recurrent neural network (RNN), and deep belief networks (DBN) are the some of the examples for the deep learning methods. Besides, the automatic feature extraction criterion of the deep learning methods diminishes the need for external feature extraction technique. Thus, in the proposed path detection model, the deep CNN (Deep CNN) is introduced for the estimation of Q-value and reward function. The architecture of the Deep CNN is depicted in Figure 3.

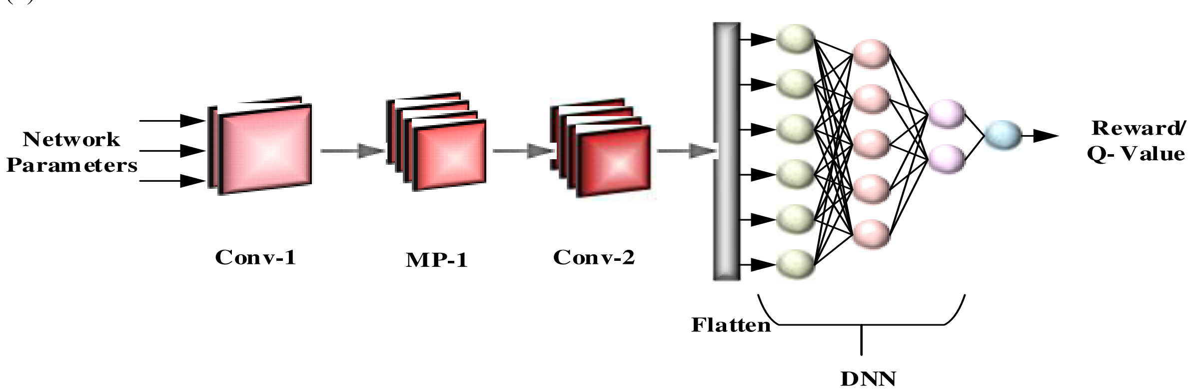

Figure 3 Architecture of Deep CNN

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The layer-wise details of the Deep CNN for estimating the Reward or the Q-value is detailed here.

Conv Layer: The input parameters of the network for energy efficient routing is acquired by the Conv layer-1 and it convolves the input with the kernel function for obtaining the feature mapping. The formulation for the conv layer outcome is defined in equation (7).

$$R-Q_v=\sum X^w * Y^w + Q^w \tag{7}$$

Where, the outcome of the conv layer is defined as $R-Q_v$. The input feature is referred as X^w and the weight is represented as Y^w. The bias value is notated as Q^w, wherein the output map corresponding to the w^{th} feature is indicated as w.

Max-Pooling Layer: The most informative attributes are extracted in the pooling operation for the minimization of the redundant features, which in turn reduces the complexity concerning the computation overhead. In the proposed method, the max-pooling operation is utilized for extracting the significant attributes. An example for the max-pooling operation is illustrated in Figure 4.

Figure 4 Max-Pooling Operation

Flatten Layer: The transformation of the features into the single dimension is employed in the flatten layer.

Fully Connected Layer: The Q-value and the reward estimation is provided at the outcome of the fully connected layer, wherein the softmax activation is utilized. The estimation of the outcome is defined as,

$$R-Q_{v\,out}=\frac{e^{z_m}}{\sum_{n=1}^{i} e^{z_n}} \tag{8}$$

Where, the softmax function is indicated as $R-Q_{vout}$, the element corresponding to the input attribute is indicated as z_m, and i refers to the outcome.

3.3. Optimal Path Detection Using the Proposed Gannet Chimp Optimization Algorithm

The possible path detected by the proposed Double Deep Q Learning consists of various paths. From the all detected paths, the optimal best path for the D2D communication is chosen by the proposed GCO algorithm. The optimal best path is chosen by the GCO based on the Multi-objective fitness function with the factors like energy consumption, packet latency, bandwidth, hop count, and trust factor.

3.3.1. Multi-objective Fitness Function

The factors considered for the estimation of the optimal best path using the proposed GCO algorithm for estimating the multi-objective fitness function are energy consumption, packet latency, bandwidth, hop count, and trust factor. The detailed description is given below.

3.3.1.1 Residual Energy

The residual energy is crucial factor for the energy efficient D2D communication between the users. The node with higher residual energy is considered for communication between the users, because the node with higher energy has enough energy for communication without any interruption due to the lack of energy. The estimation of the residual energy is formulated in equation (9).

$$RE=E_c-\left(E_{txn}+E_{rxn}\right) \tag{9}$$

Where, the energy utilized for sender is indicated as E_{txn}, the energy utilized by the receiver is indicated as E_{rxn}, the residual energy is defined as RE, and the present remaining energy of the node is indicated as E_c. The node with higher RE is preferred for D2D communication.

3.3.1.2. Packet Latency

The latency is defined as the time taken by the network for D2D communication. The estimation of the packet latency is defined in equation (10).

$$PL=a\frac{P+Q(N)}{d} \tag{10}$$

where, the packet latency is notated as PL, the count of bits in the packet is notated as a, the number of packet is represented as N, the capacity of the link is indicated as d, the size of data is indicated as Q and the bit size of header is notated as P.

3.3.1.3. Bandwidth

The larger amount of bandwidth is essential for the uninterruptable communication between the D2D users. However, the limited amount of bandwidth the resource must be utilized in minimal amount for the efficient routing. Thus, the minimal amount of bandwidth needs to be considered for the efficient information routing, which is indicated as F_{BW}. The minimal bandwidth is utilized through communication the devices using the energy efficient node sensing.

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3.3.1.4. Hop Count

The proposed D2D communication routing protocol uses multi-hop path for user communication, wherein the path with large number of hop consumes more energy. Thus, the path with minimal hop is considered for the minimization of energy consumption. The hop count is defined using the variable F_{HC}.

3.3.1.5. Degree of Connectivity

The estimation of degree of connectivity is essential for identifying the capability of the node to handle the number of devices within the specified time t. The connectivity is defined as DC_i and the neighbour node is indicated as NN_i. Then, the expression for calculating the degree of connectivity is formulated in equation (11).

$$DC_i = \frac{NN_i}{D_{i,j} \le R_T} \tag{11}$$

Where, the transmission range is represented as R_T, the distance between the nodes is indicated as $D_{i,j}$.Thus, the multi-objective fitness function is formulated in equation (12).

$$MO_{fitness} = Max(RE, DC_i)Min(PL, F_{HC}, F_{BW}) \tag{12}$$

Here, the multi-objective fitness function is indicated as $MO_{fitness}$. The fitness function is normalized within the range of $[0,1]$ for making the computation simpler.

3.3.2. Gannet Chimp Optimization

The novel Gannet Chimp Optimization is designed by combining the hunting behaviour of the Gannet with the attacking behaviour of the chimp in capturing the target. The goal of the hybridization is to accomplish the global best solution with balanced randomization and local search capability. The balanced optimization assures the best solution for solving optimization issues without trapping at local optimal solution.

Motivation behind the Proposed Gannet Chimp Optimization

The Gannet [26] is a carnivorous bird that hunts the target (fish, amphibians, crustaceans, and so on) along the sea shore and lakes. They live in flocks with powerful eyes, slender necks and stubby. The enhanced vision of the bird helps to capture the target very easily by accurately identifying from a very large distance. Thus, the target that falls within the vision of the carnivorous bird never has the chance of escaping. Besides, the V-shaped and U-shaped diving behaviour of the bird assures the better encircling of the target. High capturability behaviour of the bird by ignoring the water resistance helps to capture the target very easily. Here, for enhancing the capturability of the bird, the attacking strategy of the chimp is integrated for obtaining the solution with fast convergence rate. The chimp [27] is a great ape African species belongs to the family Hominoid. Four various types of chimp are considered for solving the optimization issues, which are attacker, chaser, barrier and driver. Here, each chimp has their own role in capturing the target. The attacking strategy of the chimp is devised through the combined behaviour of all the four categories of chimp. Thus, the local search capability of the Gannet is enhanced by hybridizing the attacking strategy of the chimp to obtain the global best solution in solving the optimization issue. In the proposed methodology, the global best solution is utilized for identifying the energy efficient best path for D2D communication among the users through the multi-hop routing strategy.

3.3.2.1. Mathematical Modeling

The initialization of the proposed Gannet chimp optimization (GCO) algorithm is the first step, wherein the candidate solutions (Gannets) and the prey (target solution) are located randomly in the feature space. The solutions accomplished by each candidate in the feature space are utilized for solving the optimization issues. The candidate initialization in the feature space is formulated in equation (13).

$$A = \begin{bmatrix} a_{1,1} & \cdots & a_{1,y} & \cdots & a_{1,V-1} & a_{1,V} \\ a_{2,1} & \cdots & a_{2,y} & \cdots & a_{2,V-1} & a_{2,V} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \cdots & \cdots & a_{x,y} & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{U-1,1} & \cdots & a_{U-1,y} & \cdots & a_{U-1,V-1} & a_{U-1,V} \\ a_{U,1} & \cdots & a_{U,y} & \cdots & a_{U,V-1} & a_{U,V} \end{bmatrix} \tag{13}$$

Where, the x^{th} candidate's location in the feature space is defined as a_x. The solution accomplished by the x^{th} candidate in the feature space with the dimension y is expressed in equation (14).

$$a_{x,y} = g_1 \times (Q_y - S_y) + S, \qquad x = 1,2,....U, \quad y = 1,2,...V \tag{14}$$

Where, V refers to the solution's dimension and the population of the candidate solution is defined as U. The random number is notated as g_1 with the value of $[0,1]$. The boundary of the solution is between Q_y and S_y, in which the upper limit is mentioned as Q_y. The solution obtained by the candidates is stored in the memory D, wherein all the

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candidates have the space for the storage. The solutions are upgraded in D by checking the past solution. If the present solution is better then, D is upgraded; else, it is maintained in the past solution.

(i) Exploring Solution: In the randomization phase, the candidate's searches for the solution by exploring the feature space by performing various diving techniques. The expressions for the diving tactics are defined in equation (15-16).

$$M = 2 * \cos(2 * \pi * g_2) * t \tag{15}$$

$$N = 2 * B(2 * \pi * g_3) * t \tag{16}$$

Where, M refers to the diving of Gannet in U-shape and N refers to the diving of Gannet in V-shape. The expression for the iteration in the randomization phase is defined in equation (17).

$$t = 1 - \frac{\tau}{\tau_{\max}} \tag{17}$$

Where, t is the iterations utilized by GCO in the randomization phase, in which the maximal value is defined as $\tau_{\max}$. g_2 and g_3 are the random numbers with range $[0,1]$. The diving angle is defined as $B(.)$ and is formulated in equation (18).

$$B(a) = \begin{cases} -\frac{1}{\pi} * a + 1, & a \in (0, \pi) \\ \frac{1}{\pi} * a - 1 & a \in (\pi, 2\pi) \end{cases} \tag{18}$$

After making various dives randomly for exploring more space in the feature area, the corresponding locations are updated in D. The possibility of both the V and U dives are assigned equally and is defined as f. The update of memory (D) is stated in equation (19-23).

$$D_x(t+1) = \begin{cases} A_x(t) + u_1 + u_2 & , f \geq 0.5 \\ A_x(t) + v_1 + v_2 & , f < 0.5 \end{cases} \tag{19}$$

Where,

$$u_2 = K * (A_x(t) - A_e(t)) \tag{20}$$

$$v_2 = L * (A_x(t) - A_c(t)) \tag{21}$$

$$K = (2 * g_4 - 1) * M \tag{22}$$

$$L = (2 * g_5 - 1) * N \tag{23}$$

Where, randomly chosen solution is referred as $A_e(t)$, the solutions evaluated at the present iteration $A_c(t)$ is averaged based on equation (24).

$$A_c(t) = \frac{1}{U} \sum_{x=1}^{U} A_x(t) \tag{24}$$

The range of u_1 is $[-M, M]$ and the range of v_1 is $[-N, N]$.

(ii) Exploiting Solution: In the randomization search, the candidates identify a solution globally, which is further exploited deeply in the local search for acquiring the solution. Here, the candidate uses its capturability behaviour for capturing the target. It is defined as in equation (25).

$$C = \frac{1}{G * t_2} \tag{25}$$

Where, the iterations utilized in the local search is indicated as t_2 and is formulated as in equation (26).

$$t_2 = 1 + \frac{\tau}{\tau_{\max}} \tag{26}$$

Let G be the energy of the candidate to capture the target, which depends on the mass and velocity. It is defined as in equation (27).

$$G = \frac{H * s^2}{P} \tag{27}$$

where, G is the mass with 2.5kg, s is the velocity with the value 1.5m/s and P is a variable that is estimated as in equation (28).

$$P = 0.2 + (2 - 0.2) * g_6 \tag{28}$$

Where, the random variable is indicated as g_6 and has the value of $[0,1]$. Then, the solution update is stated as in equation (29).

$$D_m(t+1)_{Gannet} = \begin{cases} t * \gamma * (A_x(t) - A_{better}(t)) + A_x(t), & C \geq d \\ A_{better}(t) - (A_x(t) - A_{better}(t)) * R * t & C < d \end{cases} \tag{29}$$

Where, the best candidate is indicated as $A_{better}(t)$ and the factors γ *and* R are estimated as in equation (30-31).

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$$\gamma = C * \left|A_x(t) - A_{better}(t)\right| \tag{30}$$

$$R = Levy(V) \tag{31}$$

Here, the levy flight behavior is utilized by the candidate to capture the solution and is indicated as R and is expressed as in equation (32-33).

$$Levy(V) = 0.01 \times \frac{\alpha \times \beta}{|v|^{1/\mu}} \tag{32}$$

Where,

$$\beta = \left(\frac{\Gamma(1+\mu) \times \sin\left(\frac{\pi\mu}{2}\right)}{\Gamma\left(\frac{1+\mu}{2}\right) \times \mu \times 2^{\left(\frac{\mu-1}{2}\right)}} \right)^{1/\mu} \tag{33}$$

The values of the random variables γ *and* β lie in the range of $[0,1]$ and the predefined constant μ has the value of 1.5. Here, in the Gannet optimization, the sudden turning of the cunning fish escapes from the Gannet and hence the capturing of solution is not possible and hence the Gannet searches for another fish. Thus, in order to minimize the capability of fish escaping, the attacking behaviour of the chimp is incorporated in the proposed GCO algorithm.

The solution is updated by the chimp is devised based on all the four types of chimps. Its solution update is expressed as in equation (34).

$$D_x(t+1) = \frac{D_A + D_B + D_D + D_C}{4} \tag{34}$$

where, the solution update is indicated as $D_x(t+1)$, the solution obtained by the attacker is notated as D_A, the solution acquired by the barrier is notated as D_B, the solution updated by the driver is represented as D_D, the solution acquired by the carrier is indicated as D_C. Here, the position updated by the individual chimp is expressed as in equation (35-38).

$$D_A = D_1 - k_1(q_A) \tag{35}$$

$$D_B = D_2 - k_2(q_B) \tag{36}$$

$$D_C = D_3 - k_3(q_C) \tag{37}$$

$$D_D = D_4 - k_4(q_D) \tag{38}$$

Where, q_A refers to the distance between the target and the attacker chimp, q_B refers to the distance between the target and the barrier chimp, q_C refers to the distance between the target and the carrier chimp, and q_D refers to the distance between the target and the driver chimp. The coefficient $k_1, k_2, k_3, and\ k_4$ ranges between $[0,1]$ forces the candidates to capture the target. $D_1, D_2, D_3, and\ D_4$ refers to the best solutions acquired by the attacker, barrier, carrier and driver. Then, the hybridized solution updating using the proposed GCO is formulated as in equation (39-40).

$$D_x(t+1) = 0.5 D_x(t+1)_{Gannet} + 0.5 D_x(t+1)_{Chimp} \tag{39}$$

$$W_m(T+1) = \begin{cases} 0.5\left[t * \gamma * \left(A_x(t) - A_{better}(t)\right) + A_x(t)\right] + \\ 0.5\left[\frac{D_A + D_B + D_D + D_C}{4}\right], & C \geq d \\ 0.5\left[A_{better}(t) - \left(A_x(t) - A_{better}(t)\right) * R * t\right] + \\ 0.5\left[\frac{D_A + D_B + D_D + D_C}{4}\right], & C < d \end{cases} \tag{40}$$

(iii) Feasibility Estimation: For the solutions updated in the previous stage the feasibility is evaluated through the multi-objective fitness function defined in equation (12).

(iv) Stopping Criteria: The attainment of τ_{max} or the optimal best solution stop the iteration of the algorithm. The pseudo-code for the proposed GCO algorithm is depicted in Algorithm 1.

Initialize the τ_{max}, U and V

Locate the population (candidate) of Gannet in the search space

Create the memory matrix D

Estimate the fitness for all the updated solutions

While

If $f \geq 0.5$

Update the solution using equation (18) based on first condition

Else

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Update the solution using equation (18) based on second condition

End if

If $d \geq 0.2$

Update the solution using equation (40) based on first condition

Else

Update the solution using equation (40) based on second condition

End if

Recheck the feasibility of the solution

Replace the memory matrix D with best solution

End while

$t = t + 1$

end

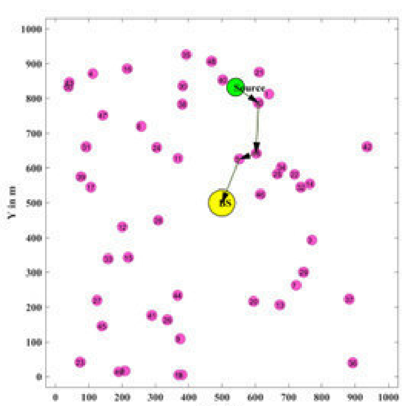
Algorithm 1 Pseudo-Code for Proposed GCO Algorithm

Thus, using the GCO algorithm, the optimal best path with multi-hop energy efficient routing is chosen for D2D communication between the users in the 5G networks.

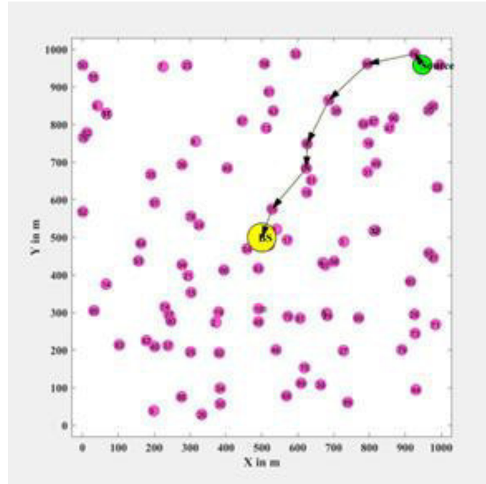
4. RESULTS AND DISCUSSION

The proposed energy efficient multi hop routing protocol is implemented in MATLAB using Windows 10 OS, and 8GB RAM PC. The experimental outcome is measured through various assessment measures to depict the excellence of the devised model. For this, the conventional energy efficient D2D routing protocols like MBLCR [25], Modified Derivative Algorithm [21], 5G-EECC [22], and DRL [24] are utilized for comparison with the proposed method.

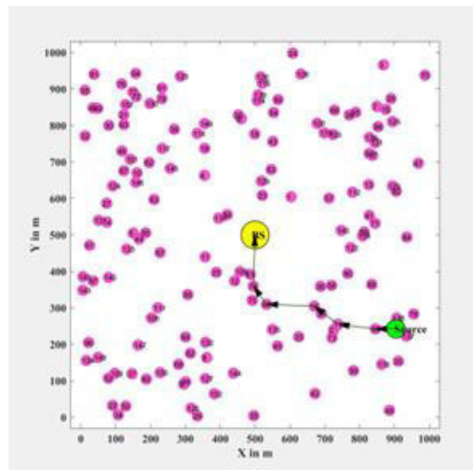
4.1. Simulation Outcome



(a)



(b)



(c)

Figure 5 Simulation Outcome of the Proposed Routing Protocol Based on (a) 50 Nodes, (b) 100 Nodes and (c) 150 Nodes

The simulation outcome of the proposed D2D communication between the users by varying the rounds is portrayed in Figure 5. Here, the communication between the users in the 5G network is devised through multi hop path by considering multi-objective fitness function. Besides, the deep learning based path detection and optimal path selection criteria enhance the energy efficiency of the proposed routing protocol.

4.2. Analysis based on Average Residual Energy

The estimation of the energy depleted by the node during the communication between the users in the network is obtained through the average residual energy estimation. The average

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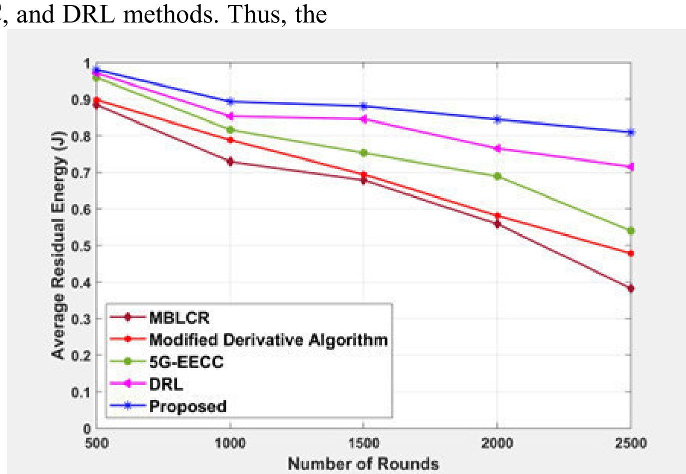
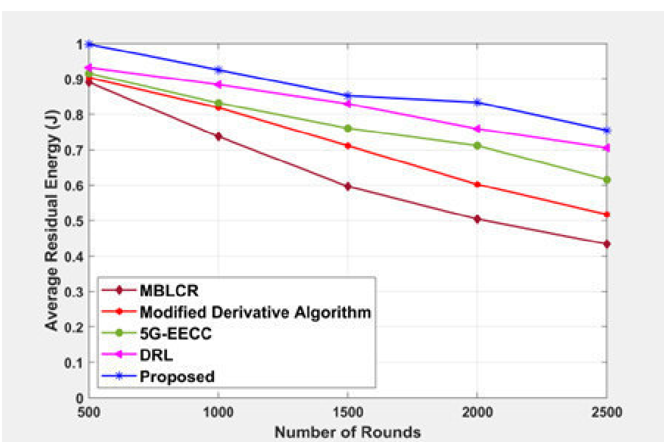
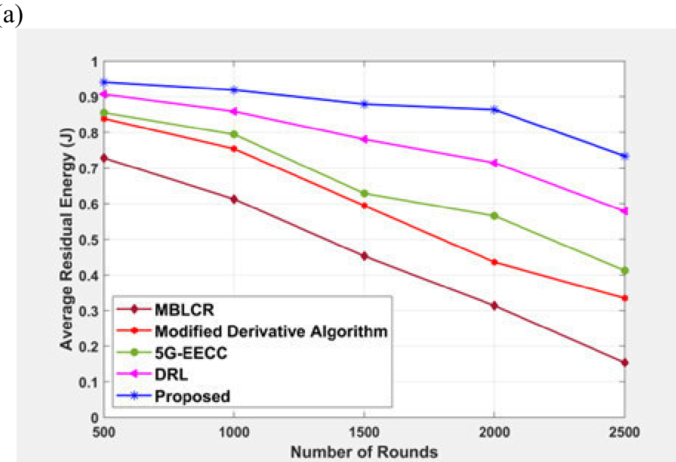
residual energy of the proposed energy efficient routing protocol along with the comparative methods is depicted in Figure 6. The average residual energy with 50 nodes is depicted in Figure 6(a), 100 nodes in Figure 6(b) and 150 nodes in Figure 6(c). The average residual energy of the proposed method with 500 rounds is 0.98, which is 9.81%, 8.37%, 2.18%, and 0.90% improved outcome than the MBLCR, Modified derivative algorithm, 5G-EECC, and DRL methods. For 2500 round, the average residual energy of the proposed method is 0.81, which is 52.80%, 40.99%, 33.41%, and 11.68% improved outcome than the MBLCR, Modified derivative algorithm, 5G-EECC, and DRL methods. Thus, the analysis by varying the number of rounds depicts that the increase in rounds depletes the residual energy due to the increase in energy consumption with larger number of rounds. However, the residual energy of the proposed method is better than the traditional methods due to the energy efficient routing protocol design. The consideration of energy consumption in detecting the possible paths using the double deep Q learning and the optimal path selection helps to accomplish the maximal residual energy compared to the conventional methods. The more detailed analysis is depicted in Table 2.



(a)



(b)



(c)

Figure 6 Average Residual Energy for (a) 50 Nodes, (b) 100 Nodes and (c) 150 Nodes

Table 2 Analysis based on Average Residual Energy

Methods/ Rounds	MBLCR	Modified Derivative Algorithm	5G-EECC	DRL	Proposed
Using 50 nodes					
500	0.88	0.90	0.96	0.97	0.98
1000	0.73	0.79	0.82	0.85	0.89

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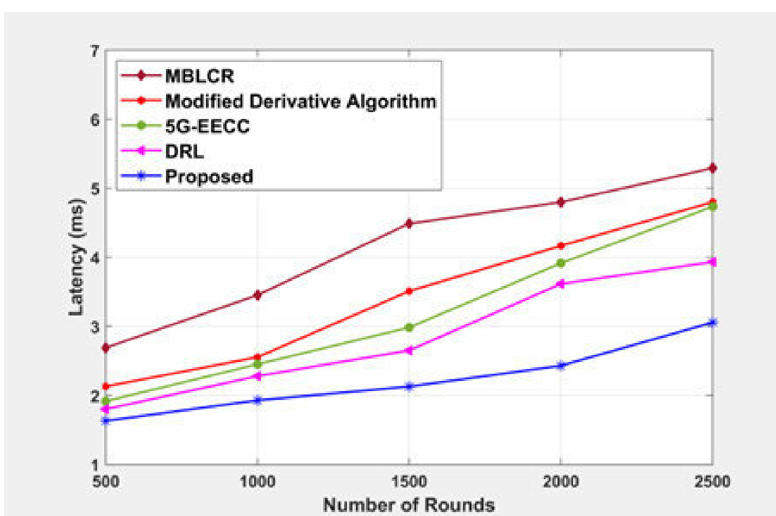
1500	0.68	0.69	0.75	0.85	0.88
2000	0.56	0.58	0.69	0.76	0.84
2500	0.38	0.48	0.54	0.72	0.81
Using 100 nodes					
500	0.89	0.90	0.92	0.93	1.00
1000	0.74	0.82	0.83	0.88	0.93
1500	0.60	0.71	0.76	0.83	0.85
2000	0.50	0.60	0.71	0.76	0.83
2500	0.43	0.52	0.62	0.71	0.75
Using 150 nodes					
500	0.73	0.84	0.86	0.91	0.94
1000	0.61	0.75	0.79	0.86	0.92
1500	0.45	0.59	0.63	0.78	0.88
2000	0.31	0.44	0.57	0.71	0.86
2500	0.15	0.33	0.41	0.58	0.73

4.3. Analysis based on Latency

The time taken for sharing the communication request between the sender and the destination measures the latency that helps to measure the communication delay in the network. The analysis of the D2D routing protocol based on the latency assessment is portrayed in Figure 7. For example, the analysis with 1000 rounds and 100 nodes, the proposed method evaluated the latency of 4.51, which is 43.84%, 29.90%, 25.74%, and 4.99% improved outcome than the MBLCR, Modified derivative algorithm, 5G-EECC, and DRL methods. Here, the analysis indicates the elevated outcome of the proposed routing protocol by acquiring minimal latency compared to the conventional methods. In the proposed GCO algorithm for the optimal path selection, a multi-objective fitness is considered, wherein the packet latency is considered as one of the significant parameter for selecting the optimal best path. Thus, the optimal path selection criterion using the proposed GCO algorithm reduces the D2D communication latency and hence enhances the efficiency of the routing protocol. The detailed description is presented in Table 3.



(a)

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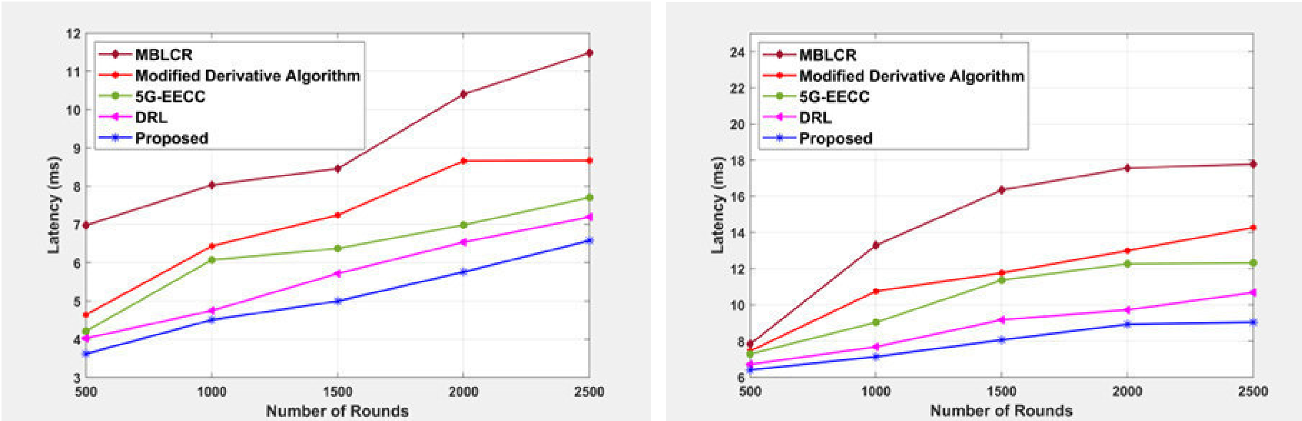

(b) (c)

Figure 7 Latency Analysis for (a) 50 Nodes, (b) 100 Nodes and (c) 150 Nodes

Table 3 Analysis based on Latency

Methods/ Rounds	MBLCR	Modified Derivative Algorithm	5G-EECC	DRL	Proposed
Using 50 nodes					
500	2.69	2.13	1.92	1.80	1.63
1000	3.45	2.55	2.45	2.28	1.93
1500	4.49	3.51	2.98	2.65	2.13
2000	4.80	4.17	3.92	3.62	2.43
2500	5.29	4.80	4.73	3.93	3.06
Using 100 nodes					
500	6.98	4.64	4.21	4.02	3.62
1000	8.03	6.43	6.07	4.75	4.51
1500	8.46	7.25	6.37	5.72	5.00
2000	10.40	8.66	6.99	6.54	5.76
2500	11.48	8.67	7.70	7.19	6.58
Using 150 nodes					
500	7.83	7.44	7.28	6.70	6.40
1000	13.29	10.75	9.03	7.67	7.13
1500	16.34	11.76	11.37	9.17	8.06
2000	17.56	12.99	12.27	9.72	8.92
2500	17.78	14.27	12.32	10.68	9.04

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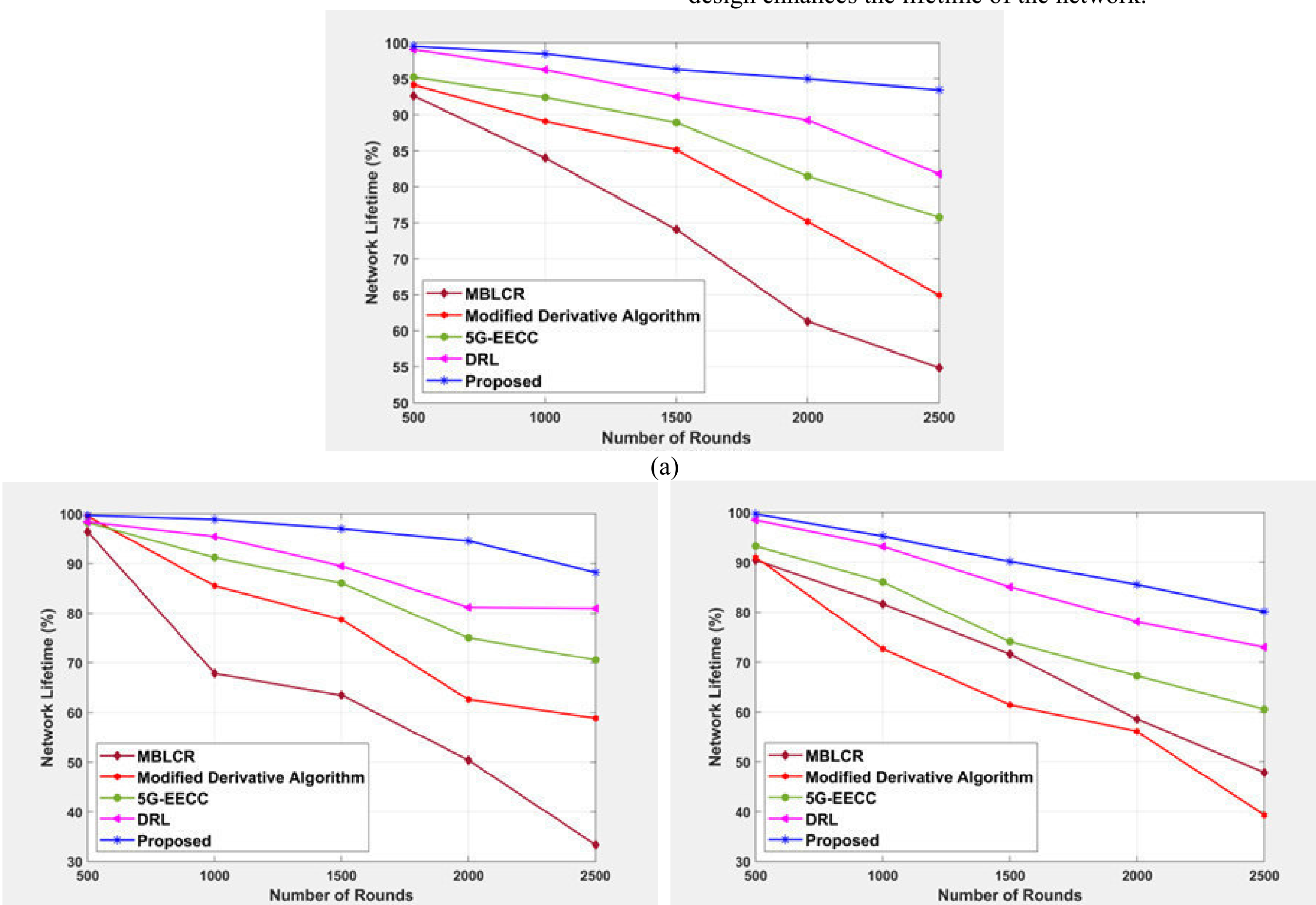
4.4. Analysis based on Network Lifetime

The time period of the network until the first node drops out of energy is considered as the network lifetime. The network lifetime based analysis is depicted in Figure 8 and its detailed analysis is presented in Table 4. For example, using 150 nodes and 2000 communication rounds, the proposed method acquired 85.52% of network lifetime, which is 31.60%, 34.48%, 21.43%, and 8.72% improved outcome than the MBLCR, Modified derivative algorithm, 5G-EECC, and DRL conventional methods. The network lifetime depends on the energy of the nodes. Once the energy of the network gets depleted and it runs out of energy, the network becomes dead and hence the lifetime gets completed. The proposed multi hop routing protocol considers energy consumption as a significant criteria for D2D communication between the users, wherein the possible multi hop paths for D2D communication utilizes energy consumption for identifying the next hop using the double deep Q learning. Here, the consideration of energy efficient node for communication between the users enhances the residual energy of the node. The network with minimal energy consumption further enhances the lifetime of the network. Thus, the energy efficient multi hop routing protocol design enhances the lifetime of the network.



(a)

(b) (c)

Figure 8 Network Lifetime Analysis for (a) 50 Nodes, (b) 100 Nodes and (c) 150 Nodes

Table 4 Analysis based on Network Lifetime

Methods/ Rounds	MBLCR	Modified Derivative Algorithm	5G-EECC	DRL	Proposed
Using 50 nodes					
500	92.62	94.17	95.24	99.09	99.55

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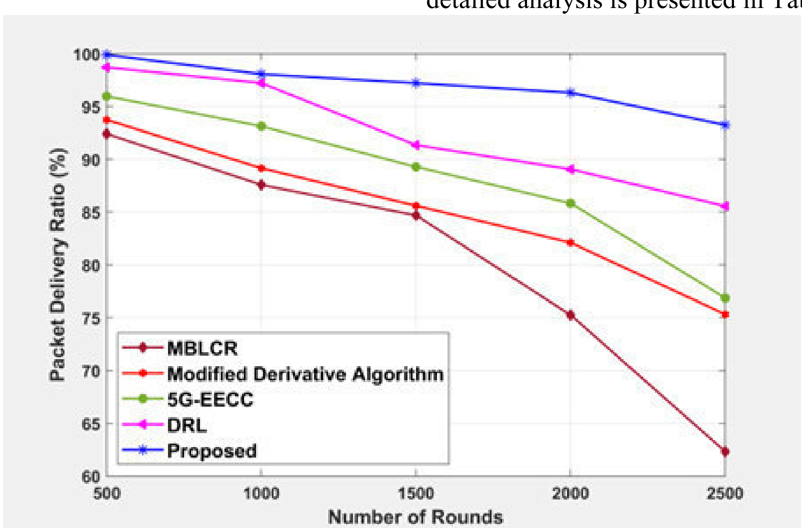
1000	84.02	89.10	92.42	96.28	98.47
1500	74.05	85.13	88.91	92.52	96.31
2000	61.28	75.15	81.46	89.24	94.98
2500	54.84	64.94	75.75	81.78	93.46
Using 100 nodes					
500	96.44	99.53	98.27	98.40	99.69
1000	67.88	85.50	91.21	95.46	98.87
1500	63.49	78.73	86.03	89.51	97.03
2000	50.40	62.61	75.07	81.17	94.55
2500	33.38	58.85	70.59	80.95	88.24
Using 150 nodes					
500	90.41	91.02	93.30	98.47	99.68
1000	81.66	72.66	86.02	93.23	95.25
1500	71.60	61.43	74.10	85.06	90.16
2000	58.50	56.03	67.19	78.06	85.52
2500	47.83	39.31	60.52	73.00	80.14

4.5. Analysis based on Packet Delivery Ratio

The ratio that estimates the number of data packets delivered to the destination to the total data shared by the sender measures the packet delivery ratio. Figure 9 depicts the packet delivery ratio by varying number of nodes in the network. In this analysis, the packet delivery ratio estimated by the proposed method is 85.38 with 150 nodes and 2500 rounds of communication that is 56.79%, 49.34%, 34.57%, and 9.62% improved outcome than the MBLCR, Modified derivative algorithm, 5G-EECC, and DRL conventional methods. The higher packet delivery rate of the proposed method depicts the efficiency of the routing protocol with minimal packet loss. The packet loss is minimized by routing the packet through the energy efficient node. The data shared through the node with higher energy minimizes the chance of information loss due to the high capability of the node in terms of lifetime. Thus, the proposed method accomplished enhanced packet delivery ratio compared to the conventional methods. The detailed analysis is presented in Table 5.



(a)

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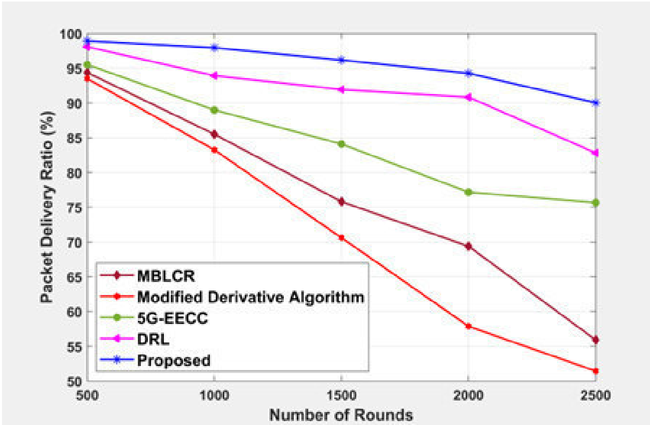

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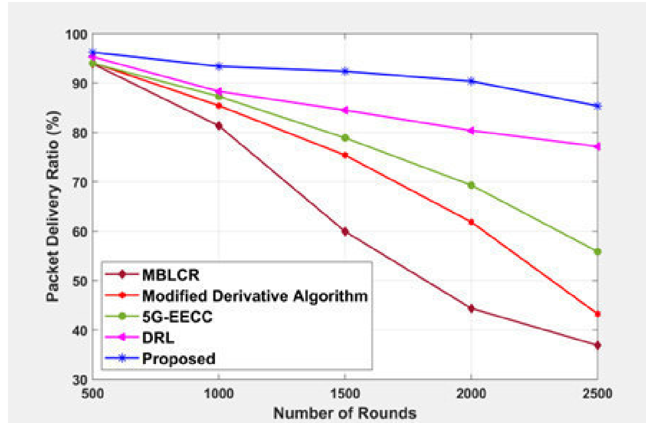

(c)

Figure 9 Packet Delivery Ratio Analysis for (a) 50 Nodes, (b) 100 Nodes and (c) 150 Nodes

Table 5 Analysis based on Packet Delivery Ratio

Methods/ Rounds	MBLCR	Modified Derivative Algorithm	5G-EECC	DRL	Proposed
Using 50 nodes					
500	92.41	93.74	95.97	98.70	99.89
1000	87.58	89.16	93.13	97.23	98.07
1500	84.69	85.61	89.28	91.35	97.22
2000	75.25	82.10	85.84	89.05	96.31
2500	62.32	75.32	76.86	85.57	93.24
Using 100 nodes					
500	94.37	93.49	95.51	98.08	98.91
1000	85.50	83.25	88.98	93.92	97.94
1500	75.80	70.61	84.09	91.92	96.16
2000	69.38	57.87	77.16	90.83	94.26
2500	55.91	51.44	75.67	82.81	90.03
Using 150 nodes					
500	93.92	94.11	94.01	95.32	96.25
1000	81.34	85.42	87.30	88.31	93.38
1500	59.94	75.39	78.90	84.51	92.38
2000	44.37	61.86	69.32	80.39	90.37
2500	36.90	43.25	55.86	77.17	85.38

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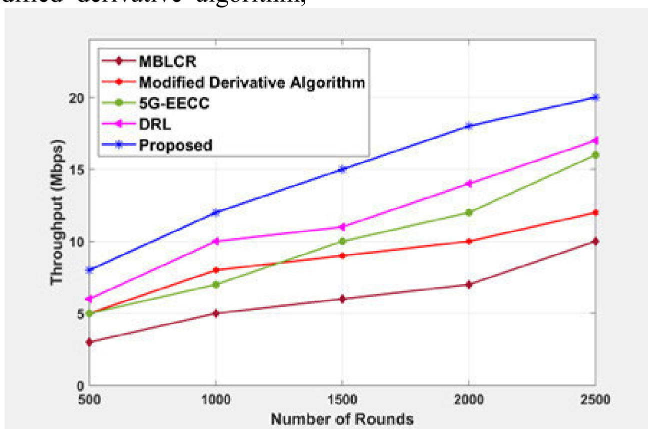
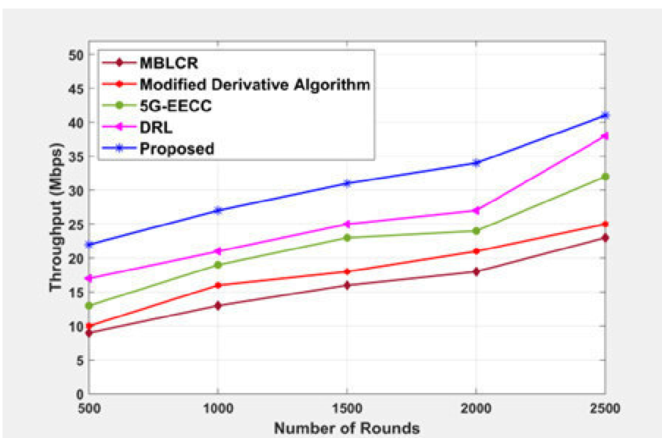
4.6. Analysis based on Throughput

The data packet received by the destination node within the specified time is measured through the throughput analysis, which is portrayed in Figure 10. The throughput estimated by the proposed method with 1000 rounds and 100 nodes is 27, which is 51.85%, 40.74%, 29.63%, and 22.22% improved outcome than the MBLCR, Modified derivative algorithm, 5G-EECC, and DRL conventional methods. The proposed optimal route selection technique chooses the best path with minimal hop count, which helps to communicate the sender faster and hence more communication is possible within the specified time. The larger amount of communication without information loss enhances the throughput of the network. The detailed analysis is depicted in Table 6.



(a)



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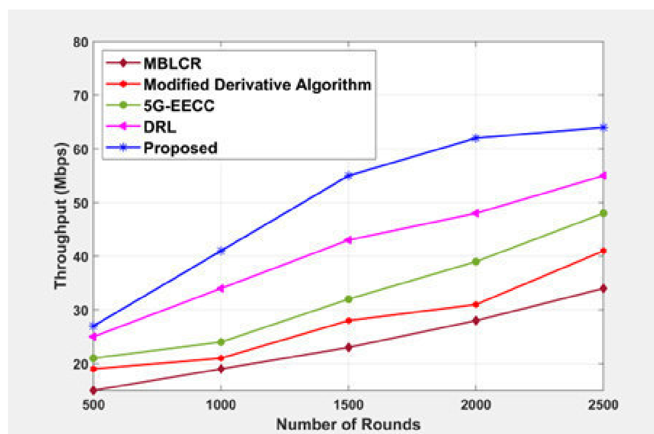

(c)

Figure 10 Throughput Analysis for (a) 50 Nodes, (b) 100 Nodes and (c) 150 Nodes

Table 6 Analysis based on Throughput

Methods/ Rounds	MBLCR	Modified Derivative Algorithm	5G-EECC	DRL	Proposed
Using 50 nodes					
500	3	5	5	6	8
1000	5	8	7	10	12
1500	6	9	10	11	15
2000	7	10	12	14	18

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2500	10	12	16	17	20
Using 100 nodes					
500	9	10	13	17	22
1000	13	16	19	21	27
1500	16	18	23	25	31
2000	18	21	24	27	34
2500	23	25	32	38	41
Using 150 nodes					
500	15	19	21	25	27
1000	19	21	24	34	41
1500	23	28	32	43	55
2000	28	31	39	48	62
2500	34	41	48	55	64

4.7. Comparative Discussion

The proposed energy efficient routing protocol with multi hop for D2D communication between the users in the 5G network accomplished enhanced performance while assessing the performance based on various measures like packet delivery ratio, latency, residual energy, throughput and network lifetime. The proposed method utilizes the multi-hop possible path detection using the proposed double deep Q learning technique. Here, the consideration of energy consumption between the nodes for selecting the next hop node identifies the best energy efficient node for communication. Besides, the consideration of Deep CNN for estimating the Q-value and reward function enhances the detection accuracy of finding the possible paths by solving the over optimistic issues. Also, the proposed GCO algorithm utilizes the multi-objective fitness function for finding the optimal best path for communication among the identified paths. Thus, the consideration of the combined behavior of the double deep Q learning along with the GCO algorithm helps to identify the optimal best energy efficient path for D2D communication and is depicted based on various assessment measures.

5. CONCLUSION

An energy efficient multi hop routing protocol is introduced in this research for D2D communication between the 5G network users. Here, a deep reinforcement learning technique named double deep Q learning is proposed for the identification of multi hop paths for D2D communication. In this, the Deep CNN is introduced for the estimation of the Q-value and reward function of the double deep Q learning for enhancing the path detection accuracy and to solve the issue concerning the over optimization. Also, a hybrid optimization named GCO is introduced by hybridizing the hunting behavior of the Gannet with the chimp to obtain the global best solution in choosing the optimal best path. The balanced exploration and exploitation capability of the proposed GCO algorithm with multi-objective fitness function chooses the best path for D2D communication. The assessment of the proposed method based on various measures like packet delivery ratio, latency, residual energy, throughput and network lifetime accomplished the values of 99.89, 1.63, 0.98, 64 and 99.69 respectively. In the future, a novel architecture will be designed based on fuzzy concept for the reduction of computational complexity.

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MACHINE LEARNING BASED PUBLIC SAFETY APPLICATIONS USING DEVICE-TO-DEVICE COMMUNICATION PROTOCOL

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Abstract — **The underutilised portion of the wireless spectrum will need to be better utilised due to the expected exponential growth in traffic volume in 5G-based networks. Apps for smartphones have caused an increase in data traffic on cell phone networks recently. As a result, expanding the network's capacity to accommodate new applications and services is critical. D2D communication with multiple hops requires more nodes for data transmission, especially when cooperatively-operated relays are used. Long-Term Evolution (LTE) is the most recent and most technologically advanced cell phone technology that is about to be introduced to the market. LTE and its advanced version appear to be an appealing solution for many businesses since they offer exceptional peak data speeds in both the uplink and downlink directions. Public safety communications is currently one of the fastest-growing fields in the world. In accordance with two homogeneous Poisson Point Processes, beacon-enabled and simple LTE terminals are dispersed in the vicinity of a significant event. This research looks into direct-to-device (D2D) communications. In this paper, we explore the likelihood of LTE mobile terminals forming in D2D networks using a stochastic geometry technique, and we then build an unique D2D protocol.**

Keywords—LTE, Machine Learning, Device to Device Communication, Public Safety Applications

I. INTRODUCTION

The term "cognitive radio" (CR) has been used to characterise radio systems that are capable of learning and adapting to their environment [1]. Knowledge and comprehension are acquired by cognoscere (to know), which is Latin for "to know." Acquiring knowledge and comprehension, which includes thinking, knowing, remembering, judging, and problem solving (cognition), is defined by cognoscere (to know). Self-programming, often known as autonomous learning, is a key component of all CR systems. [4] and [5]. In accordance with [6,] Haykin predicted that CRs would be brain-enhanced wireless devices whose goal would be to improve the utilisation of the electromagnetic spectrum. Haykin adopts an understanding-by-building strategy, which is intended to achieve two key goals: dependable communications and efficient spectrum use (or utilisation of available spectrum). [6]. It was with this new interpretation of CRs that the dynamic spectrum sharing (DSS) period began, with the goal of improving the utilisation of the crowded radio frequency spectrum. Evolution of a number of communications and signal processing techniques was demanded by the development of DSA networks [6–38]. The underlay, overlay, and interweave paradigms were used for secondary CRs in licenced spectrum bands, and they were all used in conjunction with each other. In order to carry out its cognitive duties, a CR must be aware of its radio frequency environment. It should be capable of detecting and distinguishing between all sorts of radio frequency (RF) activity in its immediate vicinity. As a result, it was discovered that spectrum sensing is an important component of CRs. A slew of new sensing approaches have been developed during the previous decade, including the matching filter, energy detection, cyclostationary detection, wavelet detection, and covariance detection [30, [41]–[46], among others. It has been proposed in [15], [33], [34], [42], [47]–[49] that cooperative spectrum sensing could improve the accuracy of wireless network sensing by addressing the hidden terminal problems that are inherent in wireless networks. Cooperative spectrum sensing has been proposed in [15], [33], [34], [42], [47]–[49]. cooperative CRs have also been examined recently, according to the authors [50]–[53]. [41], [54], and [55] are some of the most recent surveys on CRs that have been conducted. [39] provides a complete evaluation of spectrum sensing approaches for CRs, which is available online. The DSA and MAC layer operations for the CRs are investigated in numerous surveys, according to [56–60]. In addition to being aware of its environment, a CR must be able to learn and reason in order to be considered cognitive in the true sense. ([1] In accordance with the pioneering idea of [2, the cognitive engine [63]–[68] has been designated as the heart of a CR. Coordination of the CR's actions is accomplished by machine learning methods implemented by the cognitive engine. Machine learning methods have just lately gained popularity when it comes to CRs [38–72]. The process of learning is required when the precise effects of inputs on the outputs of a particular system are not understood in advance. Because of this, learning approaches are required to predict the input-output function of the system in order to ensure that the system's inputs are optimised. In wireless communications, for example, non-ideal wireless channels may cause uncertainty due to the fact that they are not ideal. In order to predict the wireless channel characteristics and to establish the precise coding rate that is required to achieve a certain likelihood of error across a wireless link [69], learning approaches can be applied. [69, 70] [69, 70] The problem of channel estimation is, according to [73], a comparatively simple one to tackle. Concerning cognitive radios (CRs) and cognitive radio networks (CRNs), the complexity of wireless systems rises with the introduction of highly reconfigurable software-defined radios, notably in the case of CRs and cognitive radio networks (CRNs) (SDRs). In this instance, a simple formula may not be able to calculate all of the setup parameters at the same time (for example, transmitting power, coding scheme, modulation scheme, sensing algorithm, communication protocol, sensing policy, and so on). This is due to the complex interplay between these components as well as the surrounding RF environment. This allows for the application of adaptive learning approaches that allow for efficient adaptation of CRs to their environment, but without the need for a thorough understanding of the relationship between these parameters [74].

According to some, threshold-learning algorithms, such as those described in [71] and [75], can be used to reconfigure spectrum sensing devices when they are operating under unknown conditions. In the case of diverse CRNs, the problem becomes far more difficult to manage. It is necessary for a CR not only to adapt to its environment, but also to coordinate its actions with the activities of other radios in the network while doing so. CRs are compelled to make educated guesses about what other nodes are up to as a result of the limited number of paths through which they can learn about their peers' behaviour. According to the DSA, for example, the CRs strive to access idle primary channels while avoiding clashes with both licenced and other secondary cognitive users. For example, in the case of Markov Decision Processes (MDPs), it is feasible that CRs operating in an unknown RF environment will be pushed to utilise unique decision-making strategies, such as Dynamic Programming in the case of MDPs [76]. Specific learning techniques such as reinforcement learning (RL) [38, [74], and [77] can assist you in solving the MDP problem even if you do not know the transition probabilities of the Markov model at the outset. Because of the need for self-adaptation in an uncertain and diverse RF environment, as well as the requirement for reconfigurability in RF environments, learning algorithms may be implemented by CRs. It is possible to incorporate low-complexity learning algorithms into the system in order to further lower the overall complexity of the system. Several learning approaches, both supervised and unsupervised, have been proposed for a range of learning tasks in recent research on CRs. These approaches include: [65], [78], and [79] [supervised learning], numerous researchers have examined CR applications that make use of neural networks and support vector machines (SVMs) for supervised learning in the context of [65], [78], and [79]. [80, 81] also discuss DSS applications for unsupervised learning, such as reinforcement learning, which have been addressed in the literature. In accordance with [77], the distributed Q-learning technique has been found to be successful in a variety of applications. The application of Q-learning to improve the identification and categorization of primary signals in the environment was demonstrated by CRs in [82]. Along with the examples in [14], [83]–[85], and others, there are countless additional instances in which RL has been used in conjunction with CRs as well. In [86], a weight-driven exploration technique was used to introduce new techniques to enhancing the efficiency of RL's performance, and the results were promising. When it comes to signal classification, it was proposed in [13] to use Bayesian non-parametric learning based on the Dirichlet process, which was later employed for signal classification [72]. Using an unsupervised learning strategy, such as that described in [87], it is possible to categorise signals, which is also beneficial for signal classification. RL algorithms, such as Q-learning, have been shown to be beneficial when used in conjunction with autonomous unsupervised learning [88–91]. While their performance in non-Markovian and multiagent systems has been demonstrated [88–91], it has been proven to be inadequate. The methodologies of evolutionary learning [89], [92], imitation, instruction, and policy-gradient approaches have all been shown to outperform RL on certain difficulties when used in this environment. Many studies have proved that the policy-gradient approach is more efficient in partially observable settings than other approaches [90, 91], primarily because it searches directly for optimal policies within the policy space [90, 91]. Recent years have seen an increase in the number of studies conducted on multi-agent learning, which has implications for the development of learning algorithms for CRNs. Several studies have compared the behaviour of human civilizations that exhibit both individual and group behaviours to cognitive networks [95], and a strategic learning framework for cognitive networks has been proposed. [pages 94 and 95] [page 94] It was in [96] that adaptive learning in cognitive users during strategic interactions was originally proposed, employing an evolutionary game paradigm to explain how they learn. The distributed nature of CRNs, as well as their interactions with one another, must be taken into consideration while attempting to obtain effective learning approaches based on cooperative schemes. Individual nodes in a CRN are less likely to behave selfishly as a result of this. When dealing with scattered CRNs, coordination of actions is a key challenge [88]. [numbers 89 and 90]. Network-wide policies that are centralised can be used to generate the greatest possible cooperative activities for the benefit of the entire network, hence maximising its overall efficiency. However, implementing centralised systems in a distributed network is not always feasible due to the nature of the network. The goal of cognitive nodes in distributed networks is to apply decentralised laws that ensure near-optimal behaviour while simultaneously minimising communication costs, which is referred to as decentralisation. Knowing how to convey knowledge (i.e., teach) across a wireless media has been discussed in depth in [3] and [97], and it is based on the concept of "docitive networks," which is derived from the Latin word docere, which literally means "to instruct" (to teach). Docitive networks are designed to reduce cognitive complexity, accelerate learning, and generate better and more trustworthy judgements, among other things. Radios in a docitive network are able to learn from one another because they are exchanging information with one another. [3] The radios are meant to teach not only the end results, but also how to get there. It is possible for new radios in a docitive network to pick up certain policies from older radios. There is, of course, a communication overhead in the transfer of knowledge. However, as shown in [3] and [97], the policy improvement achieved through cooperative docitive behaviour compensates for this overhead.

A new technology called cognitive radio (CR) can dynamically allocate spectrum to each device in order to maximise the capabilities of each one in low-bandwidth areas. There are devices that can be programmed to change their frequency based on a programme, like software-defined radios (SDR). Dr. Joe Mitola at the University of Stockholm introduced cognitive radio in a research paper. Cell networks and handsets were designed to adapt their communication methods based on their immediate surroundings. Figure 3 depicts the behaviour in more detail. The Radio Knowledge Representation Language was designed to provide "a standard language within which such unanticipated data exchanges can be defined dynamically". This, in turn, could be used in cognitive radios to increase battery life and performance. System selection of "the most appropriate network based on user service requests" is another feature. Wi-Fi calling is a recent addition to mobile phones that incorporates this feature.

II. PROPOSED DESIGN

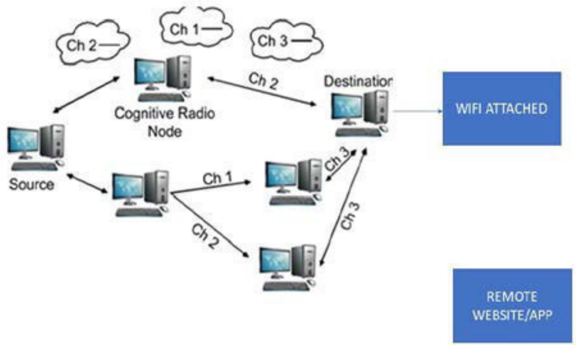

Figure 1 Design of multihop protocol

Using multi-channel and multi-hop protocols, the efficiency of communication will be increased as shown in Figure 1. We can monitor online network dynamics from a remote location using a website or an Android app that connects to the system via wifi.

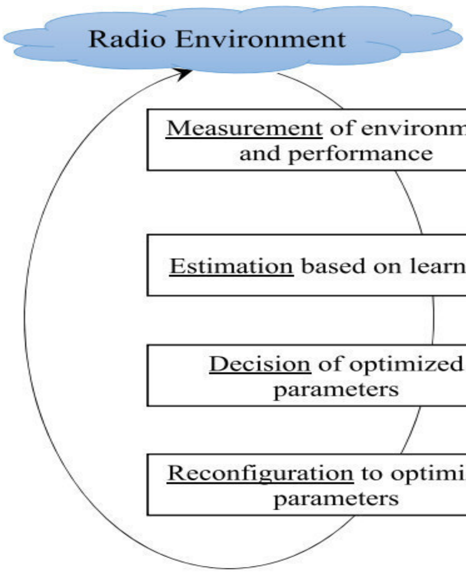

Figure 2. Concept of Cognitive Cyles

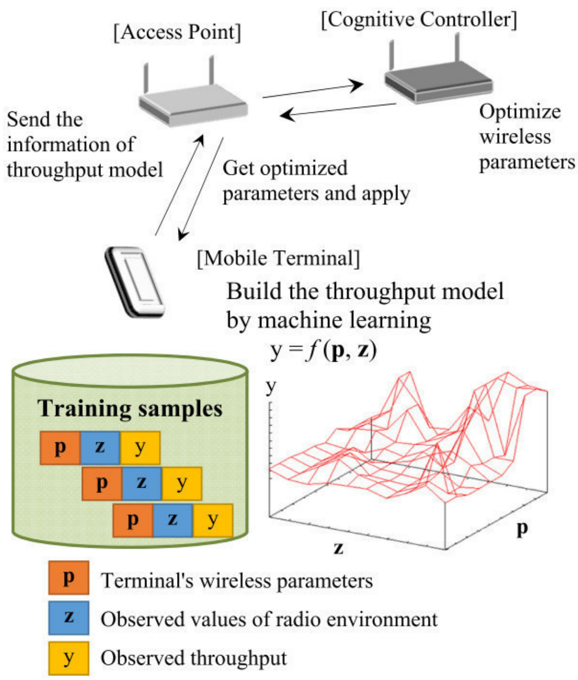

Figure 3. Proposed System concept Design

In a number of studies [100-102], it has been demonstrated that machine learning may improve the performance of wireless networks. In an experimental testbed, it has been demonstrated that using a neural network to choose channels in IEEE 802.11 WLAN access points (APs) can boost throughput [103-105]. Despite the fact that this approach is intriguing, it only takes into consideration one AP at the time. However, rather of concentrating on a few key metrics (MTs), our strategy seeks to improve the overall system's performance. The proposed approach is depicted in action in Fig. 3. Mobile terminals collect information about the radio environment and use it to develop a performance model that reflects the relationship between wireless parameters and throughput. This is accomplished through machine learning. Access points provide information about the throughput model to the cognitive controller, which is then used to make decisions. The cognitive controller is represented by the network reconfiguration manager. This system determines the wireless parameters for all MTs and transmits those parameters to the MTs through the access points. The wireless parameters are relayed to mobile terminals, which then adjust their settings in accordance with the new information. MTs collect information about the status and performance of the wireless network by repeating the cycle described above. As more training data is collected, the performance of the network increases, resulting in a more accurate throughput model being produced.

A. *A machine learning-based approach to parameter optimization.*

ThisSystem follows the previous research in [5] by using support vector regression (SVR) as a learning algorithm. It is an analogue output version of support vector machines (SVMs) Function f can be expressed as follows in SVR. [99].

$$f(\boldsymbol{x}) = \sum_{i=1}^{l} (\alpha_i' - \alpha_i) K(\boldsymbol{x}, \boldsymbol{x}_i) + b,$$

It is necessary to note that this equation contains two unknown input sets for the learning algorithm (p and z), as well as one unknown training sample input set (xi). The unknown parameters are obtained, according to [9], by the use of an optimization technique, with the training samples p, Z, and Y being used as the training samples. In order to establish the ideal wireless parameters p for the MTs, the cognitive controller must solve the following optimization problem for it to be success

$$\arg\max_{p} \sum_{n=1}^{N} \log(1 + f(\boldsymbol{p}_n, z_n)),$$

It can be expressed in terms of how many MTS there are and how many parameters each MTS can have. For example, for MTS-1, we can say that there are N possible parameter sets, while for MTS-2 we can say that there are N possible parameter sets for MTS-1 and MTS-2. Consider the fairness of MTs when using the logarithmic utility function for throughput. When it comes to objective function, MTs with lower throughputs have larger gains compared to MTs with higher throughputs. **Figure 4 shows** Probability a D-beacon is received correctly by a UE varying the probability (p) a b-UE is active for a threshold and Figure 5 shows path loss exponent.

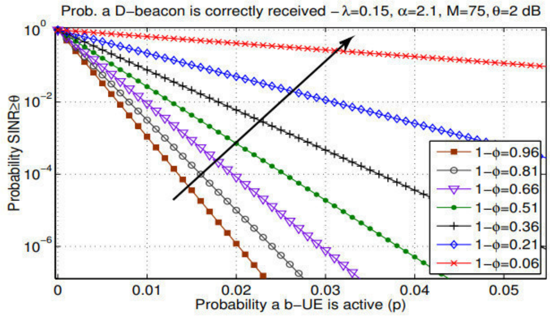

Figure 4 Probability A D-beacon is appropriately received by a UE by altering the likelihood (p) that a b-UE is active for a threshold period of time.

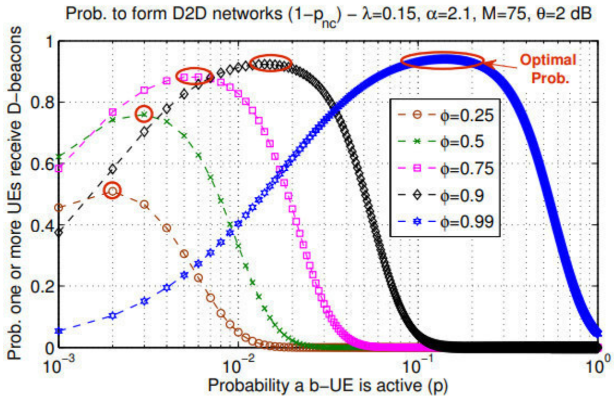

Figure 5 Path loss Exponent

III. CONCLUSION

Wireless communication quality has deteriorated as a result of the extensive use of mobile devices and the restricted availability of radio resources. It has been created cognitive radio technology in order to address these challenges. For the purpose of developing a wireless network optimization approach in this paper, we applied a machine learning algorithm based on the cognitive cycle. To put the proposed optimization approach through its paces, wireless LANs were deployed and the throughput performance was tested. Tests carried out in a real-world scenario demonstrated that the proposed strategy was effective.

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Certificate

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Device to Device Communication over 5G

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Abstract. The dependency on small cells, the cost of establishing a 5G infrastructure, and traffic at the Base Transceiver Station (BTS) can be reduced by distributing ideal data over an active WiFi connection in nearby mobile devices. Besides, unloading and distributing the unused data over WiFi to nearby devices will not affect the speed of 5G. Therefore, without compromising on the promised speed by the 5G cellular network, a massive sum of ideal 5G data can be distributed via a WiFi connection to other nearby handsets connected to the given 5G cellular network. Recent studies have suggested a "delayed offloading" methodology to offload ideal 5G data to a nearby environment with an active WiFi connection. In the present study, we propose a device-to-device (D2D) method for rerouting ideal 5G cellular data from an inactive WiFi using the "delayed offloading" principle to a neighboring headset with an active WiFi connection provided by the given 5G cellular network. However, if there is not a single handset found in an active WiFi environment, the offloaded 5G data will be sent to BTS in a conventional manner.

Keywords: 5G · Device-to-device communication · Cellular network

1 Introduction

1.1 5th Generation

In the new world of the Internet of things (IoT) and fifth-generation (5G), data is increasing explorational such as videos in this reference, data traffic increase 50% every year. [1, 2]. This new generation proposes the use of millimeter-wave (mmWave) frequencies to offer a completely new spectrum and multi-Gigabit-per-second (Gbps) data rates to a mobile device [3]. The 5G is based on the millimeter wave, whereas the 2G, 3G, and 4G networks are based on microwave frequency. The 5G provide a higher bandwidth (about ten times greater than today's 4G LTE) to support a large number of uses in term of data speed up to 10 Gbps and lower data traffic outstanding. Figure 1 shows the different wired and wireless technologies and their corresponding data speeds [4].

With all the advantages of the millimeter-wave, there remain some challenges. The millimeter waves have lower penetrating powers than microwaves, and thus it will not be easy to transmit such signals over a great distance or even through building walls.

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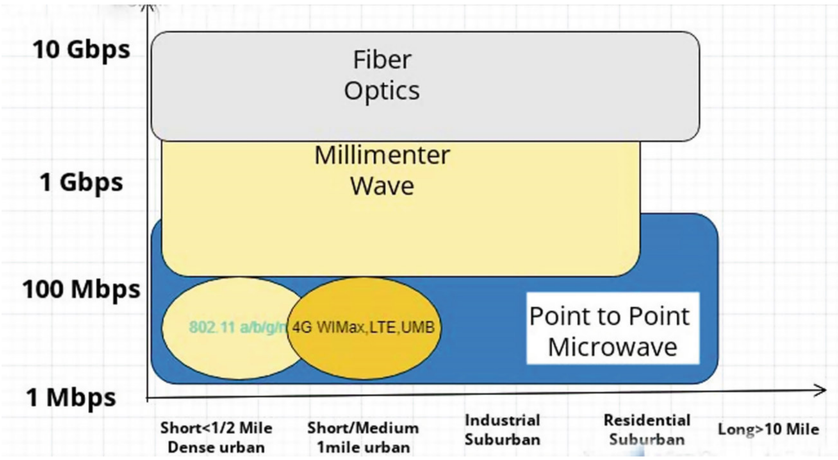

Fig. 1. Distance/Topology/Segments versus data speeds

Therefore, addressing this problem and many other, many new techniques such as the use of femtocells, beamforming, network slicing, etc. have been introduced and proposed in recent papers.

The 5G wireless technology will also make use of cloud computing. This will allow intelligent and efficient handling of all the data, further reducing traffic and delays.

1.2 5th Generation Advantages

The 5th generation of telecommunication networks proposes to bring much good into the world. 5G will achieve up to 10 times the speed of the existing 4G networks. The immensely high data speeds themselves bring forward lots of advantages. For example, it will help improve the population's lifestyle and make work more efficient.

1.3 5th Generation Disadvantages

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2 Literature Review

This paper [5], show that d2d communication in 5G is a significant area for research. In addition, it analyses the past research paper in terms of resource allocation. Finally, machine learning (ML) and deep learning (DL) will help offload the data traffic from the base station (BTS). The previous user also uses this trace to predict the location using the Hidden Markov Model (HMM) algorithm. HMM is helpful to find the shortest route [6].

The paper [7] gives WCETT, the Weighted Cumulative Expected Transmission Time to offload to BTS through multi-hop D2D communication. According to [7], the 1st term of WCETT expression, that reproduced $(1 - \beta)$, computes the assets expended in a given path, whichever the channels utilized, and secondly, the channel diversity represented by the 2nd term, subjective by β [8]. In [9], the authors mention first on-the-spot WiFi offloading and second delayed WiFi offloading. In this paper, we are using the latter; delayed offloading. In delayed offloading, all the user's traffic will be sent over WiFi when there is an active WiFi connection in the user's handset; else, all traffic is forwarded to the cellular interface after the traffic has waited for a deadline in the queue for the WiFi to come back.

Cisco [10] predicts that by 2025, more than 11.6 billion mobile-connected devices and traffic will reach an annual rate of 30.6 Exabytes (8×10^6 Terabytes) per month. This considerable amount of mobile device traffic will be challenging for the cellular network to handle all on its own.

[6] measured the average round-trip delay of 6.71 ms for one-hop D2D where 20 ping packets were sent from a transmitting device to a 70 m far apart receiving device. The maximum discovery distance and transmission rate for D2D communication are 354 m and 50 Mbps, respectively, greater than WiFi, 35 m and 11 Mbps (IEEE 802.11b), respectively.

In this paper, they review the recent article related to d2d communication found that traffic congestion is the main issue for delay packets. Path selection is one of the best challenges in B5G [11].

This paper prosed the DAIS algorithm, artificial intelligence-based transmission in the d2d network. Finally, it achieved a low computational load and high spectral efficiency [12].

In [13], the author experimented with SImuTE for network-assisted routing for d2d. The result shows around 35% saving in energy of base station and 15% packet transfer.

3 Methodology

The design and simulation of telecommunication studies are all based on probabilistic equations. For 5G, stochastic geometry has been used to build its model. Queuing theory is also an essential part of any communication.

3.1 Stochastic Geometry

Probability theory has a branch of Stochastic geometry (SG), which discusses random elements. Random mosaics, random networks, random unions of convex sets, random graphs, and the cluster are part of Stochastic geometry. This area includes many applications due to its strong relation with communication theory and spatial statistics. Nodes geometric pattern, response times, or congestion are handled through queuing theory, part of Stochastic geometry (SG).

It analyzes the extensive wireless communication network in a probabilistic way. Dealing with the Euclidean plane or space makes it more vital to explore the network. By the characteristics (connectivity, stability, capacity, etc.) as functions of a relatively small number of parameters.

3.2 Deterministic vs. Stochastic Geometry

Deterministic and stochastic geometry are the two known available approaches for cellular network designing and analysis. GSM, UMTS, and LTE networks have used deterministic based on a hexagonal cell to design the cellular network's coverage [14]. The deterministic method is only effective for networks with a fixed number of cell radii. When 5G is implemented will have many access nodes, co-tier interference, cross-tier interference, new backhauling solution, cloud system, and many more. The cell site area will not be hexagonal, and each cell site area will differ from the other. On top of all these, the cell sites will have a high-powered base station under which there will be many small cells. The small cells will be inside the larger cell covered by the high-powered base station, creating cross-tier interferences. The existing hexagonal methods will be a total failure for designing a heterogeneous network as they are only suitable for topologies with fixed cells. There is HetNet stochastic approach better result, so it is used for prediction.

Stochastic geometry is the study of random spatial patterns. Stochastic geometry can be used to model K-tier heterogeneous network, where the small base stations are positioned by a stochastic process in an unexpected random way. In stochastic geometry, the properties of the heterogeneous networks like small cells positions and macrocells positions, location of user's and user's mobility, co-tier and cross-tier interferences between access nodes are considered an arbitrary stochastic process of specific probability distribution (pdf) [15].

3.3 Different Stochastic Probability Distribution

The most effective probability distribution to model small cells in a heterogeneous network is still a debate. In addition, there are different node positioning models, and work is going on to include as many parameters as possible to generate a more realistic topology related to the 5G network.

Poisson Point Process (PPP): PPP can easily model a heterogeneous network with an infinite number of nodes in the endless coverage area. PPP define the base station position of different tier cellular networks [16].

Binomial Point Process (BPP): BPP is also used to model the position of base stations of single or K-tier cellular networks, except that the network node number is finite and the coverage area is also limited. The wireless sensor network behaviour in LAN used the BPP model [17].

Matern's Hard-Core Point Process (Matern's HCPP): HCPP is a developed model of PPP. There are many problems with PPP, such that PPP returns random network topology without any limitations of a minimum distance between neighbour transmitters.

Thus, with PPP planning, some BSs may appear in the same place or very close to each other. This results in unrealistic network topology and inaccuracy in modeling and calculating distance-dependent network parameters such as transmission power and signal to interference to noise ratio (SINR). HCPP is used to model a more realis-tic network topology by exploiting the strict minimum distance between any base station pair. HCPP is obtained from PPP eliminating all points which are not satisfying. However, HCPP is more complex and provides inaccuracy in simulation because of violation of the probabilistic distribution of network parameters [18, 19].

Voronoi Tessellation: It is used to model the arbitrary coverage area of small cells in a dense urban location. It uses the PPP or HCPP or other probability distribution to know the position of the small cells, and then it defines the coverage area for all the small cells. Voronoi tessellation is formed by taking pairs of neighbour points and drawing an equidistant line between them and perpendicular to the line joining both ends [20].

Poisson Cluster Process (PCP): In real life, user equipment (UEs) is concentrated around social places, bus stations buildings, and shopping centres with a hotspot or WiFi. So PCP considers that users are found clustered together most of the time, and hence there will be more small cells required in a building or shopping malls. PCP method creates network topology with K-clustered access nodes [21].

New parameters are being added to such stochastic models to make the model more realistic. Some parameters are crucial and must be included in the stochastic modelling for the position of small cells, while others provide minor improvement in the stochastic model.

3.4 Queuing Theory

Queuing theory is explicitly used to analyse and design any system that involves waiting in lines for a service, such as restaurants, banks, mobile data, etc. The queues can be formed at the receiving end, transmission end, or both ends. They act as data buffers and protect data packets from crashing into one another. However, queues can be a wasteful downtime.

The notation usually identifies queuing models: I/S/s/C, where I denotes the inter-arrival time distribution, S denotes the service time distribution, s denotes the number of servers, and C represents the number capacity of the queue [22]. If C is omitted, it is assumed that $C = \infty$. The inter-arrival time is the time between the arrival of one customer and the arrival of the next customer. It is calculated for each customer after the first and is often averaged to get the mean inter-arrival time, represented by lambda. Service time is well-defined as the time needed to serve a customer. There are lots of different queuing models, and a few single server models have been discussed below:

Markov(M)/Markov(M)/1: In exponential or Poisson distribution Markov (M) is commonly used. Hence an **Markov(M)/Markov(M)/1** queue included one server, inter-arrival time and service time which is exponentially distributed [23, 24]. The integral equations for M/M/1 models are:

$$L = \sum_{n=0}^{\infty} n(1-\rho)\rho^n = \frac{\lambda}{\mu - \lambda} \tag{1}$$

$$L_q = \sum_{n=1}^{\infty} (n-1)P_n = \frac{\lambda^2}{\mu(\mu - \lambda)} \tag{2}$$

$$W = \frac{1}{(\mu - \lambda)} \tag{3}$$

$$W_q = \frac{\lambda}{\mu(\mu - \lambda)} \tag{4}$$

where L denotes expected no. of customers in the system, Lq indicates desired queue length, waiting time of system represent W, and waiting time in queue represent Wq.

M/G/1: Here, the inter-arrival time is given by exponential distribution, and the general distribution provides the service time. This model involves non-exponential distributions and offers the following equations:

$$L_q = \frac{\lambda^2\sigma^2 + \rho^2}{2(1-\rho)} \tag{5}$$

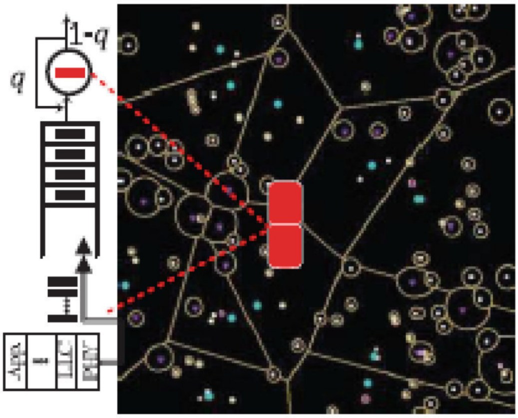
$$L = \rho + L_q \tag{6}$$

$$W_q = \frac{L_q}{\lambda} \tag{7}$$

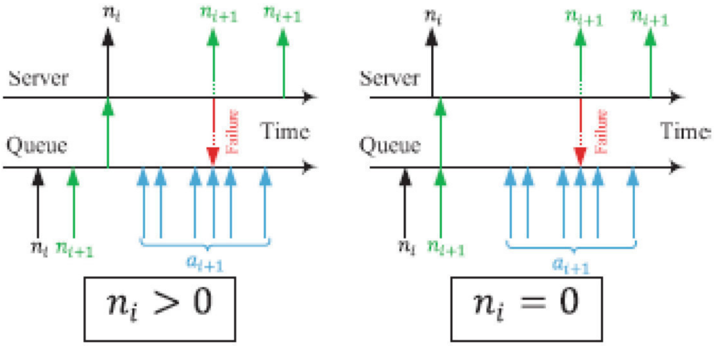
$$W = W_q + \frac{q}{\mu} \tag{8}$$

where L denotes the expected no. of customers in the system, Lq denotes desired queue length, system waiting time represents W and waiting time in queue represents Wq.

A modified M/G/1 queue has been used for the HetNet [21]. The queuing model introduced in [21] is an M/G/1 model with limited feedback. This feedback mimics the possibility of an outage. High interference, fading, lower availability of power resources, no coverage by any base station (BS) within the HetNet, etc., are some of the main reasons for the outage. Therefore, the probability associated with this transition would be the outage probability seen from the UE's perspective. This queue model is illustrated in Fig. 2(a–b) shows the time diagram notation.



(a) Queue Model



(b) Time Diagram Notation

Fig. 2. UE queue model in a 3-tier HetNet

4 Result

4.1 New Routing Scheme

Currently, a considerable amount of research has been done on WiFi offloading and D2D communication to offload and reroute the data to neighboring devices in an active WiFi environment. The “WiFi offloading” and D2D communication mechanism of offloading 5G data direct a minimum amount of traffic to BTS, thereby reducing the dependency on small-cells and reducing the cost of establishing a 5G infrastructure. [9] The present study can be regarded as a comprehensive work where the data packets are unloaded over an active WiFi environment. Otherwise, if active WiFi is inaccessible, the data packets are offloaded via cellular network until a deadline is gotten. The current proposed routing scheme is presented below:

Scenario 1: The user's cell phone will check WiFi availability. If WiFi is available, it will send its data to WLAN with the help of WiFi offloading, managing base stations' power consumption, traffic overload, and higher data rate.

Scenario 2: If WiFi is unavailable, data traffic flow will wait until a given deadline. In the meantime, when the data is in a queue waiting for the deadline period to end, the data in an inactive WiFi environment will run a Device 2 Device (D2D) communication with the neighboring handsets for an active WiFi connection provided by the same 5G cellular network. If a handset with active WiFi is found, a D2D link is made between the two handsets in the two WiFi environments. Once the D2D connection has been made, the handset in an ideal WiFi connection offloads most of the 5G data over WiFi to the neighboring handset in the same 5G cellular environment.

Scenario 3: Suppose the user's cellular handset does not locate any adjoining handset with an active WiFi connection. Then using the usual cellular communication data in the inactive environment will communicate with the base station to offload the 5G cellular data.

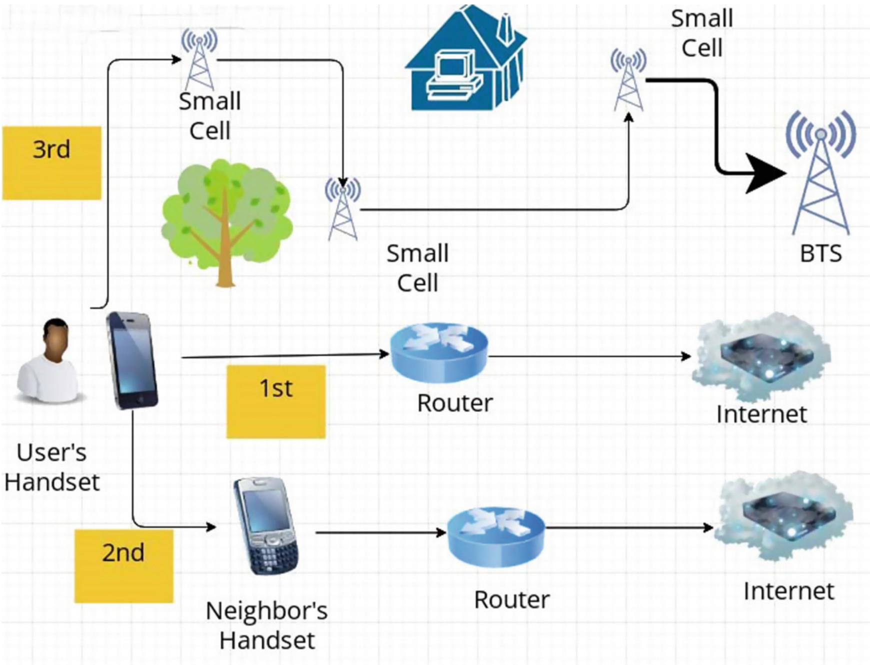


Fig. 3. Pictorial representation of the three different techniques to offload 5G cellular data

Markov's Chain. 2D Markov chain was used to model their WiFi queue. In the pre-sent study, their model was extended by considering D2D in the Markov chain, as shown in Fig. 2. States with {i, Wi-Fi} represent WiFi connectivity, {i, Cellular} represent states with only cellular connectivity and states with D2D connectivity {i, D2D}. Here, the number of customers represents i in the system (service+queue). While in the WiFi states, the system empties at the rate of μ and in both D2D state and cellular at a rate of $i\xi$. The frequency of offloading the abandoned data packets in the WiFi queue is represented as $i\xi$. Upon termination of the deadline, the neglected data packets are offloaded by the D2D state/cellular state.

Table 3. Shorthand Notation and Variables.

Variable	Definition/Description
λ	Average packet arrival rate at the mobile user
η	The rate of leaving the WiFi state
μ	The servicing rate while in WiFi state
γ	The rate of leaving the cellular state
τ	The rate of leaving D2D state
ξ	The reneging rate or the rate of abandoning WiFi state
i	Number of customers in the system (service + queue)
{i, Wi-Fi}	WiFi connectivity state
{i, Cellular}	Cellular connectivity state
{i, D2D}	D2D connectivity state

WiFi Queue. Cisco predicts that by 2025, more than 11.6 billion mobile-connected devices and traffic will reach an annual rate of 30.6 Exabytes (8×10^6 Terabytes) per month. This considerable amount of mobile device traffic will be challenging for the cellular network to handle all on its own. One solution to this problem is to deploy a substantial number of small cells in our environment. But telecommunication companies are feeling reluctant to bear the enormous cost of buying, installing, and maintaining these small cells. To date, WiFi offloading seems to be an easy and inexpensive solution to the problem. WiFi-AP are already found at the customer's end: WiFi routers installed at homes and work. The company needs to install fewer small cells when sending the user's traffic over WIFI. We proposed an excellent environment for telecommunication companies so they can reduce the traffic at BTS.

In [9], the author mentions two types of WiFi offloading 1) on-the-spot offloading and 2) delayed offloading. In this study, we are using the latter; delayed offloading. In delayed offloading, all the user's traffic will be sent over WiFi when there is an active WiFi connection in the user's handset; otherwise, all traffic is sent over the cellular interface once the deadline is reached. We extended this routing scheme and made it better and less dependent on small cells by including D2D in the routing scheme.

It has been presumed that the 5G cellular network will be available at all times, and the data of the inactive user handset gets offloaded as per the First Come First Served (FCFS) queuing principle. Each time the WiFi link gets gone, the packets available in the WiFi queue will be provided with a deadline. The deadline time of the packets increases from the first to the last queued data packets, i.e., the first data packet in the queue will

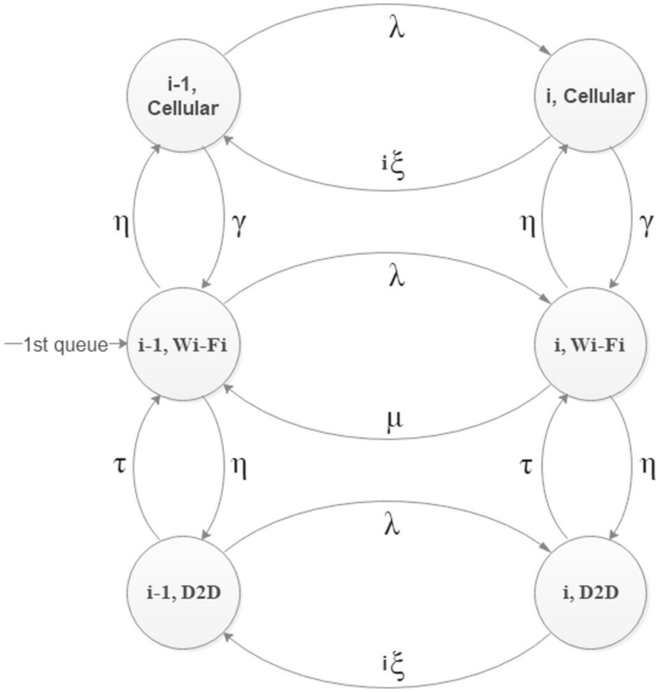


Fig. 4. The 2D Markov Chain for the Wi-Fi queue in delayed offloading with consideration to D2D.

have a lower deadline time than the second packet in the WiFi queue. Consequently, provided the WiFi link does not appear in the given deadline period, the First Come First Served (FCFS) queuing discipline was used to offload packets data to the neighboring handset via D2D or cellular network.

One-hop device-to-device (D2D) Communication. D2D communication is another promising solution in minimizing the cost of implementing 5G cellular infrastructure and reducing traffic at the BTS. D2D communication in the cellular network refers to the direct communication between the mobile users without Base Station (BS) or the core network elements. Many papers have shown procedures for neighbor discovery and data offloading using D2D communication. Our routing scheme restricts one-hop D2D communication, which involves transmitting data by a single hop. The reason for limiting to only one-hop D2D is that current technology is only just enough to do one-hop D2D and proves unreliable for multi-hop D2D.

D2D is of two types: Network-centric and Device centric. Network-centric means communication between mobile users depends on the network infrastructure. This means that the user of a particular network, Airtel, will only do D2D. Whereas the proximate device manages device-centric means network setup. This means that the user of a specific mobile handset, for example, Samsung, will only be able to do D2D will each other. So, users of the same mobile network operator or same banded handsets can allow each other to offload their data.

In [6] and [10], the author measured the average round-trip delay of 6.71 ms for one-hop D2D, where 20 ping packets were sent from a transmitting device to a 70 m far apart receiving device. The maximum discovery distance and transmission rate for D2D communication are 354 m and 50 Mbps, respectively, greater than WiFi, 35 m and 11 Mbps (IEEE 802.11b), respectively [8].

In the present routing schema, the user's set will explore any other set with an active WiFi link to a WLAN in its nearby environment. Once such a handset has been identified, the user's handset will try to link with the neighbor's handset via allocating an IP address as suggested by the authors in the article [25]. Abstract Protocol Notation (APN) based algorithm required by the user's set to determine adjoining set with an operational WiFi link has been described below:

Step 1 : Consider the boolen variable $WiFiAck = true$ and $WiFi\ Reply = true$
Step 2 : Initialize the variable $find\ \ WiFi = true$
Step 3 : Start to $find\ \ WiFi\ \ send\ \ request$ $(WiFiAck)$ to broadcast.
Step 4 : Timer start for reply during this time $find\ \ WiFi = false$
Step 5 : When $Recive\ \ reply$ $(WiFi\ Reply)$ from server stop reply timer
Step 6 : If WiFi reply is true then send $acknowledgement\ \ to\ \ find\ \ IP\ \ addressother -$ $wise\ \ it\ \ will\ \ be\ \ end.$

Provided below is Abstract Protocol Notation (APN) based the algorithm showing how the adjoining set with an active WiFi link would reply to the request of the customer's set:

Step 1 : Consider the Variable $Available\_WiFi = True$ and $WiFi\ Reply$
Step 2 : Start to check $receive\ \ request$ $(WiFi\ Reply)$ from client.
Step 3: if $Available\_WiFi = True\ \ and\ \ WiFi\ \ Reply = True$ then reply to client otherwise $WiFi\ Reply = False$

The user's handset transmits an invitation to locate an operational WiFi handset in a given environment. A timer is turned on as the message is sent from the user's handset. If a confirmatory response of the active WiFi handset approaches, the user's handset sends one more invitation to create a D2D link with the operational WiFi handset of a neighboring environment. Or else, if there is no neighboring active WiFi handset, the packets of the user's handset will offload the data packets to the cellular network (Fig. 5).

Total Expected Delay. A data packet experiences a delay at every stage along its transmission as it moves from a source to a given destination. The types of total delay experienced by a data packet are queuing, transmission, nodal processing, and propagation delay. Our model assumes that the data traffic reaches with rate λ through a Poisson process, the available and unavailable WiFi phase and the deadline as an exponential distribution with rate "η," "γ," and "ξ," respectively. Moreover, the file sizes are also exponentially distributed. The WiFi queue is constructed using the Markov chains principle as represented in Fig. 4. The Eq. 9 states the total expected delay of the proposed model:

$$E[D] = p_1 D_{WiFi} + p_2 D_{D2D-WiFi} + p_3 D_{CELLULAR} \tag{9}$$

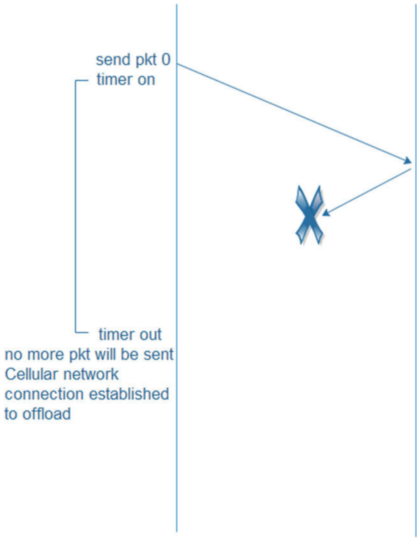


Fig. 5. Pictorial representation of the mechanism involved in timing out of timer upon deadline.

Here p_1 is the possibility of WiFi availability in the customer's set, D_{WiFi} signifies a total end-to-end delay related to unburdening data via WiFi, p_2 represents the probability of active WiFi availability in the neighbor's handset provided that the user's handset does not have an active WiFi. Likewise, $D_{(D2D\text{-}WiFi)}$ in Eq. 9 signifies a sum of end-to-end delay linked to offloading data packets to the neighboring handset using WiFivia one-hop D2D communication. The probability that the D2D communication and WiFi are unavailable provided that the cellular network is continuously offered is denoted by p_3, and likewise, a complete end-to-end delay linked to offloading via the cellular network is represented by $D_{CELLULAR}$.

To calculate the end-to-end delay for scenario-2 where the D2D transmission is possible with the neighbor's handset, and the user' WiFi is unavailable, the delays namely, the delay happened to owe to delaying until the deadline in the WiFi queue is terminated, the delay sustained is to accomplish D2D transmission and lastly the delay accrued while transmitting data packets over the neighbor's active WiFi network need to be accounted separately. Therefore, the study offers WCETT (Weighted Cumulative Expected Transmission Time) through multi-hop D2D communication to offload data packets to BTS. Thus, the WCETT [21] is represented as:

$$WCETT = (1 - \beta) \times \sum\nolimits_{i=1}^{n} ETT_i + \beta \times \max X_j \tag{10}$$

where $Xj = \sum_i ETTi$ and $ETT = ETX \times \frac{S}{B}$.

ETX stands for the number of anticipated retransmission before a packet is effectively transferred, the packet's size is denoted by S, and B signifies the bandwidth of the link. the first term of WCETT expression that multiplied $(1 - \beta)$ computes the resources expended in a given path, whichever the channels utilized, and secondly, the channel diversity represented by the second term, weighted by β. From Eq. 10, we can calculate the delay equation for one–hop D2D as follows:

Meant for Unit-hop

$$X_J = \sum_i ETT_i \tag{11}$$

$$X_1 = \sum_1 ETT_1 \tag{12}$$

$$X = ETX \times \frac{S}{B} \tag{13}$$

Therefore,

$$WCETT = (1-\beta) \times \sum_{i=1}^{n} ETT_i + \beta \times \max X_j \tag{14}$$

$$WCETT = (1-\beta) \times ETX \times \frac{S}{B} + \beta \times ETX \times \frac{S}{B} \tag{15}$$

$$D_{One-hopD2D} = WCETT = (1-\beta) \times ETX \times \frac{S}{B} + \beta \times ETX \times \frac{S}{B} \tag{16}$$

From the research paper, we get the model's delay related to calculating the delay faced by a packet while the data is offloaded over WiFi. The equation required to calculate the delay in the model for offloading data over WiFi is shown below:

$$E[T] = \frac{1}{\lambda}\left[\left(1+\frac{\gamma}{\eta}\right)\frac{\lambda - \mu(\pi_w - \pi_{0,w})}{\xi} + \frac{(\lambda-\mu)\pi_w + \mu\pi_{0,w}}{\eta}\right] \tag{17}$$

$$D_{WiFi} = E[T] = \frac{1}{\lambda}\left[\left(1+\frac{\gamma}{\eta}\right)\frac{\lambda - \mu\left(\pi_w - \pi_{0,w}\right)}{\xi} + \frac{(\lambda-\mu)\pi_w + \mu\pi_{0,w}}{\eta}\right] \tag{18}$$

The end-to-end delay in data to offload via D2D over WiFi is estimated as:

$$E[D] = p_1 D_{WiFi} + p_2 D_{D2D-WiFi} + p_3 D_{CELLULAR} \tag{1}$$

$$E[D] = 0 + p_2 D_{D2D-WiFi} + 0 \tag{20}$$

$$E[D] = p_2 D_{D2D-WiFi} \tag{21}$$

here,

$$D_{D2D-WiFi} = D_{Deadline} + D_{D2D} + D_{WiFi} \tag{22}$$

Simulation. We have employed the MATLAB to model the packet arrival rate versus transmission delay for scenario-2, as shown in Fig. 6. The target rate is $\xi = 0.9s^{(-1)}$, and

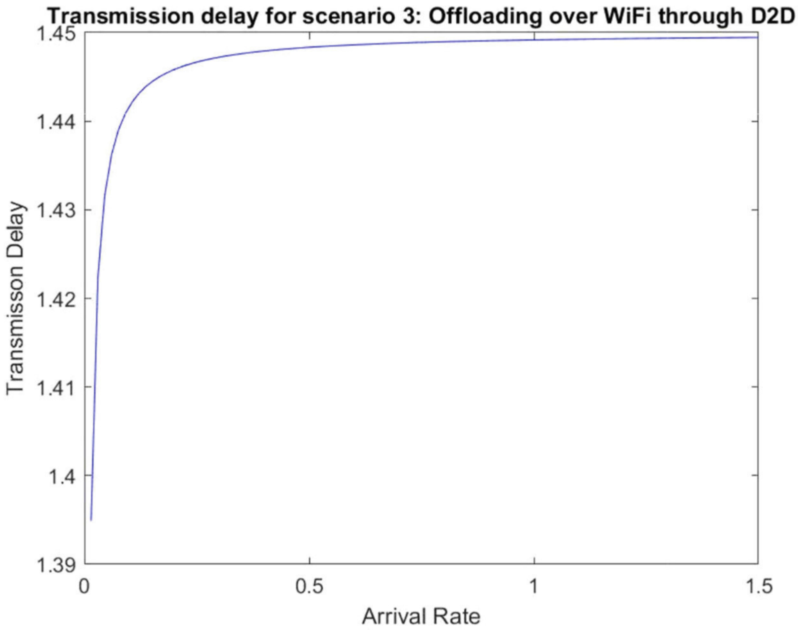


Fig. 6. Pictorial representation of the average delay in offloading over WiFi via D2D.

the deadline time is selected to be 1.11 s. The data rate for transmission over WiFi is 1Mbps, the bandwidth for D2D is 6 GHZ, and the packet size is 7.5 Mbyte.

This showed three scenarios that could occur while offloading data from the user's handset. The scenarios depend on the availability of WiFi and the feasibility of D2D communication. The Equ models the total expected delay. 1. Furthermore, the MATLAB simulation is shown too.

The MATLAB/Simulink simulation software was used to model and test the newly proposed routing scheme. In addition, to replicate the data offloading scheme, the SimEvents library of Simulink was utilized smartly, and the description and results of the simulation are provided in the below subtopics:

SimEvents Model. The SimEvents library has been profoundly used for the designing of the proposed system. Firstly, a FIFO was applied, and subsequently, an data packages generator was employed to duplicate the files. Subsequently, M (Markov)/M (Markov)/1 model was employed. There's only one server, and both the service time and the inter-arrival time were fixed to exponential distribution such that the model ensues the M/M/1 model. The timeout time was selected based on a small survey, and based on the survey for the simulation two minutes was selected. The Simulink model and the survey results are pictorially represented in Figs. 7 and 8, respectively.

The proposed routing model simulation results using a 500 units simulation time are represented in Figs. 9, 10, 11, and 12. The Figs. 9, 10 and 11, respectively illustrates the utilization factors of WiFi, D2D, and Cellular network. The Fig. 12 pictorially represents the average queue length of D2D route and WiFi route. The average queue length signifies

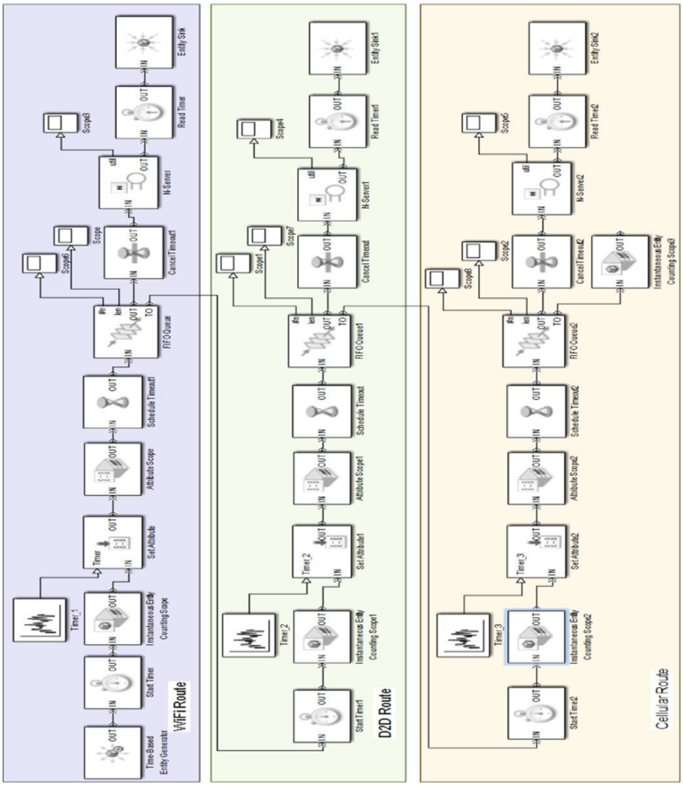


Fig. 7. SimEvents library based Simulink model based on novel routing system

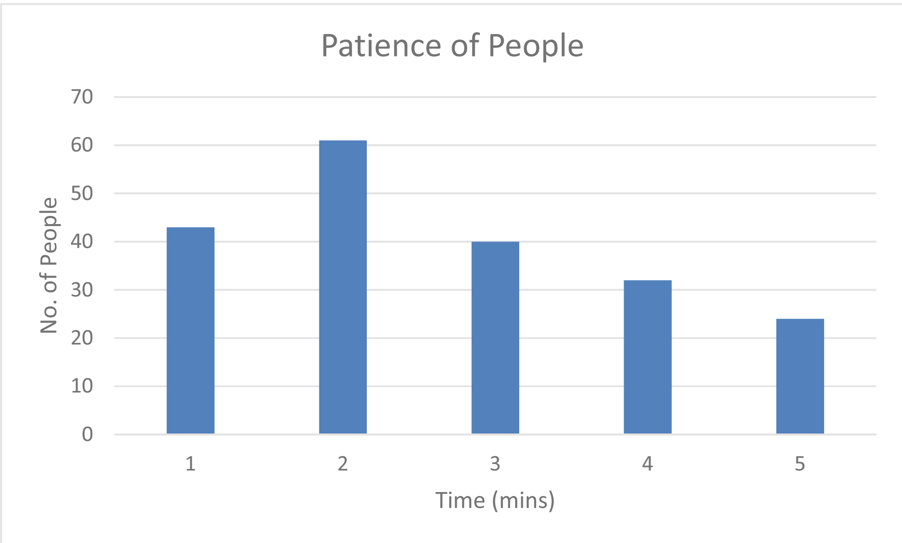


Fig. 8. Survey of waiting for time (in mins) versus number of people

the number of data packets or entities are in the queue at a particular time in a specific server, and the utilization factor represents the percentage of servers in a busy state, and.

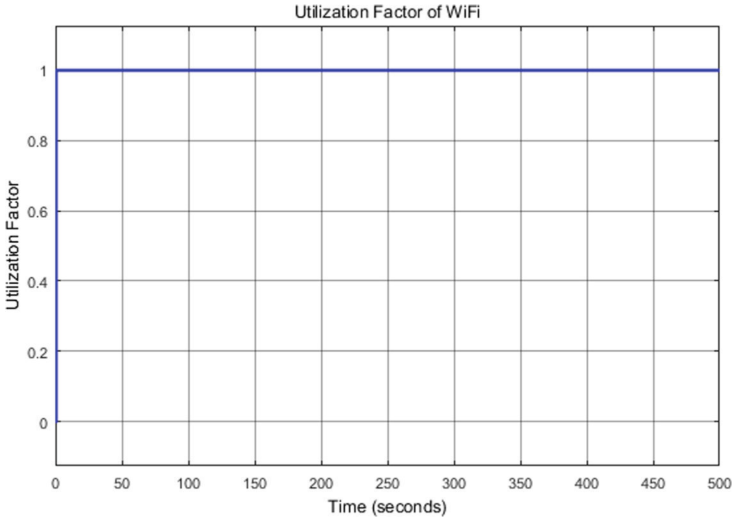


Fig. 9. WiFi route's utilization factor.

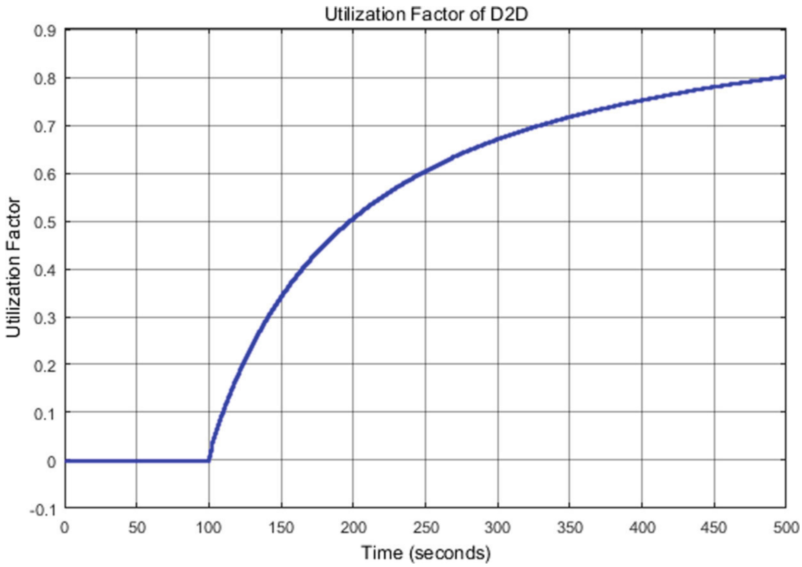


Fig. 10. Of Device to Device route's utilization factor.

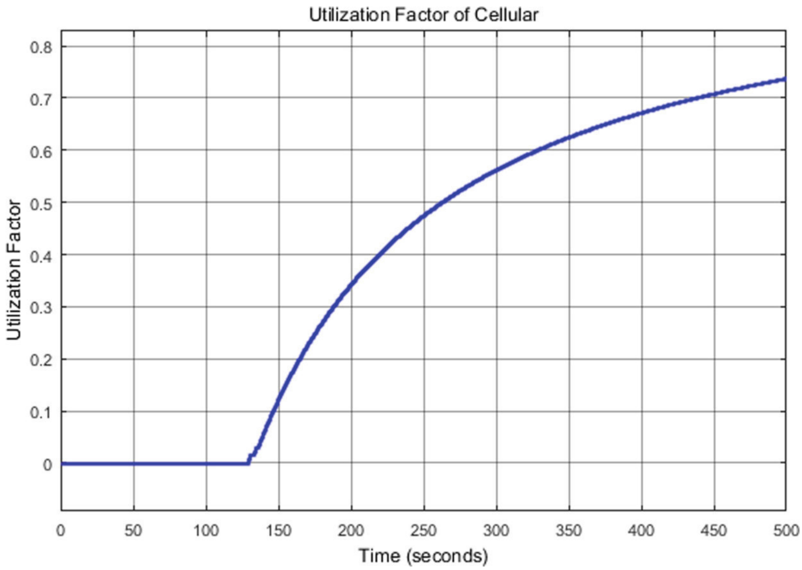


Fig. 11. Cellular network's utilization factor.

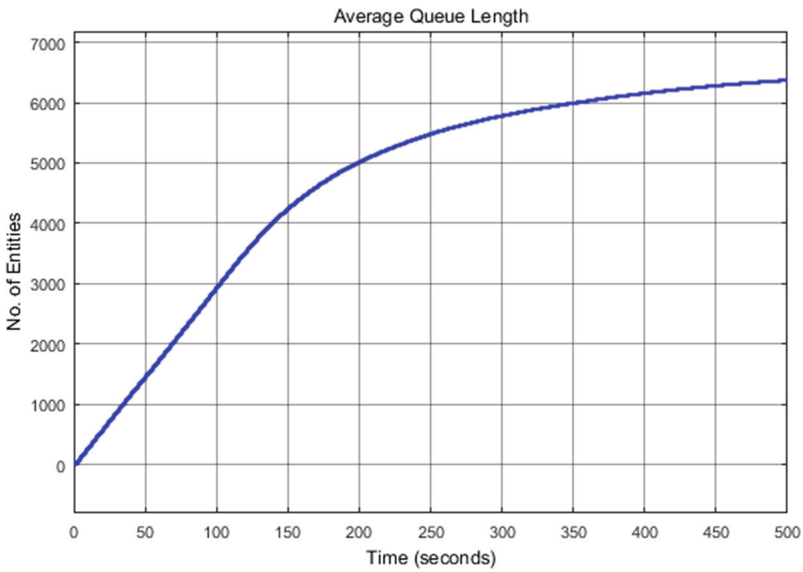


Fig. 12. WiFi route's average queue length.

5 Conclusion

We propose a scenario that could occur while offloading data from the user's handset. The designs depend on the availability of WiFi and the feasibility of D2D communication.

The total expected delay was modeled and simulated via MATLAB simulations. Results of MATLAB simulations are better in terms of total expected delay time. In Future studies, work will be based on machine learning and network layer. Moreover, machine learning techniques will be employed to enhance the beamforming selection, and thereby, the network layer will help reduce the latency, improving the results.

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Machine Learning-Based Application for Predicting 5G/B5G Service

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***Abstract*—In a 5G/B5G (Beyond 5G) network, Service level agreement (SLA), network efficiency, and service management are key issues for a network provider. A user equipment requests services (UE) are based on a key performance indicator (KPI) and key quality indicator (KQI) while selecting the network slice. Earlier predicting the benefits of 5G/B5G will be helpful for the service provider to improve the quality of service (QoS). Therefore, we aim to build a data-driven predictive application to screen the multiple services of 5G/B5G. In this context, multi-classification supervised machine learning models are applied to the publicly available dataset to classify the services of 5G/B5G. We performed different simulations with the ML algorithm, first with all features (KPI and KQI parameters), second with alone KPI, and finally with features selection methods. The multiclass Decision jungle (MDJ) model shows better performance in terms of accuracy of 90%, precision, and recall. Moreover, an application programming interface (API) of the MDJ model implemented and deployed in https://predictor5g.herokuapp.com/ and source code are available at https://github.com/tabrejmsc/5GServicePredictor.**

Keywords—5G/B5G service classification; ML; predictive model; KPI; KQI; Application

I. Introduction

This Next generation wireless networks, such as 5G and B5G, are rapidly evolving to provide higher-speed services that are more reliable and compatible with the current broadband infrastructure. 5G networks promise massive increases in network throughput and are being billed as the next major step in wireless evolution. however, the 5g service classification problem involves classification of ten [1] of thousands of services, and manual inspection is not an option due to the large number of services and the lack of human expertise. The automated solutions proposed in the literature are generally based on a limited number of data inputs such as the number of users and the number of locations and are thus inadequate for the task of classifying services. However, the complexity and diversity of services and their related technologies has made it difficult for network operators to identify the most suitable technology for specific use cases.

The discussion on 5G service classification has been ongoing since the development of both B5G and 5G services. The 5G Forum1 has classified B5G services as early adopters, generalists, and specialists. The 5G services are classified as "network slicing", "massive [2] IoT", "ultra-reliable low latency communications", "enhanced mobile broadband", "advanced mobile services", and "cloud access networks". However, the 5G services are still under development by the industry stakeholders. Therefore, there remains a need to classify the various 5G services in a meaningful way (Sekaran et al., 2017). The 5G service classifications based on a use case approach, and classification scheme considers the following aspects:

a) The B5G services are classified based on the expected demand for the services; b) The use cases are classified based on the type of network that is used to deliver the services; c) The type of end user applications is taken into consideration; and d) The planned 5G network architecture is considered along with the possible impact to the services.

5G or B5G will be the next-generation mobile network technology and it is predicted to provide much higher data speeds and better user experience than 4G LTE. 5G/B5G Service Classification [3] Using AI provides deep insights on expected future 5G/B5G networks from different viewpoints such as KPIs, KQIs, SLAs and application performance. Moreover, it provides algorithm to forecast the effects of emerging technologies on 5G network such as QoS, mobility and others. It can help research community to better understand the potential applications of 5G networks.

the network service level agreement (SLA) between network providers and their customers, it is essential to manage services in a way that meets the needs of both provider and customer. However, in 5G, with network slicing [4] and service level agreements (SLAs), which is a new paradigm in the field of networking, it is difficult to guarantee that each network slice meets both the SLA requirements and the customer's KPIs. One solution to this problem is to use Artificial Intelligence (AI) to manage the network and guarantee the required level of performance of different slices.

Network slicing, as a key technique of 5G, [5] provides a way that network operators can segment multiple virtual networks from a common physical infrastructure by dynamically allocating resources and creating connections between the segments. This approach allows for decoupling of the network resource allocation from the services offered by the network operator, allowing efficient deployment of the network and a wide range of services to meet customer requirements.

Network slicing, as used in the context of 5G, is [6] facilitated by software-defined networking (SDN) technology. SDN is a networking architecture that allows network resources to be configured and reconfigured on demand to meet application requirements. By providing on-demand provisioning of networking resources, SDN allows network providers the flexibility to create multiple virtual networks based on the requirements of individual customers without requiring physical changes to the network infrastructure.

SDN uses [7] the OpenFlow protocol to program network switches. The switches can be programmed to perform

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various actions depending on the type of traffic that is received. A flow is defined as a set of rules that dictate how network traffic will be routed through the network. For example, if a user sends a request to access a web page, the packet information contains information that determines the destination of the packet and the type of traffic. This information is used by OpenFlow [8] to determine the type of network that the packet should be routed to.

In the network service level agreement (SLA) between network providers and their customers, it is essential to manage services in a way that meets the needs of both provider and customer. However, in 5G, with network slicing[1] and service level agreements (SLAs), which is a new paradigm in the field of networking, it is difficult to guarantee that each network slice meets both the SLA requirements and the customer's KPIs. One solution to this problem is to use Artificial Intelligence (AI) to manage the network and guarantee the required level of performance of different slices [9].

Network slicing, as a key technique of 5G,[10] provides a way that network operators can segment multiple virtual networks from a common physical infrastructure by dynamically allocating resources and creating connections between the segments. This approach allows for decoupling of the network resource allocation from the services offered by the network operator, allowing efficient deployment of the network and a wide range of services to meet customer requirements.

Network slicing, as used in the context of 5G, is [11] facilitated by software-defined networking (SDN) technology. SDN is a networking architecture that allows network resources to be configured and reconfigured on demand to meet application requirements. By providing on-demand provisioning of networking resources, SDN allows network providers the flexibility to create multiple virtual networks based on the requirements of individual customers without requiring physical changes to the network infrastructure.

A key challenge in deploying and managing network slices is that few if any analytical tools are available to measure the performance of these virtual networks in real time and provide insight about bottlenecks or bottlenecks [12].

The rest of the paper is organized as follows: The second section inspects several related researches works. The following section discusses the machine learning pipeline that has been proposed. The next section describes the 5G services dataset that was used in this study. After that, Sec.4 discusses the result and discussion. Sec. 5 concludes the paper.

II. Related Work

This Many large companies are now moving to 5G/B5G networks, due in part to the promises of increased data speeds, lower latency and enhanced user experiences. Machine learning [13] is particularly well-suited to operate with 5G networks since it requires massive amounts of data to predict activity accurately and 5G technology enables high data rate transmissions. These characteristics make machine learning-based applications an attractive option for predicting 5G/B5G services. This thesis presents one such application based on a support vector machine (SVM) model.

In this thesis,[14] the SVM model was trained to predict the number of simultaneous users in a 5G/B5G network under various traffic scenarios including voice, video streaming and video gaming. The input variables for the model were derived from the normalized throughputs of the different traffic classes. Various performance metrics were compared to determine the optimum settings of the classifier including the accuracy, sensitivity, specificity and F1 score.

The best results [15] were obtained when the SVM model was trained using (i) a 7-fold cross-validation approach and (ii) a linear kernel function and a gamma tuning parameter of 0.005. Based on these results, the model was then used to simulate the number of simultaneous users under different scenarios and the predicted numbers were compared with the actual values obtained from the test network. The model was able to predict the number of simultaneous users with a high accuracy of 97%.

The accuracy, sensitivity, specificity and F1 score [16] of the SVM model under various traffic scenarios. The results show that the SVM model performs well under all conditions. The results indicate that the SVM model has the potential to accurately predict the number of simultaneous users in 5G networks. This model also demonstrates the practical value of machine-learning techniques for accurately predicting the performance of future 5G networks.

M. S. Almutairi et al.[17] proposed the stacked LSTM model for cost evaluation of holistic handover policies between heterogeneous networks. A. P. Hermawan et al. [18] developed a neural network architecture that provides efficient resource allocation and improves network performance by exploiting inter-cell interference in wireless cellular networks. R. Ahmed et al. [19] proposed a deep learning algorithm to classify network traffic flows such as TCP traffic as web downloads or uploads from smartphones.

P. Veitch et al.[20] proposed a framework for learning-based slicing of channel resources for the distributed control plane of 5G/B3G/B11G systems. Wang et al. investigated the impact of dynamic spectrum access on spectral efficiency as well as intra-cell and inter-cell interference mitigation. developed a model for intelligent mobility management based on the routing prediction in LTE-A networks using deep learning techniques.

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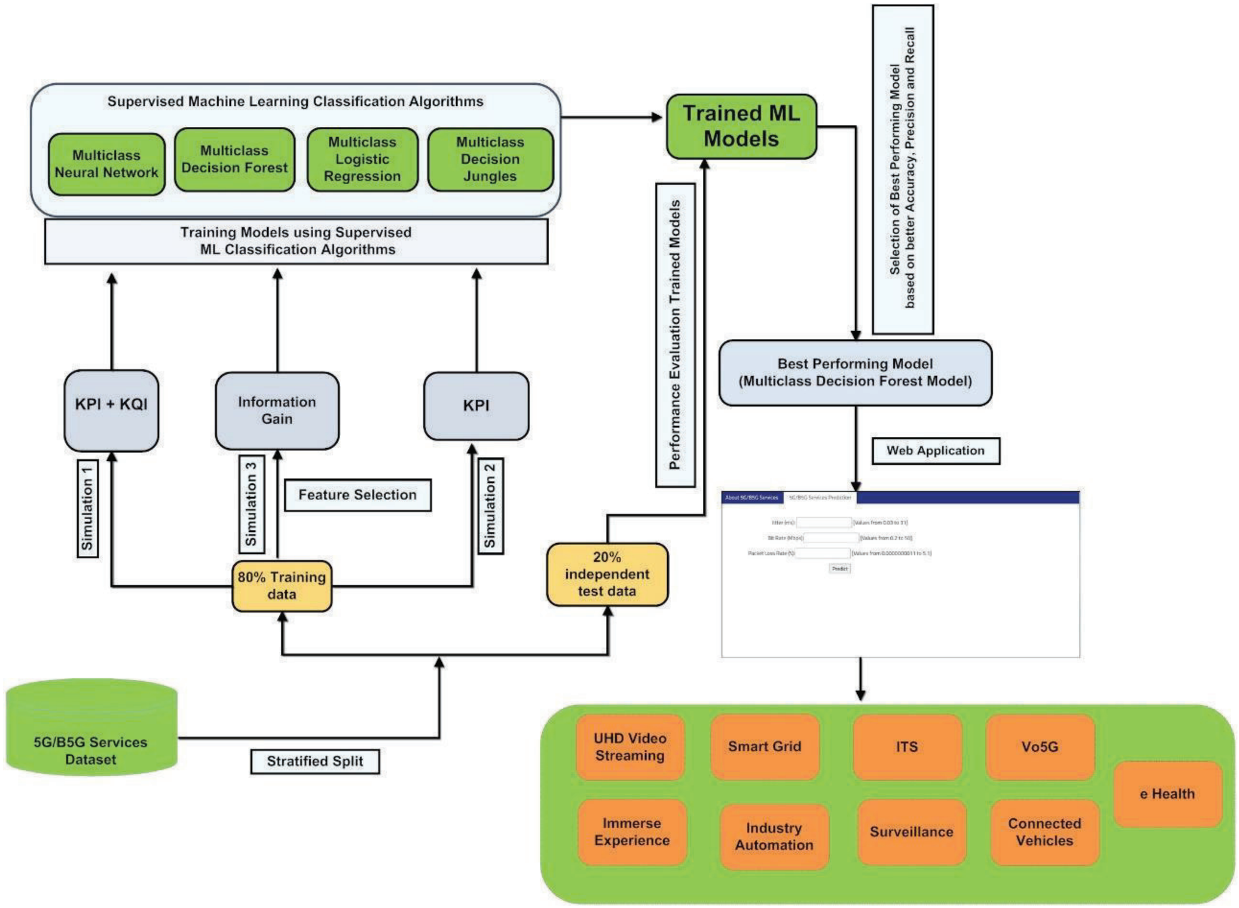

Fig. 1. A flow diagram of the methodology employed to build a 5G predictor application.

The 5G-NORMA project [21] developed an architectural framework that links 5G slicing service quality requirements to multi-vendor component and protocol interoperability evaluations at multiple layers in the ecosystem. Simulations were conducted to evaluate the impact of different cell configurations on performance. The results show that the increase in transmission power is not linearly correlated with an increase in throughput; instead, there is a nonlinear relationship between the two parameters.

According to C. Mannweiler, [22] "the main challenges in research are the existing limitations of the technologies that will be used to deploy the system". One of the challenges is availability, which can be reduced by using reliability-based maintenance. Heterogeneous networks are emerging as a promising solution for meeting the communication requirements of a wide range of current and future applications. Yang et al. proposed a time-based scheduling method for LTE uplink transmissions to improve the utilization of network and battery power. The proposed method employs visible light communication [23] (VLC) and LTE downlink transmission in heterogeneous networks (HetNets) to improve quality of service (QoS) and reduce energy consumption.

III. Materials and Methods

A. Machine Learning Pipeline

Fig. 1. Shows the methodology flow diagram to build a Machine learning-based application to classify 5G/B5G services. The first phase includes building a machine-learning model using the best subset of features. The next phase includes the implementation of the Azure-based predictor application [24].

To apply the machine learning algorithms, we split the dataset into two-part 80% train dataset for training the model and other 20% independent test data for evaluation of the model. The classification is a model carried out in three ways first, with all features of 5G/B5G services, with a second KPI-related subset of features, and finally, with feature selection methods. In addition, we evaluate our model in each experiment with different classifiers to find the best subset of features along with the best classifiers. Finally, the best ML predictive model with the best subset of a feature deployed in the cloud-based Heroku platform.

B. Dataset

The KPI-KQI B5G service datasets are publicly avaible. This is synthetic data based on KPI and KQI parameters using ITU standard document and European standard project. The dataset consists of 165 records with 14 columns. First 13 column feature set is based on KPI and KQI while last

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column is label of 5 G services [1].The description of dataset are mentioned in Table I.

TABLE I. 5G SERVICE DATASET DESCRIPTION

Number of features	KPI Features	Label (Services)
8	Latency (ms), Jitter (ms), Bit Rate (Mbps), Packet Loss Rate (%), Peak Data Rate DL (Gbps), Peak Data Rate UL (Gbps), Mobility (km/h)	UHD_Video_Streaming, Immerse_Experience, Smart_Grid, ITS, Vo5G, e_Health, Connected_Vehicles Industry_Automation, Surveillance
	KQI Features	
5	Reliability (%),Service Availability (%),Survival Time (ms), Experienced Data Rate DL (Mbps), Experienced Data Rate UL (Mbps), Interruption Time (ms)	

C. Partitioning of datasets

The dataset with 165 samples was randomly partitioned into 80% train datasets and 20% independent test dataset. The 80% training set consist of 132 sample and remining 20% consist of 33 samples. The training dataset is used to perform 5-fold stratified cross validation to train the model whereas 20 % independent test data is used for evaluation of our ML model.

D. Evaluation Metrics

There are many evaluation metrics are using to evaluate the multiclass classification as follow.

1) Confusions matrix

A confusion matrix contains information about actual and predicted classifications done by a classification system as shown in Table II. The performance of such systems is commonly evaluated using the data in the matrix [25].

TABLE II. CONFUSION MATRIX

		Predicted	
		Negative	**Positive**
Actual	**Negative**	a	b
	Positive	c	d

Where

a is the number of correct predictions that an instance is negative (true negatives (TN)),

b is the number of incorrect predictions that an instance is positive (false positives (FP)),

c is the number of incorrect of predictions that an instance negative (false negatives (FN)), and

d is the number of correct predictions that an instance is positive (true positives (TP)).

2) Accuracy (overall and average):

The accuracy (AC) is the proportion of the total number of predictions that were correct. It is determined using the equation (1):

$$AC = \frac{a + d}{a + b + c + d} \tag{1}$$

3) Precision/Sensitivity

Finally, precision (P) is the proportion of the predicted positive cases that were correct, as calculated using the equation (2):

$$P = \frac{d}{b + d} \tag{2}$$

4) Recall

The recall or true positive rate (TPR) is the proportion of positive cases that were correctly identified, as calculated using the equation (3):

$$TP = \frac{d}{c + d} \tag{3}$$

E. ML Algorithms

1) The Multiclass Decision Jungles

Multiclass decision jungle is based on decision jungle. In addition, it is extension of decision forest. Decision forest is based on ensemble of decision directed acyclic graphs (DAG). In azure machine learning different parameter are associated with multiclass decision jungle such as Number of decision DAG, Maximum depth of decision DAG, Maximum width of decision DAG and Number of optimization step per decision DAG [26].

2) Multiclass Neural Network

A neural network is consisting of multiple interconnected layers. The first layer, input layer is associated with features of datasets and connected with hidden layer finally with output layers. The training of ML model through neural network is optimization of weight using activation function [26].

In Azure Machine learning Multiclass Neural Network component have many parameters such as hidden layers specification, number of hidden nodes, learning rate, number of iterations etc. In this study we used default parameters.

3) Multiclass Decision Forest

One of the ensembles' learning methods is decision forest algorithms. It creates multiple decision tree and voting the most popular output class. In this experiment we number of decision tree is 8, maximum depth is 32, minimum number of samples per leaf is 1 [26].

4) Multiclass Logistic Regression

It is statiscal methods used for classification. Logistic regression is based on probability to predict the multiple outcomes. In this experiment we use default parameters such as L1 and L2 regularization weight is 1 [26].

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F. Feature selection strategy

Feature selection is applied on training dataset for optimal subsets of features. All the features are not important to classify the 5G services. Reducing the features means reduce the model variance.

In this study we applied filter based mutual information gain feature selection methods [27]. The mutual information between the attributes are higher means more dependency and if it is zero means both attributes are independent to each other.

The mutual information of two attributes can be represented as:

$$I(att1; att2) = H(att1) - H(att1 \mid att2)$$

Were

$H(att1)$: *is entropy of attribute*

and $H(att1 \mid att2)$: *is conditional entropy of another attribute*

IV. RESULT AND DISCUSSION

To achieve the better classification of 5G services we performed the three simulations. The first simulation contains only 5G/B5G KPI services. Second simulation contain combination of KPI and KQI services and Third Simulation use the features selection methods.

A. KPI BASED CLASSIFICATION MODELS EVALUATION

In first simulation we selected the KPI features from dataset which are namely, Latency (ms), Jitter (ms), Bit Rate (Mbps), Packet Loss Rate (%), Peak Data Rate DL (Gbps), Peak Data Rate UL (Gbps), Mobility (km/h) and Mobility (km/h). Using Azure machine learning we use four supervised multiclass machine learning classification algorithm such as Multiclass Decision Jungle, Multiclass Neural network, multiclass decision forest and multiclass logistic regression. The result of classification algorithm is mentioned in Table III.

TABLE III. PERFORMANCE EVALUTION OF FIRST SIMULATION (KPI)

ML Algorithms	Overall accuracy	Average accuracy	Micro-averaged precision	Micro-averaged recall	Macro-averaged recall
Decision Jungles	0.909091	0.979798	0.909091	0.909091	0.87037
Multiclass Neural Network	0.787879	0.952862	0.787879	0.787879	0.888889
Multiclass Decision Forest	0.939394	0.986532	0.939394	0.939394	0.928571
Multiclass Logistic Regression	0.515152	0.892256	0.515152	0.515152	0.642857

We can summaries from Table III multiclass decision forest is best in term of overall accuracy, average accuracy, Micro averaged precision, micros averaged recall and macro averaged recall. This means that Multiclass Decision Forest model are more confident to classify relevant 5G/B5G class then the irrelevant class because of high precision (0.94). Hight recall also indicated that relevant result is correctly classified.

B. KPI + KQI BASED CLASSIFICATION MODELS EVALUATION

The second simulation contains all features of datasets which include KPI parameters and KQI parameters. The model was trained using multiclass supervised classification. The result of classification model are tabulated in Table IV.

TABLE IV. PERFORMANCE EVALUTION OF SECOND SIMULATION (KPI+KQI)

ML Algorithms	Overall accuracy	Average accuracy	Micro-averaged precision	Micro-averaged recall	Macro-averaged recall
Decision Jungles	**1**	**1**	**1**	**1**	**1**
Multiclass Neural Network	**0.727273**	**0.939394**	**0.727273**	**0.727273**	**0.805556**
Multiclass Decision Forest	**1**	**1**	**1**	**1**	**1**
Multiclass Logistic Regression	**0.636364**	**0.919192**	**0.636364**	**0.636364**	**0.727513**

The result obtained shows that Decision jungle and multiclass decision forest perform best in term of Overall accuracy, Average accuracy, Micro-averaged precision, Micro-averaged recall and Macro-averaged recall.

C. Feature Selection based Classification model evaluation

The third simulation includes all the features with filter-based feature selection. In this experiment, mutual information features selection applied to dataset. feature selection is technique though which we can remove the redundant feature and select the best subset of features. The three best features obtained using the mutual information (MI) are Packet Loss Rate (%), Jitter (ms) and Bit Rate (Mbps). As show in Fig. 2. Multiple Decision Forest model performed best average accuracy with three subsets of features.

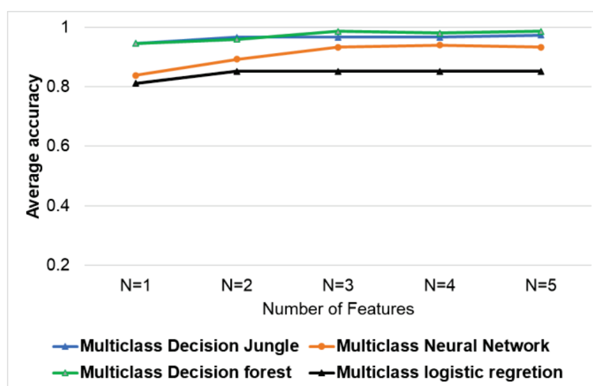

Fig. 2. Comaprative performance evlation of classifer with different subset of features

Fig. 3. shows the confusion matrix during the testing process by each model. To overcome the overfitting or

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underfitting k (K=10) fold cross validation techniques was used. In confusion matrix diagonal represents the correct predictors and values besides diagonal represents the how much wrong predictors. The Connected Vehicles and Vo5G classes are 33.3% ,14.3% respectively not predicted correctly.

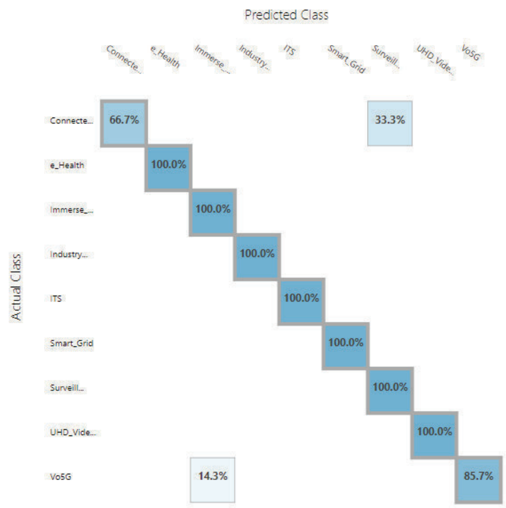

Fig. 3. Confution matrix of multicalss decision forest classifer with three subset of features

D. Predicting Web Application for 5G/B5G Services

The web-based ML application is implemented based on three attributes selected using Mutual information gain namely Packet Loss Rate (%), Jitter (ms) and Bit Rate (Mbps). The machine learning model based on Multiple Decision Forest algorithm implemented using flask and finally deploy in Heroku environment.

V. CONCLUSION

The presented study is proposed an ML based application to classify new generation network services. Moreover, the identification and characterization of requested services by UE is crucial during network slicing in 5G. The KPI and KQI parameters play pivotal role to provide right services. The ML based methods help to service provider to provide implicitly better quality of services. In this experiment we perform three simulation, first simulation is based on KPI where we obtained multiclass decision forest algorithm perform best result in term of accuracy (94%), sensitivity (93%) and precision (94%). In second simulation incorporating KQI with KPI improved the result around 6%. Finally using feature selection method KPI is important parameter to identify the future network services. In this study, using information gain feature selection method Packet Loss Rate (%), Jitter (ms) and Bit Rate (Mbps) are important parameters. The predictive ML based application can classify the 5G/B5G services among the future network services. Further, presently our model can be used by the network provider to predict the right services to UE. In the future we can carry out similar type of study with other datasets.

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Current Research Trends Machine Learning in 5G: A Bibliometric Analysis

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Researchers are attracted to emerging field 5G with machine learning. Many review articles have been carried out to analyze in a different direction of 5G with machine learning. However, no researcher presented bibliometric analysis on machine learning in the 5G research field to a detailed analysis of research status and future trend network in this research area. A bibliometric analysis was done in the current study using the bibliometric R tool and VOS viewer software. The relevant literature was collected period 2001 to 2021 from the Web of Science (WoS) Core Collection and Scopus database. The quantitative analysis was done in terms of a yearly published article, most trend research topic, and future direction in ML in 5G technology. Finally, the result indicated that China, the U.S.A., and India are the top countries to publish this field because China, the U.S.A., and the U.K. are the most cited countries. Beijing University of Posts and Telecommunications is the most relevant organization, Wang most appropriate and most influential author in this research area (5G in AI/ML). IEEE Access, IEEE transactions on vehicular technology, and Sensor are the most relevant journal. The main challenges in this field are low latency communication, resource allocation, resource management spectral efficiency, millimeter wave, 5G with the Internet of things (IoT), a device to device communication, power control, and massive MIMO. Deep learning, machine learning, cognitive radio, and reinforcement learning are artificial intelligence techniques used in 5G.

Keywords: First 5G, Machine learning, Artificial Intelligence, wireless communication, Internet of things.

2021. In Rahul Srivastava & Aditya Kumar Singh Pundir (eds.), *New Frontiers in Communication and Intelligent Systems*, 437–451. Computing & Intelligent Systems, SCRS, India. https://doi.org/10.52458/978-81-95502-00-4-46

1 Introduction

The International telecommunication union -radio communication (ITU-R) is responsible for 5Gstandardisation of 5G requirements. Major Telcom vendors and operator is associated with third-generation (3Gpp) consortium for technical requirements such as modulation scheme, radio protocol, data protocol, etc. The 5G is mapped to different use case scenarios such as enhanced mobile broadband (eMBB), Massive ma-chine type communication (mMTC) and ultra-reliable low latency communication (uRLLC). IoT, Smart city, Smart building, 3D video, UHD screens, Augmented reality (A.R.), Industrial automation, and self-driving car applications are using 5G networks [1]. In 5G architecture, there is three leading components user equipment (U.E.), a Next-generation radio access network (5G New Radio (N.R.), next-generation node b (gNB)), and a 5G core network. The main key features of 5G N.R. are small cell, dual connectivity, cloud R.A.N., Beamforming and stirring radio enhancement, and increased spectrum. OFDM, flexible numerology, resource block, Network function virtualisation (N.F.V.), network slicing, handover in 5G characteristics make an efficient 5G network [2]. IoT is developed very fast still spectrum is limited resources. Non-orthogonal multiple access (NOMA) technology is used in 5G still have spectral efficiency, energy efficiency problem [3] Deep learning (DL) can improve wireless network efficiency [4]. Increasing the cellular network and its complexity suggested that machine learning provides the right solution for future networks. In VNET, millimeter-wave and MIMO improve the fast data rate; however, they efficiently require beamforming to connect device to device. In this context, band measurement and device position information can reduce to find the beam pair. Beam selection is a problem due to actuation, mobility, and other issues. IEEE 802.11 and 5G train the beam for standardisations. DL and ML efficiently provide beam selection [5]. Due to many users and coordination between them in the 5G network, IEEE 802.11 Channel allocation capacity leads to sub-optimal performance. DL is used for dynamic Channel allocation with optimized spectrum selection [6]. Delay, jitter, loss performance predicts the accurate network model. Analytical models are fast but not accurate, while the packet-level simulator is costly. Graph neural network (G.N.N.), a machine learning algorithm, provides a promising solution to build a distinct network to control and manage networks [7]. Internet Traffic increases the problem of network bandwidth, computing, and storage. ML and DL are used for radio network traffic prediction, which is more accurate, mainly demand prediction [8]. Sensors, control systems, safety analysis, congestion detection, lane changing, etc., are implemented in autonomous smart transportation. ML and DL can improve for these types of applications in the wireless network. Dynamic spectrum access is the solution to utilize the inefficient spectrum way. Cognitive approaches with machine learning are used in 5G wireless networks [9].

Therefore, it is essential to a comprehensive analysis of AI/ML in 5G to explore the research trend, key technology, and future trend of the research topic. In this study, bibliometric analysis in AI/ML in 5G is helpful for research scholars and industry practitioners to gain deep insight knowledge of published research articles in 5G with machine learning. Much bibliometric analysis is done in research areas5G and 5G with security, and it has been used widely to understand the corpus knowledge, identify the scientific area [10-14].

This paper contains three sections. Section 2 details the research methodology and research question, section 3 discuss the data analysis, and section 4 discusses the conclusion.

2 Research Methodology

Bibliometric analysis is one way to review a large number of articles in a particular research area to know the importance of literature. Web of Science (WoS) and Scopus are some of the extensive peer-review research articles databases. We selected Scopus and Web of a science research article in a particular area 5G with Machine learning in this study. In phase one, we decide the topic. Later on, we search the web of science and the Scopus database for data collection. Finally, we refined the datasets using some criteria [15-19]. Figure 1 is a graphical representation of methodology.

2.1 5G and ML Research questions for study

1. The trend of publication and citation of 5G and machine learning research
2. Find the Topmost organisations, contributed authors for publication, contributed countries
3. Find the Topmost journals in which 5G with machine learning researchers published their work.
4. Find the 5G with machine learning (5G/ML) authorship pattern.
5. Find the most used keyword in 5G with ML research.

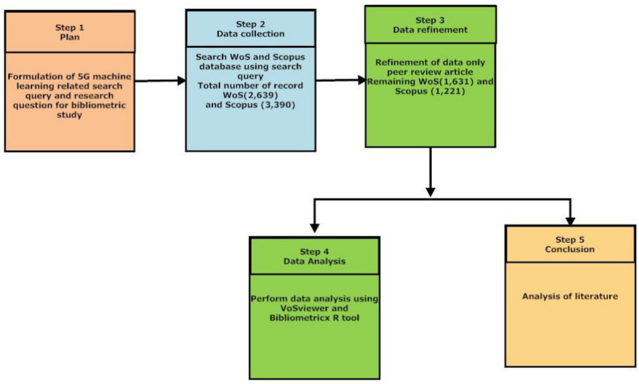


Fig. 1. The proposed method for 5G with ML bibliometric study

3 Data analysis (5G with ML)

To interpret the data in a bibliometric study involved various phases. First data collection from Scopus and web of science. Second refinement of data. We have finally used comprehensive software to visualise the result. For the current study, we used VOS viewer [20] and Bibliometrix (R Tools) software [21] to analyse the bibliometric data. We performed keyword analysis, analysis of scientific production year-wise, country scientific production, the Most cited country of scientific output, Most cited country in terms of citation year-wise, top 10 relevant organisation, top 10 authors publication wise, top 10 authors H-index wise, most trend topic year-wise within 5G and ML, top 10 relevant journals, keyword clustering, WordCloud, country collaboration map and finally we did factor analysis to find the top highest contributing papers and cited articles [22].

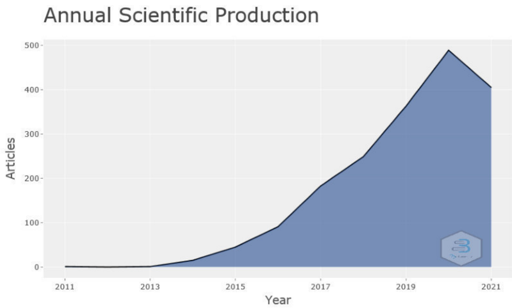
Table 1. Different search queries and results in WoS and Scopus.

S. No.	Queries 5G within ML	No. of results (WoS) with 5G within ML	No. of results (Scopus) 5G within ML
1	("5G" AND "Machine learning") (Topic) or ("5G" AND "cognitive radio")	2,639	3,390

	(Topic) or ("5G" AND "device to device") (Topic) and 2003-2021 (Year)		
2	("5G" AND "Machine learning") (Topic) or ("5G" AND "cognitive radio") (Topic) or ("5G" AND "device to device") (Topic) and 2003-2021 (Year) Refined By: Document Types: Articles or Review	1,631	1,221

3.1 Scientific production year-wise (5G and ML)

In the current study, we have taken the publication from Scopus and web of science database. We consider only peer-review journals so that they will be more authentic. In this respect, published article is taken for the study period from 2001-2021 as tabulated in Table 1. The graph of scientific publication is shown in Figure 2 (annual scientific production), highlighting the publication trend year-wise. The year-wise publication shows the variation of publication over a particular time. The analysis represents that publications related to 5G and machine learning (device to device communication) peaked from 2019 to 2021. researchers have been active for the last nine years. The most productive year is 2020, with 489 publications, whereas 2011 is starting publication related to 5G and ML topics. From the data, we can predict 2021 (405 publications) will be the most paper related to 5G and machine learning Top 10.



Year	Articles
2011	1
2013	1
2014	15
2015	45
2016	91
2017	183
2018	249
2019	363
2020	489
2021	405

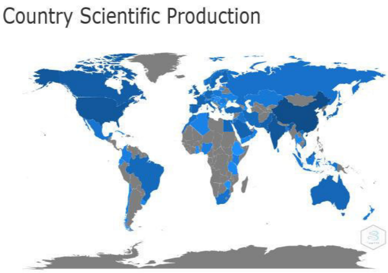
Fig. 2. Yearly publications within 5G Machine learning

3.2 Productivity analysis (5G and ML)

In terms of productivity analysis within 5G and machine learning, our aim is to focus on most scientific publications in terms of countries, most relevant organisation, the relationship between the organisation, country, and keywords in a specific topic, most contributed authors, year-wise trend topics, most relevant journals, keyword analysis and global collaboration within the 5G and ML. The research is presented in the following section.

3.2.1 Countries

Figure 3 represents country-wise scientific publication of the top 20 countries in the 5G Machine learning (ML) research area. Figure 4 represent the Top 20 country contribution in term of total citation, and Figure 5 Top 20 country contribution in term of several citations per year. In current analysis indicated that the highest number of research publications is from china, the most cited country. In contrast, Israel has the highest average citations per year in the research area of 5G and machine learning (5G and ML) with 1214, 7370, and 111.5, respectively. Regarding publication and citation, the U.S.A. is the second country with a value of 395 and 5301. Similarly, in terms of publication and citation, India is the third country with a value of 387 article publications and 2169 total citations, the U.K. with 247 publications, and South Korea (S.K.) with 239 publications and 1021citation. Israel, the number of citations per year is highest at 111.5.



region	Freq
CHINA	1214
USA	395
INDIA	387
UK	247
SOUTH KOREA	239
CANADA	201
PAKISTAN	149
MALAYSIA	108
SAUDI ARABIA	107
FRANCE	99
ITALY	99
SPAIN	95
FINLAND	81
GERMANY	77
AUSTRALIA	72
JAPAN	71
EGYPT	62
BRAZIL	57
TURKEY	56
SWEDEN	55

Fig. 3. Country specific publication within 5G Machine learning

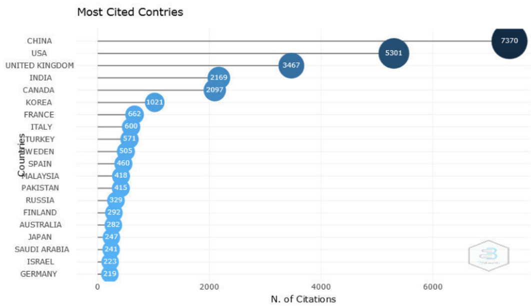


Fig. 4. The top 20 countries were contributing total citation within 5G Machine learning

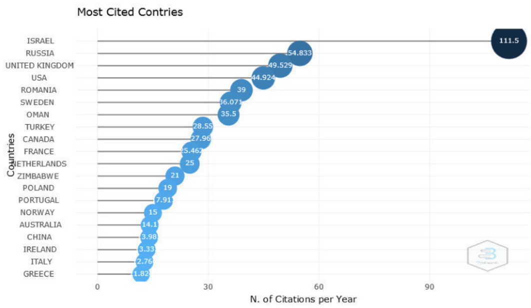


Fig. 5. Top 20 average number of citations per year within 5G Machine learning

3.2.2 Top 10 Most Relevant organisation

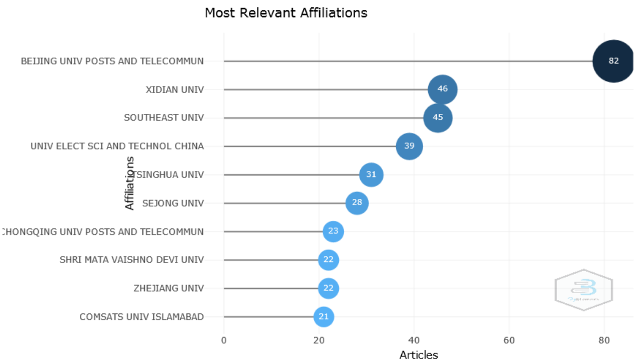


Fig. 6. Top 10 most relevant organisations within 5G Machine learning

3.2.3 Three-Fields Plot (Organization country and keywords)

Figure 7 shows the relationship among subject areas (keywords), organisations, and countries on 5G machine learning literature. The top 9 subject areas of 5G (5G ma-chine learning, 5G, 5G mobile communication, resource allocation, a device to device communication, cognitive radio, resource management, energy efficiency, and Internet of things) have a relationship with five research organisations (Beijing University of Posts and Telecommunications, Southeast univ, xidianuni, tsingghua univ, univ elect sci and technol china, Sejong univ, chongqing univ posts and telecommun, comsats univ Islamabad and Zhejiang univ). These are from these countries (China, U.S.A., France, UK, Canada, Korea, Pakistan, Saudi Arabia, Malesia, and India).

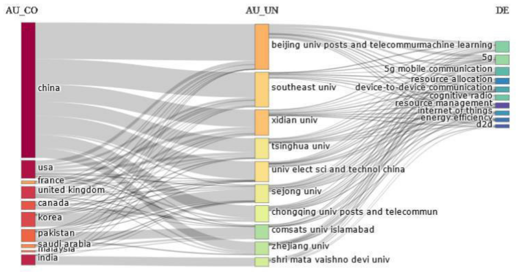


Fig. 7. Three-Fields Plot (Organization country and keywords)

3.2.4 Authors (5G and ML)

This author's section related to 5G and machine learning represents the top ten most relevant authors who contributed most in this area, as shown in Figure 8. Similarly, Figure 9 and Figure 10 highlight the top ten authors whose H-index is high and the top ten authors whose total citation is increased concerning publications. As mentioned in the figure, Wang X from the National University of Defense

Technology has the most publications (39), followed by Liu. Y from the Queen Mary University of London, London, UK, and Wang Y, from the Guangdong University of Technology with 32 and 30 publications, respectively. However, Wang X has the highest publication in terms of the publication. Still, the total citation is the highest of author Ding (2811), which indicates that it is not necessary who has more publications has top citation as well.

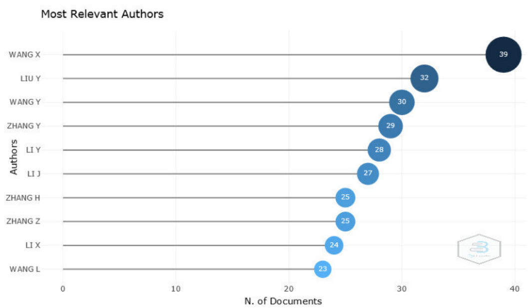


Fig. 8. Top 10 author-publication wise within 5G machine learning

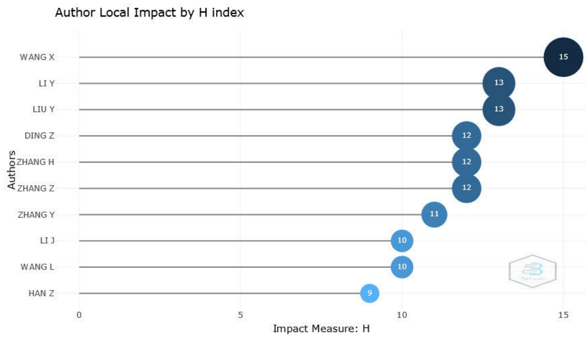


Fig. 9. Top 10 author H index wise within 5G machine learning

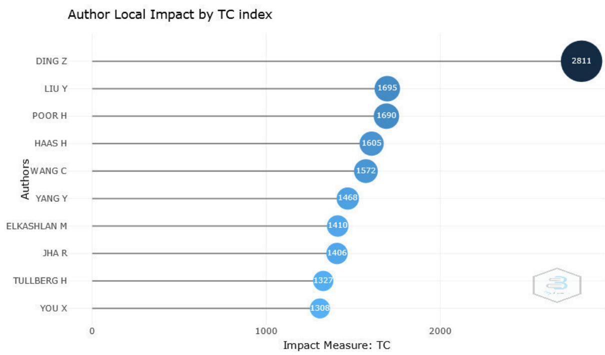


Fig. 10. Top 10 author total citation wise within 5G machine learning

3.2.5 Most trend Topics year-wise within 5G

This section highlights the most trend topics year-wise concerning5G and machine learning, as shown in Figure 11. Millimeter-wave, low latency communication, spectral efficiency, Internet of things (IoT) are the most trendy topics in 2021. from 2019 researchers are published the research article on different issues such as wireless and network challenges, 5G Performance, non-orthogonal multiple access of 5G, resource allocation of 5G, Internet of things, spectral efficiency.

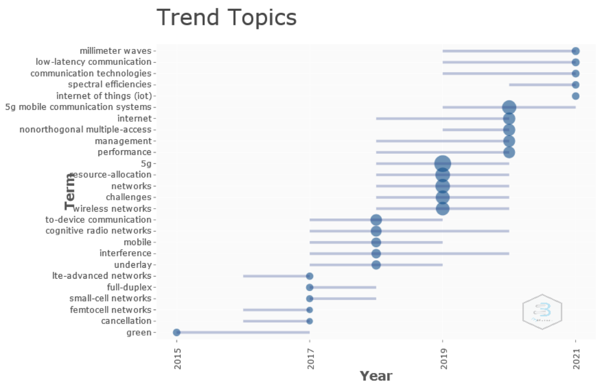


Fig. 11. Top 5 trend topic year-wise within 5G machine learning

3.2.6 Top 10 Most Relevant Journal for 5G Machine learning

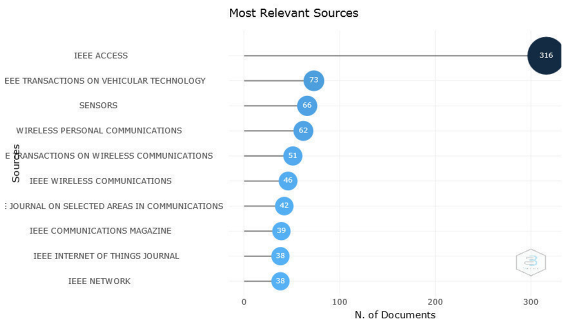


Fig. 12. Top 10 most relevant journals within 5G machine learning

This section highlights the top ten journals concerning topic 5G and machine learning. In addition, we highlight the source clustering through Bradford's Law, as shown in Figure 12 and Figure 13, respectively. Figure 12 highlights the top 10 journals concerning the number of publications related to 5G machine learning (5G/ML) research. In this context, the IEEE Access journal is the most relevant source venue, with 316 research articles published. Similarly, IEEE Transaction on vehicular technology (73 publications) and Sensors (66 research publications) and Wireless personal communication Journal (62 research publications) are the fourth choices. IEEE Access has the most publications because it fast peer-review journal, so the number of publications is more. In addition, we did Source clustering through Bradford's Law to find the pattern on the source on the particular topic in this study. We found IEEE ACCESS, IEEE Transaction of vehicular technology, sensors, wireless personal communication wireless communication are core sources.

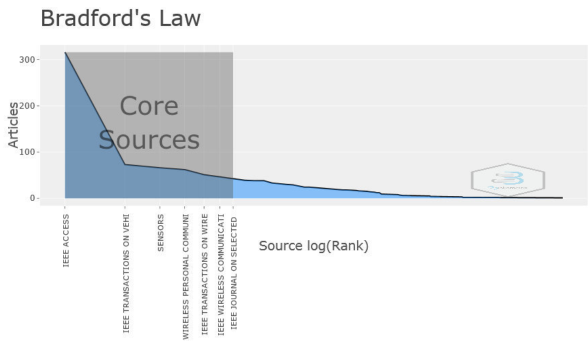


Fig. 13. Source clustering through Bradford's Law within 5G machine learning

3.2.7 Keyword analysis

This section analyses the keywords used in research articles (author keyword and keyword plus). We use VOSviewer to analyse the keyword's co-occurrences. Results are shown in Figure 14—the bigger node size, as the number of occurrences, is the largest.

In figure 14 shows 5G, Machine learning (ML), Cognitive Radio (C.R.), Internet of things (IoT), wireless network, and device-to-device connection (d2d) are frequently used keywords. In addition, the weight of edge connecting nodes shows how frequently used together keywords such as 5G with massive MIMO, 5G with security, 5G with resource allocation, 5 G with machine learning, 5G with cognitive radios, etc.

Figure 15 shows the density visualisation graph, and it indicates the cluster's colour with the default colour blue and green. There are two types of forces, attractive and repulsive, which show the association between the nodes. If two nodes are nearby, they have an attractive power with the highest association. However, if two nodes are apart, it means repulsive force in nature they have less association. Figure 14 shows that 5G, machine learning, and cognitive radio are attractive in nature and suggesta high association. In contrast, device-to-device communication and the queueing network have a high association.

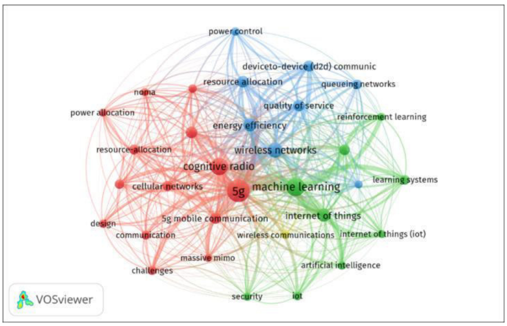


Fig. 14. Keyword co-occurrences network

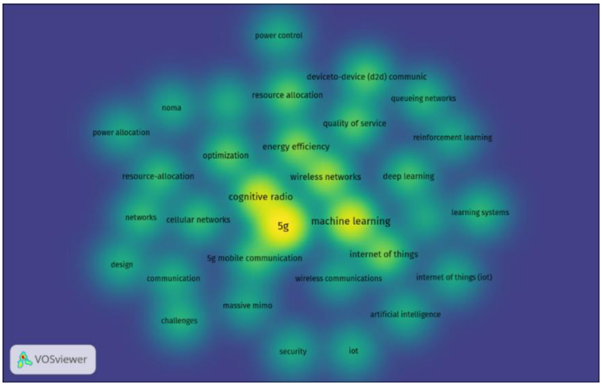


Fig. 15. Keyword co-occurrences density

Table 2 indicates four clusters that we get from keywords co-occurrences analysis through VOSviewer software. In terms of use in literature, keyword divides concerning research topic 5G and machine learning (5G/ML).In figure 14, the giant cluster, namely Cluster 1, has 14 keywords shown in red. The second biggest cluster, namely Cluster 2, has eight keywords, as shown in green. The third biggest cluster, Cluster 3, has eight keywords as shown in blue colour, and the fourth cluster, namely Cluster 4, has one keyword as shown in yellow colour. In cluster 1 most frequently used keywords in literature are about 5G mobile communication challenges, cellular networks, cognitive radio (C.R.), resource management, resource-allocation, Massive MIMO, NOMA, and optimisation in 5G.In Cluster 2 most frequently used keywords in literature are about the field of artificial intelligence, deep learning (DL), machine learning (ML), reinforcement learning, security, and the Internet of things (IoT). Cluster 3 shows most of the research publications discussed device-to-device communication, energy efficiency, network architecture, power control, quality of service, queueing networks and, resource allocation. Finally, in cluster 4, most of the research articles discuss wireless communications.

Table 2. Different search queries and results in WoS and Scopus.

Cluster #	**Colour**	**# Of keywords**	**Cluster keywords**
1	Red	14	5G, 5G mobile communication, cellular networks, challenges, cognitive radio, communication, design massive Mimo, networks, noma, optimisation, power allocation, resource management, resource allocation
2	Green	8	artificial intelligence, deep learning, Internet of things (IoT), learning systems, machine learning, reinforcement learning, security
3	Blue	8	Device-to-device (d2d) communication, energy efficiency, network architecture, power control, quality of service, queueing networks, resource allocation wireless networks
4	Yellow	1	wireless communications

Figure 15 shows that 5G, machine learning, and cognitive radio are attractive in nature and mean high association, whereas device-to-device communication and the queueing network have a high association.

3.2.8 Most Frequent Words

Figure 16 and Figure 17 highlights the top keywords with most occurrence in published literature 5G (371) followed by Machine learning (307), cognitive radio (186), 5G mobile communication (184), the device to device communication (127), Internet of things (111), resource allocation (105), energy efficiency (102) and resource allocation (84) times respectively. Figure 17 shows that WordCloud, a more important word, is primarily used in5G and Machine learning research literature.

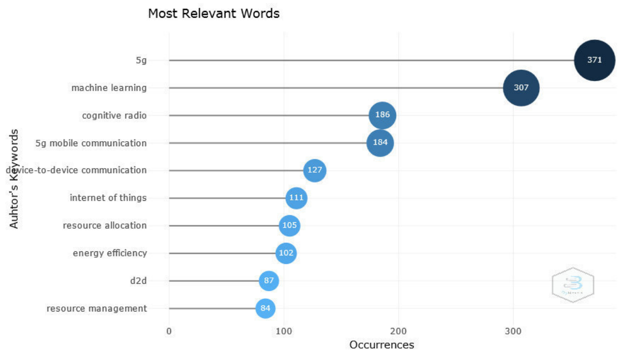


Fig. 16. Top 15 keywords within 5G machine learning research

Fig. 17. WordCloud within 5G machine learning research

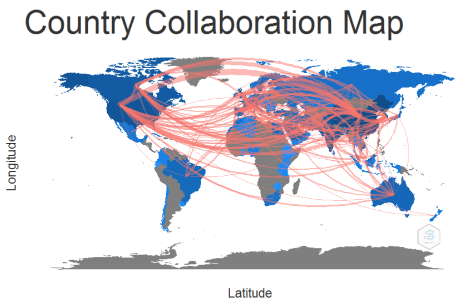


Fig. 18. Global collaboration map within 5G machine learning research

Figure 18 represents the global collaboration between the countries regarding research publication. Teamwork is essential for the research community to progress in research areas. At least one author should be another country indicating that international collaboration. Individual research is less productive concerning global production. To conduct this study, we used bibliometric R tools to view how authors collaborate with other country research areas5G and machine learning. Figure 18 represents. The country collaboration network map Indicating that the two countries with the highest collaboration are China and Australia. China– Australia, Canada–Saudi Arabia, Canada –Pakistan, Brazil–Portugal, and Canada –U.A.E. are the top five collaborating pairs countries. In addition, Canada is connected with Saudi Arabia, U.A.E., Pakistan, Bangladesh, and France are the top 5 collaborating countries.

3.2.9 Factorial Analysis

A popular exploratory data analysis tool is multidimensional scaling, which illustrates the connections between the studied topics [23]. The keywords used in the multidimensional scaling analysis were found to be dispersed across the coordinate plane in the resulting graph. Because the keywords move closer, their relative positions represent their convergence. In the context of our discussion, more convergent words create a set. They provide a foundation for relevant literature to the extent that a term is situated toward the middle of the cluster (Hoffman & De Leeuw, 1992). In the end, a factorial map of the clusters can be calculated as a result of the research. Figure 19 demonstrates the multidimensional scaling methodology used to generate the factorial map.

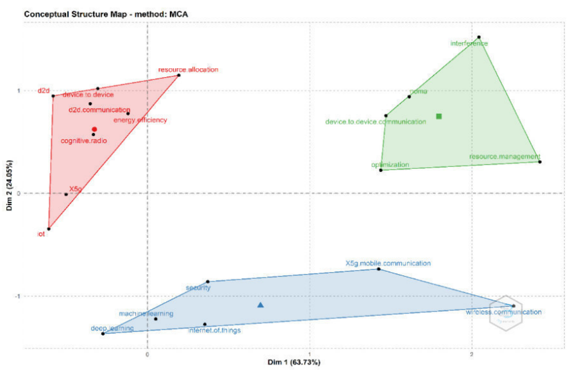


Fig. 19. Multidimensional Scaling Analysis of Keywords

The first cluster includes the concepts of IoT, device-to-device communication, resource allocation, energy efficiency, cognitive radio, and 5G. The factorial map shows that the idea of cognitive radio occupies a more central position. It can be interpreted as the importance of cognitive radio for d2d communication in a 5G environment so energy efficiency and resource allocation will improve in the IoT environment.

Cluster 2 includes machine learning, deep learning, 5 g wireless communication, security and IoT, and the Internet of Things close to the centre. It can be represented as machine learning, and deep learning is used for IoT,5G, and wireless communication security.

The third cluster includes d2d communication, NOMA, resource management, and Optimisation. In this cluster, the idea of NOMA is more central, and it shows that NOMA is used for d2d communication.Figure 20 shows that cluster wise top 2 publications. Similarly, Figure 21 shows thatcluster wise top two most cited research articles.

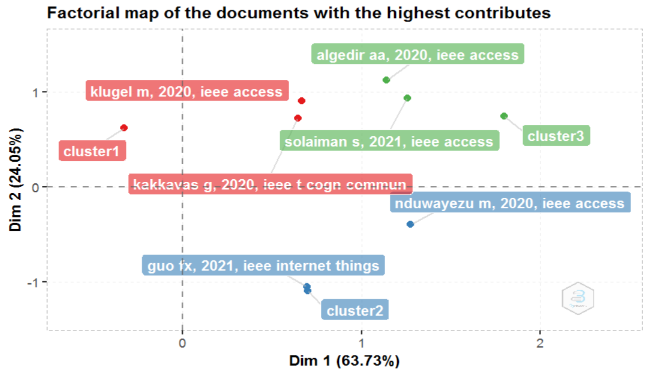


Fig. 20. Top 2 cluster wise publications with highest contribute

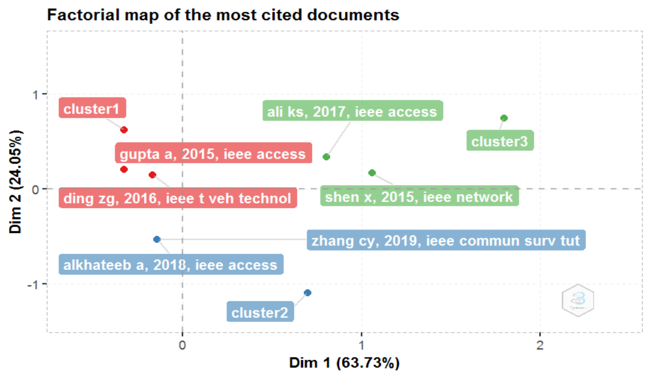


Fig. 21. Top 2 cluster wise most cited publication with highest contributes

4 Conclusion

This study performed bibliometric analysis on 5G and machine learning topics. We present a comprehensive analysis of existing research. In this research, We performed keyword analysis, analysis of scientific production year-wise, country scientific production, the Most cited country of scientific output; Most cited country in terms of citation year-wise, top 10 relevant organisations, top 10 authors publication wise, top 10 authors H-index wise, most trend topic year-wise within 5G and ML, top 10 relevant journals, keyword clustering, WordCloud, country collaboration map and finally we did factor analysis to find the top highest contributing papers and cited articles. The 5G technology is increasing the scope of the device to device communication, Internet of things. In addition, we need to optimise the resource used in 5G infrastructure using cognitive radio, deep learning, machine learning. The implementation of IoT needs 5G in an efficient way, such as power management or control using machine learning, resource allocation in an efficient manner using deep learning. Bibliometric analysis is a popular method for a new researcher to identify the research area in a particular field.

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Annexure 3: Conference Certificates

3rd International Conference on Communication and Intelligent Systems ICCIS 2021

Organized by

National Institute of Technology Delhi

Technically Sponsored by

Soft Computing Research Society

E-CERTIFICATE OF PARTICIPATION

Md.Tabrej Khan

presented the paper titled

Current Research Trends Machine Learning in 5G: A Bibliometric Analysis

authored by

Md.Tabrej Khan and Ashish Adholiya

in the International Conference on Communication and Intelligent Systems held online during December 18-19, 2021.

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Annexure 4: Plagiarism Checking Report

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by Md. Tabrej Khan

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