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.

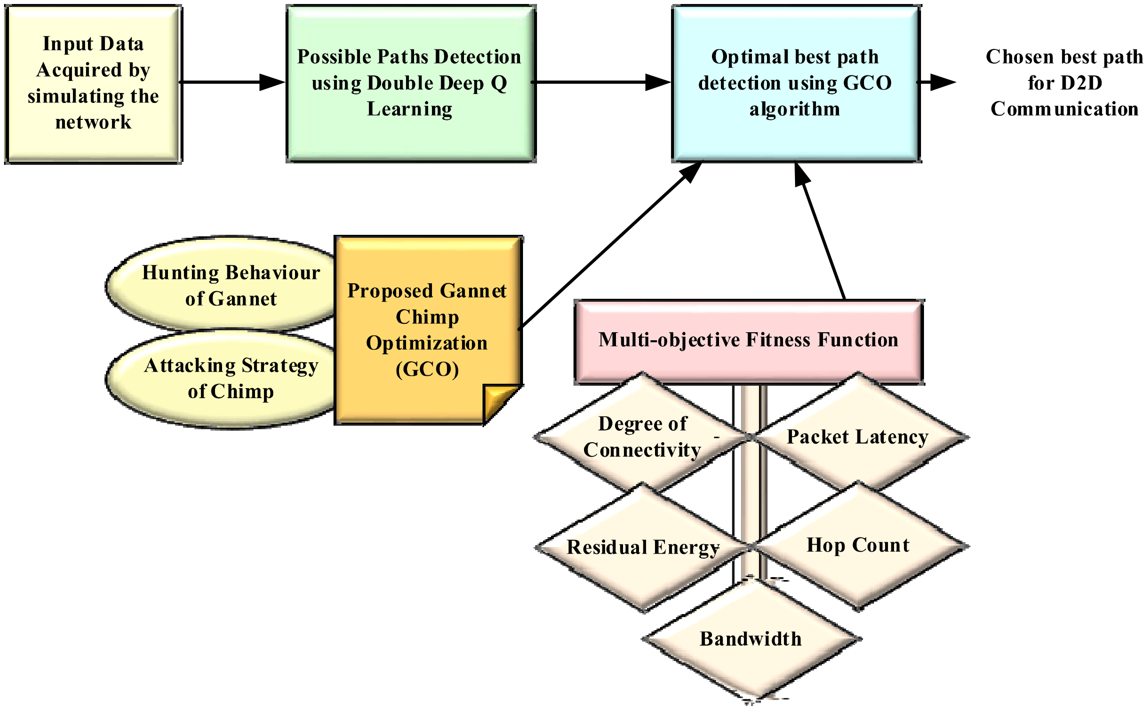


Figure 5.1: Newly devised Energy Efficient D2D communication protocol

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.

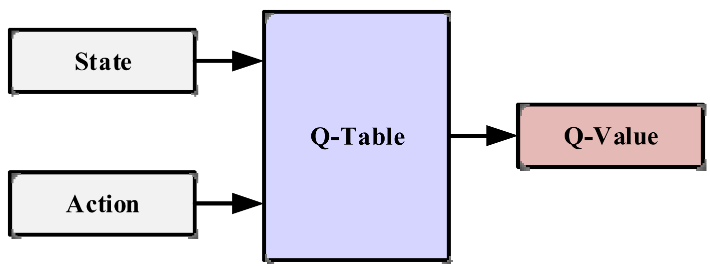
5.3.2 Double Deep Q learning for path detection

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

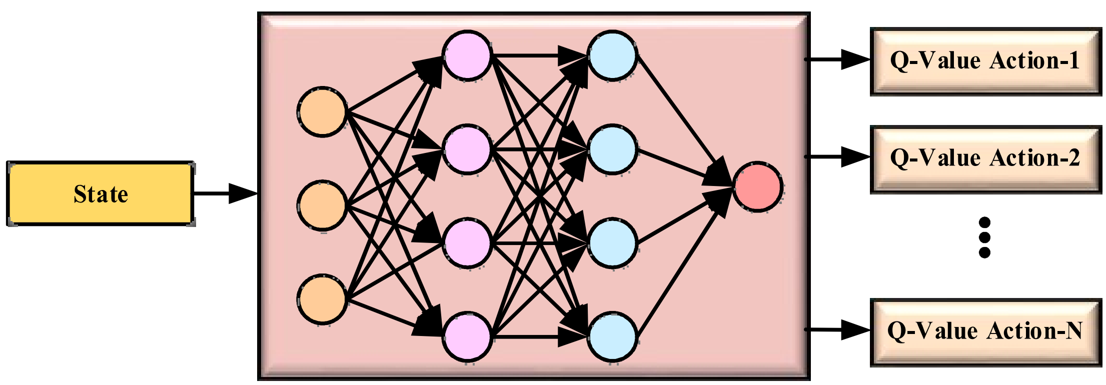
DNN to estimate the reward and Q-value, the double deep Q learning effectively addresses the overly optimistic problem.

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,

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

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,

$$\mathrm{Re}\,ward = E_X \times Y_{m_c,m_b}^{f_c} + E(1-E_X)\times Y_{m_c,m_b}^{f_c} \tag{5.5}$$

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,

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

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.

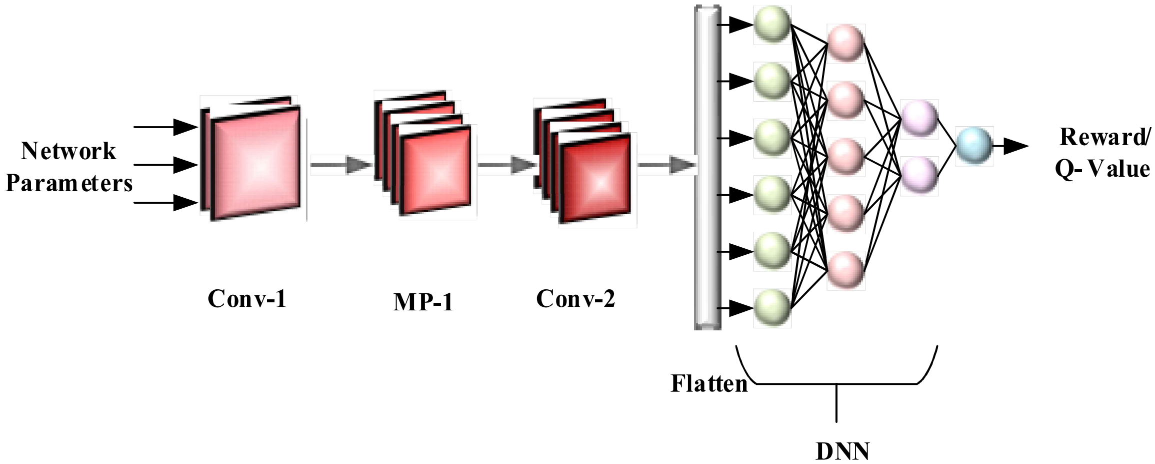


Figure 5.3: Architecture of DeepCNN

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.

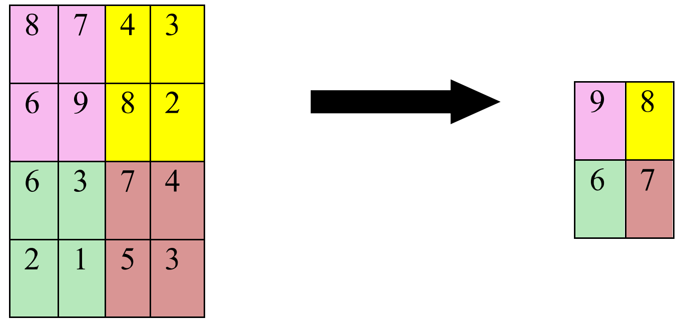


Figure 5.4: Max-pooling operation

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:

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

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,

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

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:

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

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,

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

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

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

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

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,

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

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

(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

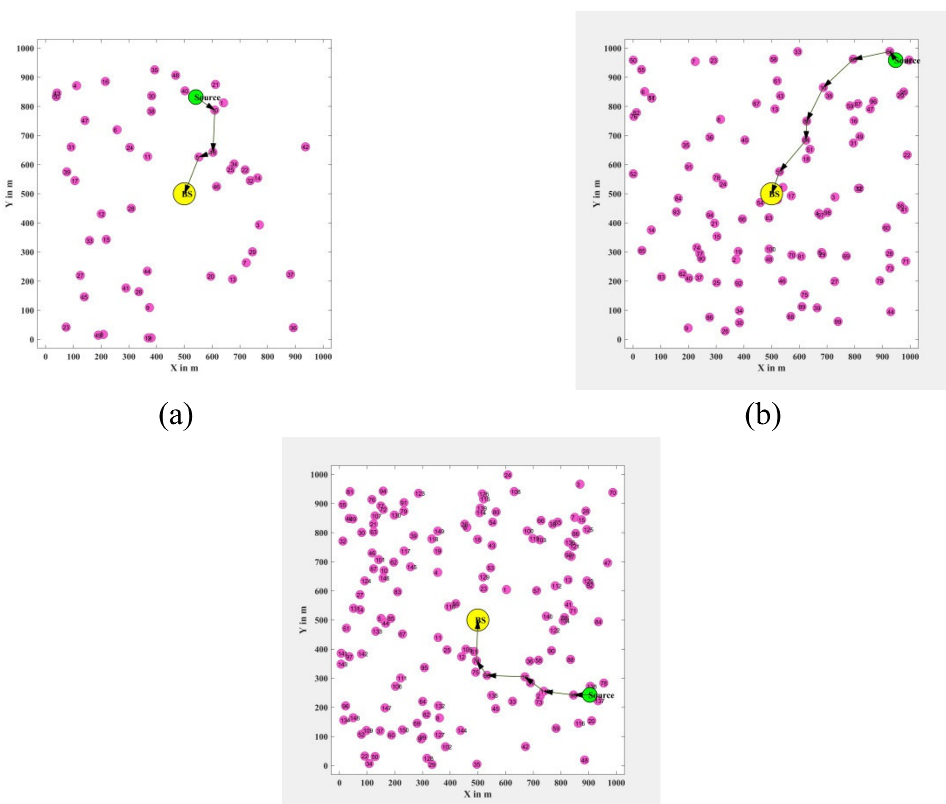
In the 5G networks, the ideal path for D2D communication between users is thus selected using the GCO algorithm, which also provides energy efficient routing with multi-hop.

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.

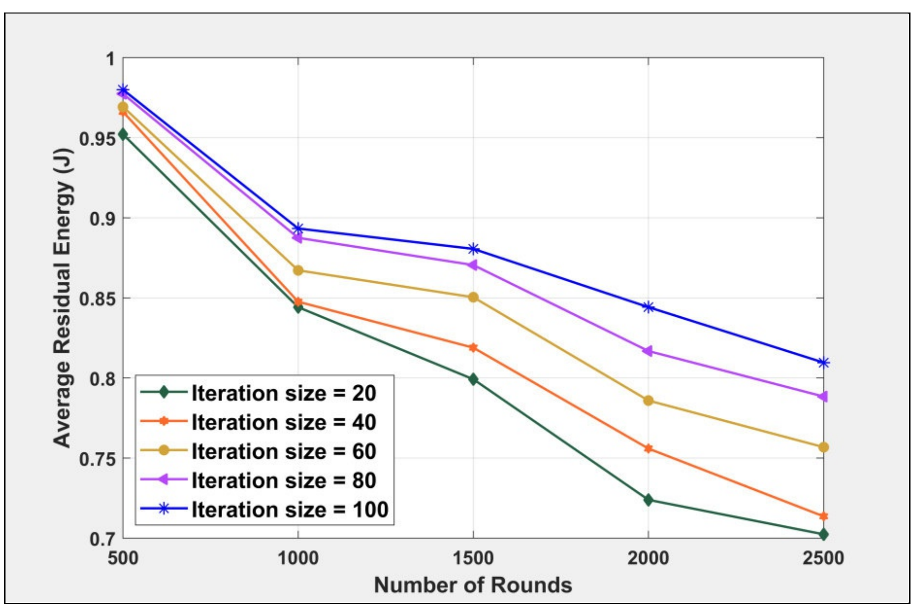


Figure 5.6: Average Residual Energy based on Iteration with 50 users

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.

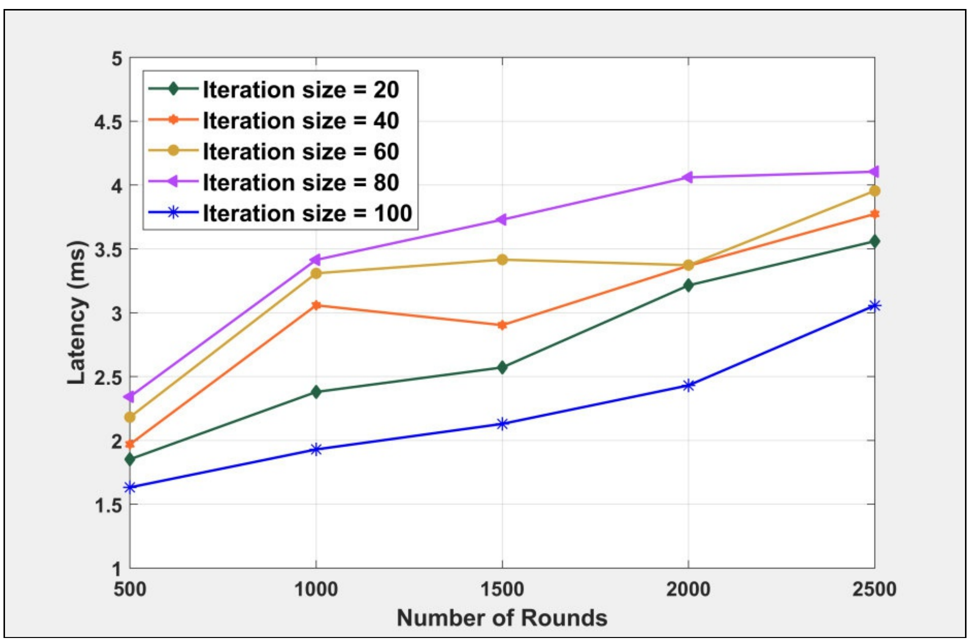


Figure 5.7: Latency based on Iteration with 50 users

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.

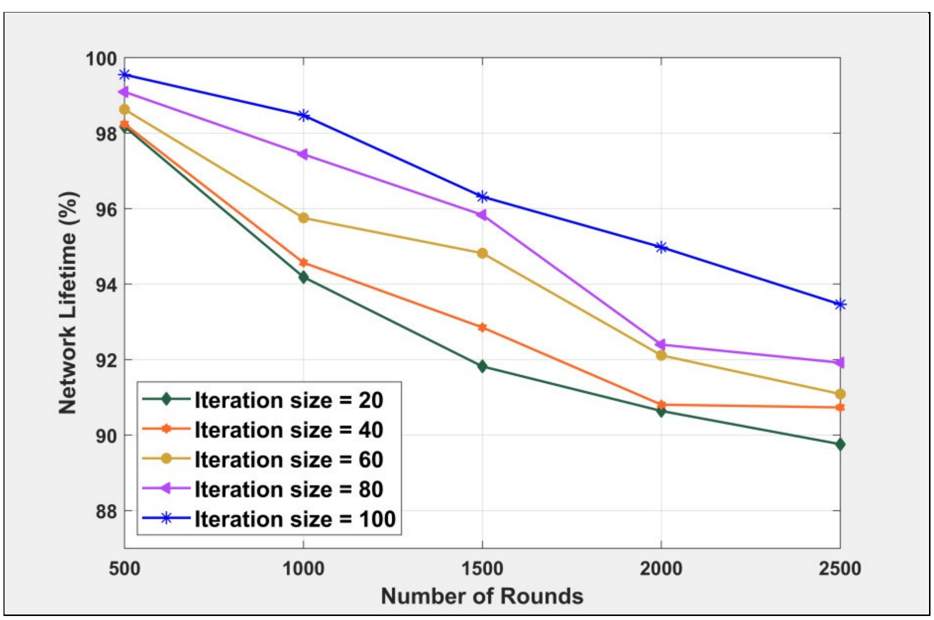


Figure 5.8: Network Life Time based on Iteration with 50 users

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.

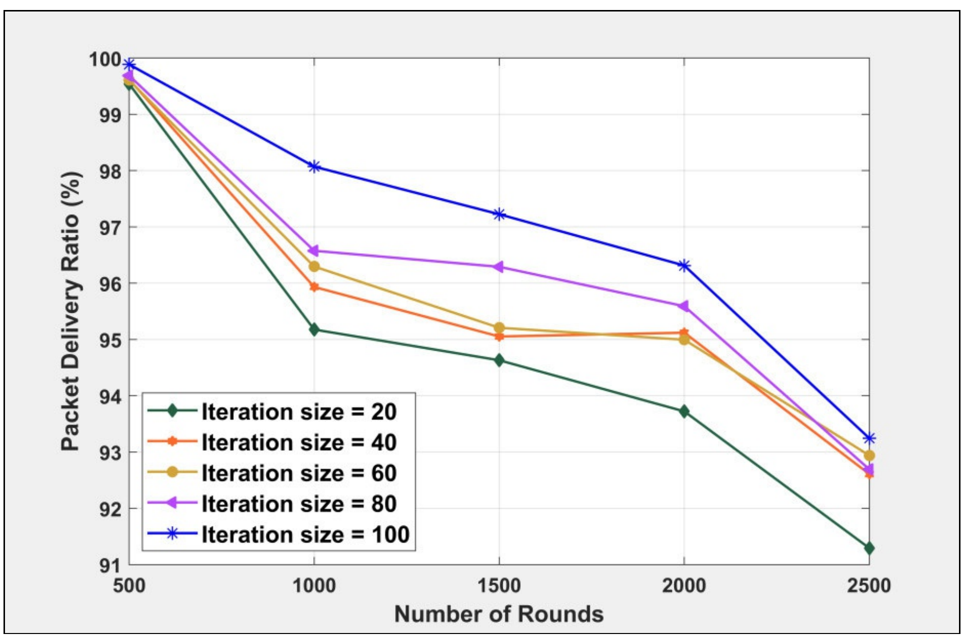


Figure 5.9: Packet Delivery Ratio based on Iteration with 50 users

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.

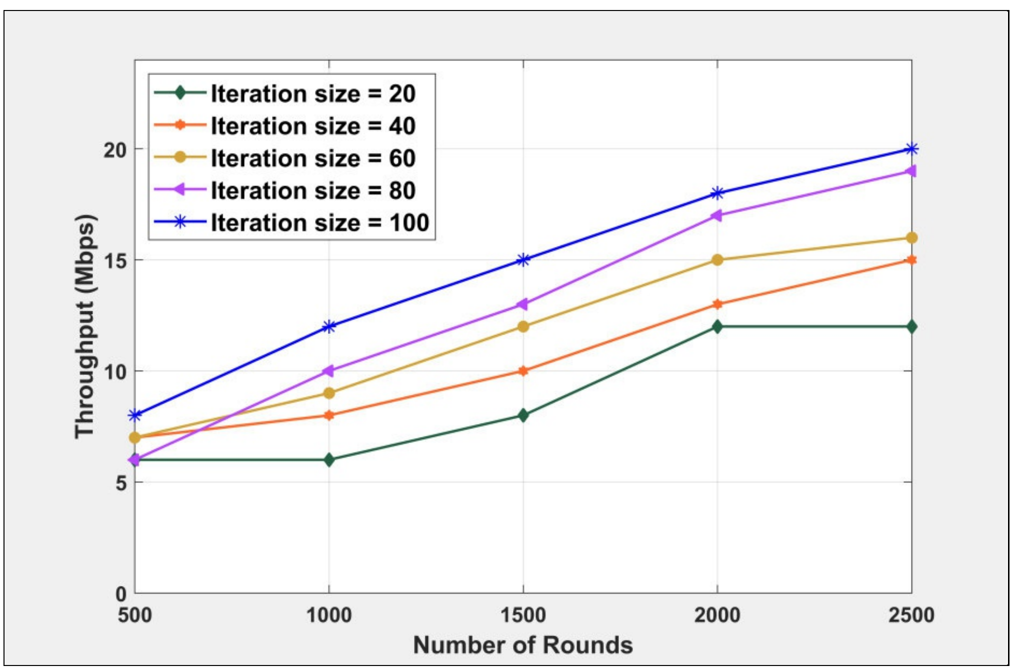


Figure 5.10: Throughput based on Iteration with 50 users

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.

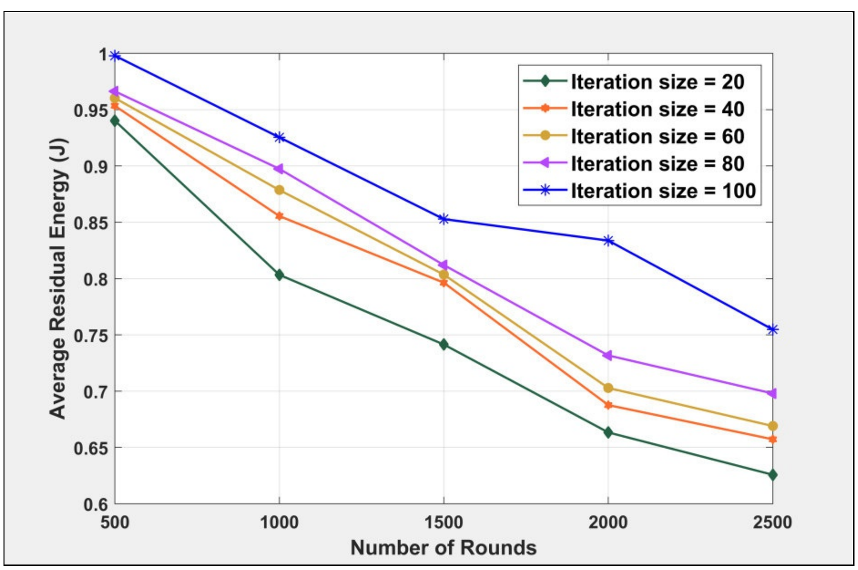


Figure 5.11: Average Residual Energy based on Iteration with 100 users

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.

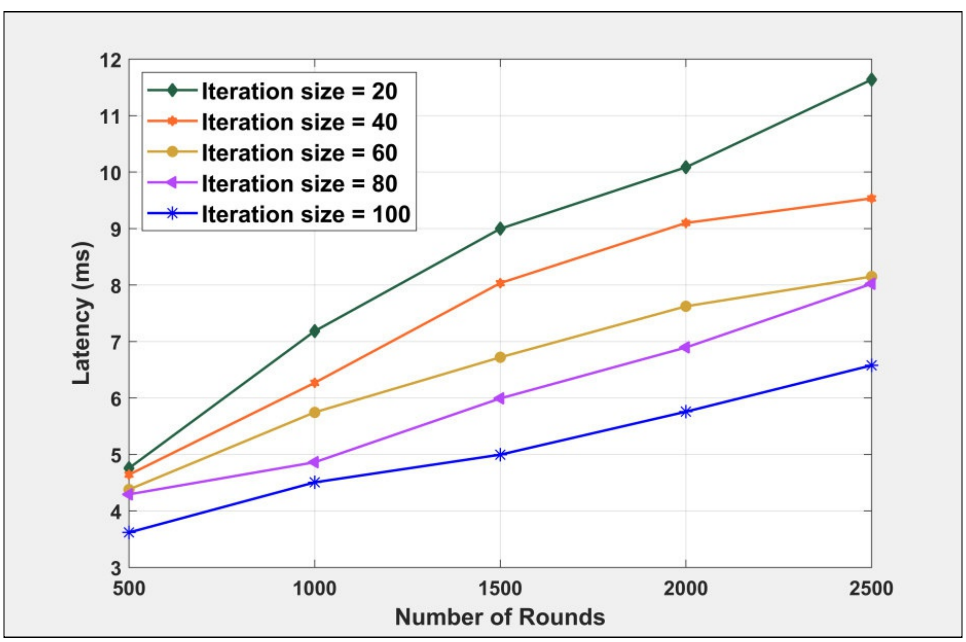


Figure 5.12: Latency based on Iteration with 100 users

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.

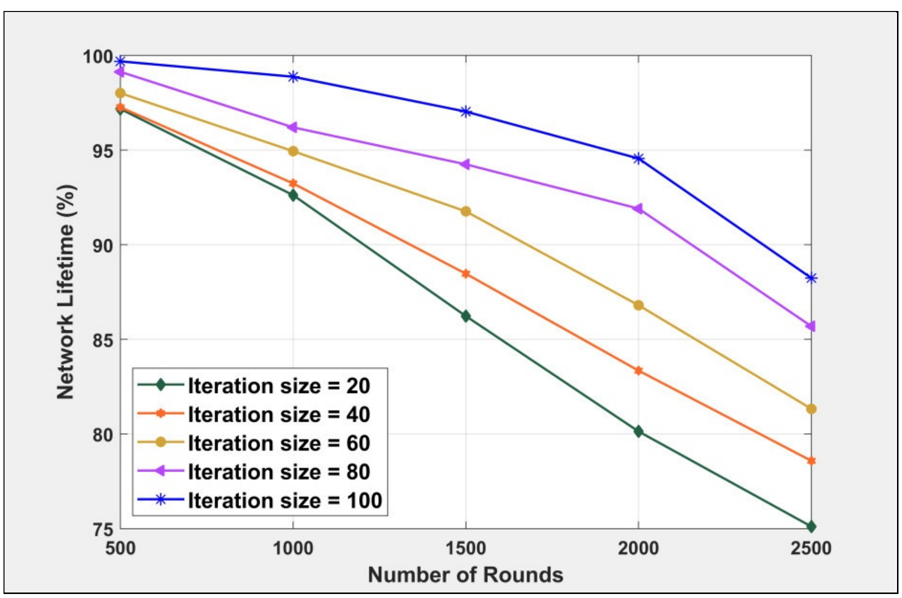


Figure 5.13: Network Life Time based on Iteration with 100 users

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.

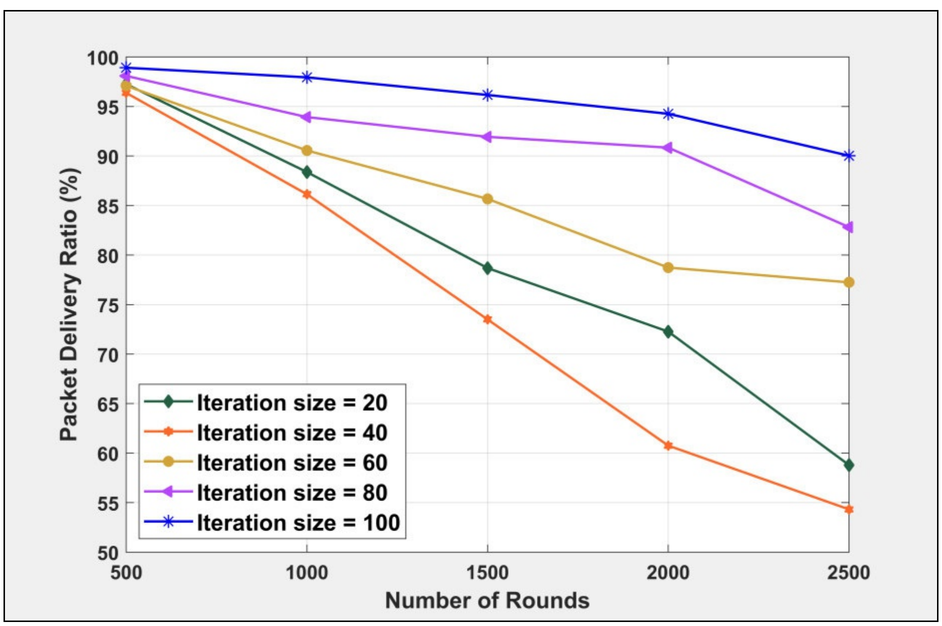


Figure 5.14: Packet Delivery Ratio based on Iteration with 100 users

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.

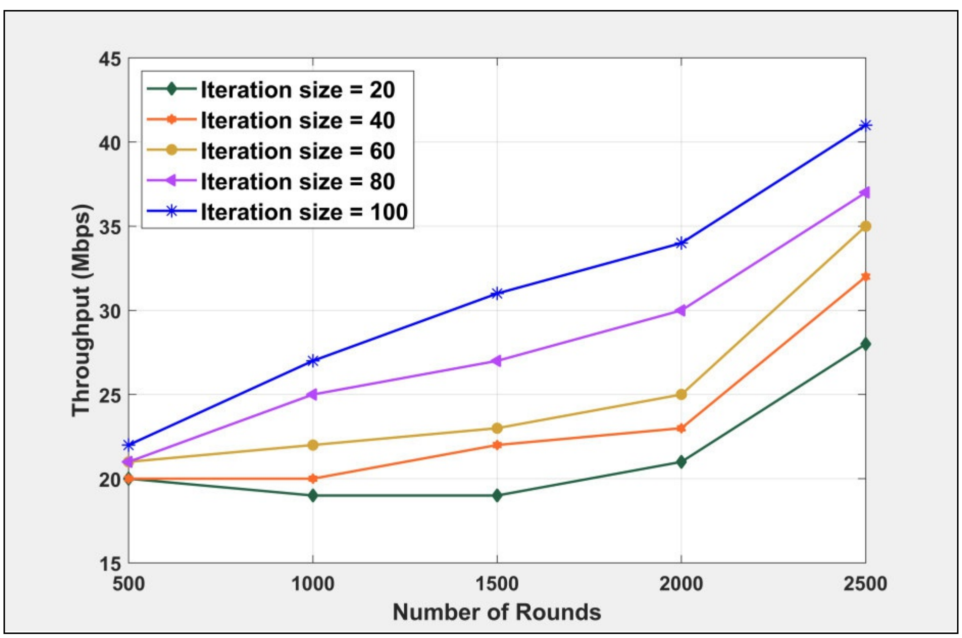


Figure 5.15: Throughput based on Iteration with 100 users

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.

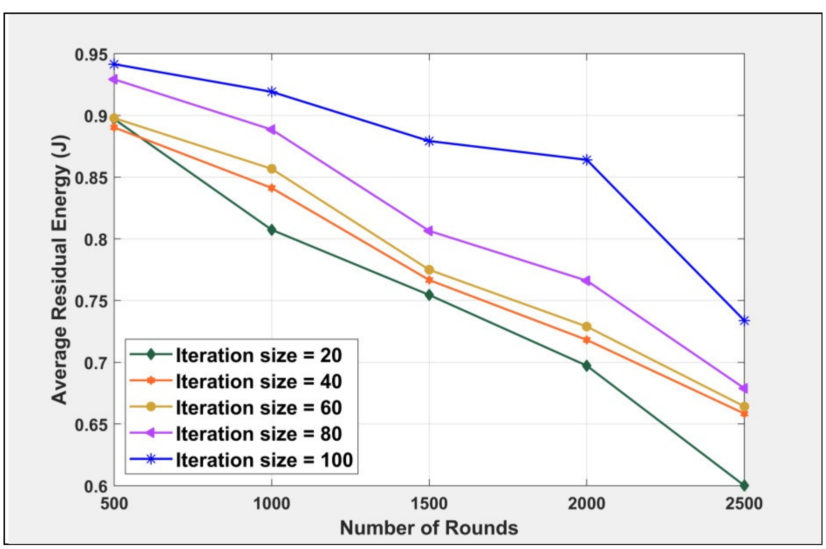


Figure 5.16: Average Residual Energy based on Iteration with 150 users

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.

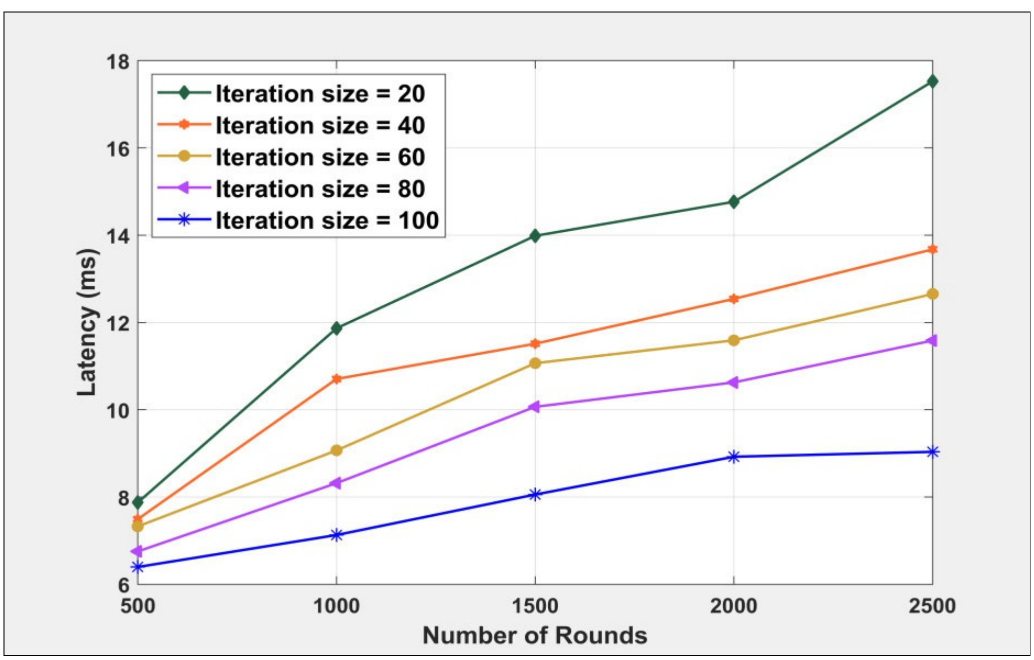


Figure 5.17: Latency based on Iteration with 150 users

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.

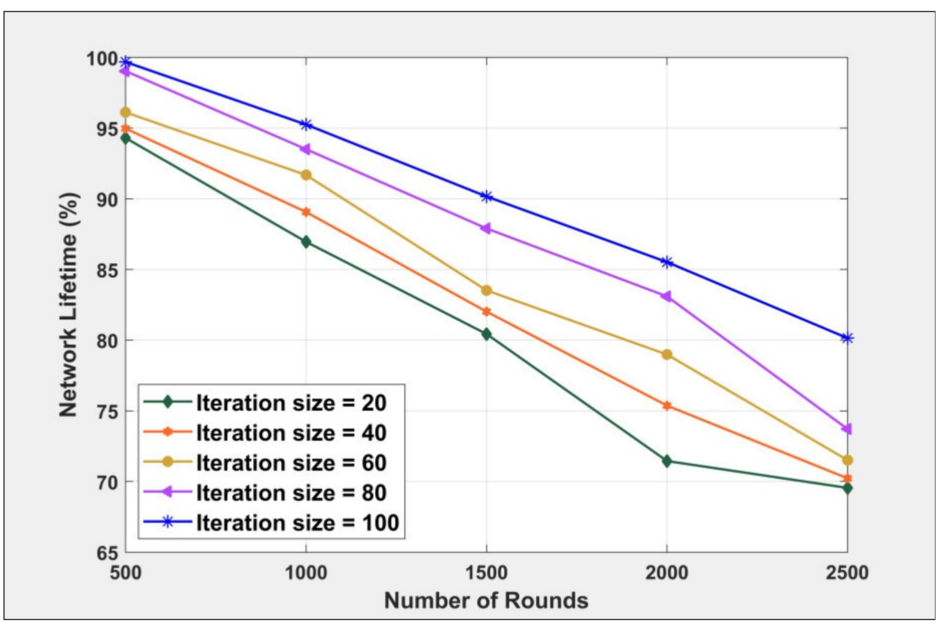


Figure 5.18: Network Life Time based on Iteration with 150 users

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.

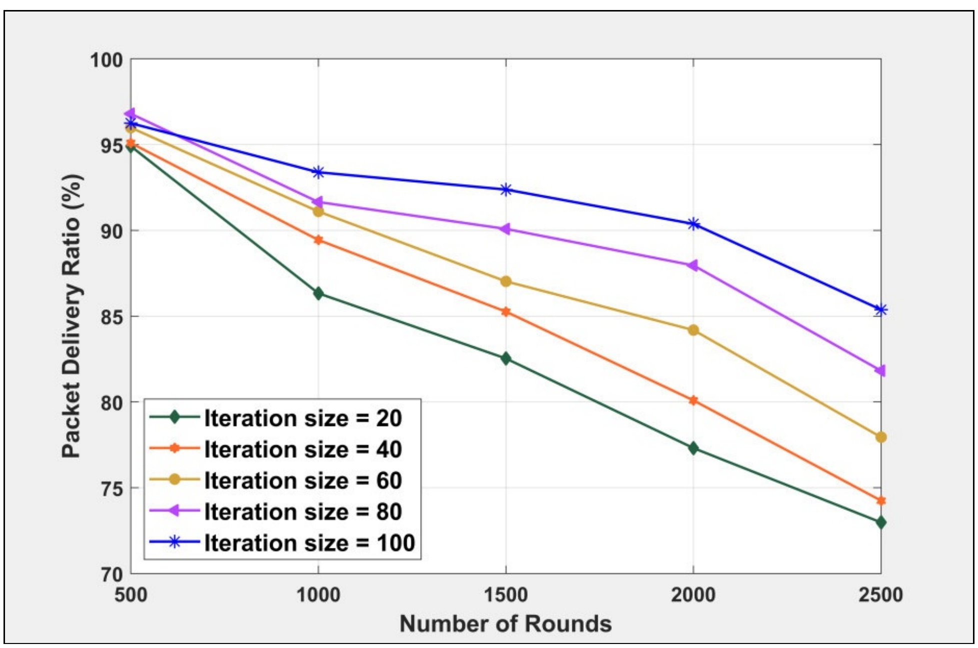


Figure 5.19: Packet Delivery Ratio based on Iteration with 150 users

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.

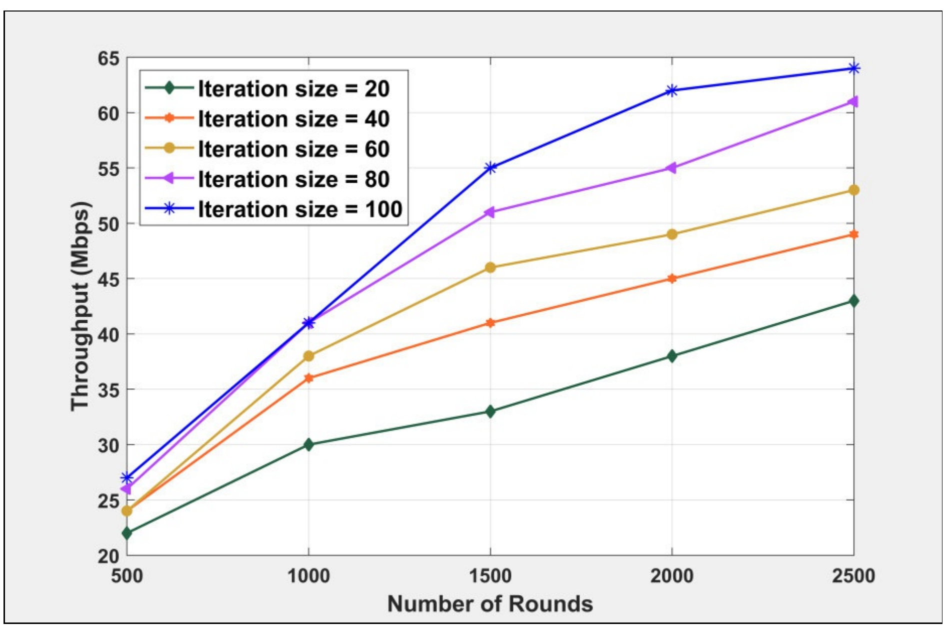


Figure 5.20: Throughput based on Iteration with 150 users

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.

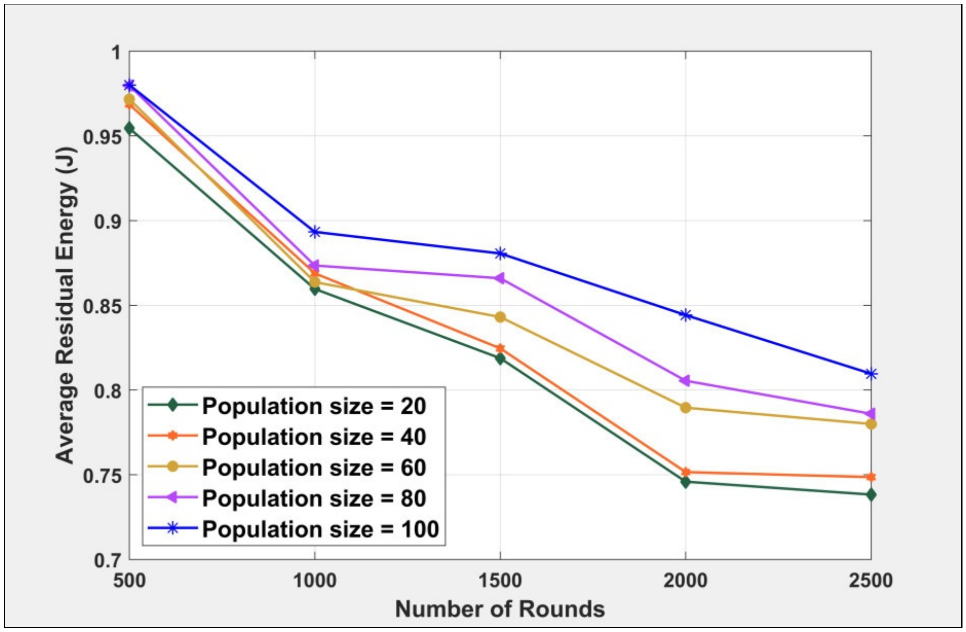


Figure 5.21: Average Residual Energy based on Population size with 50 users

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.

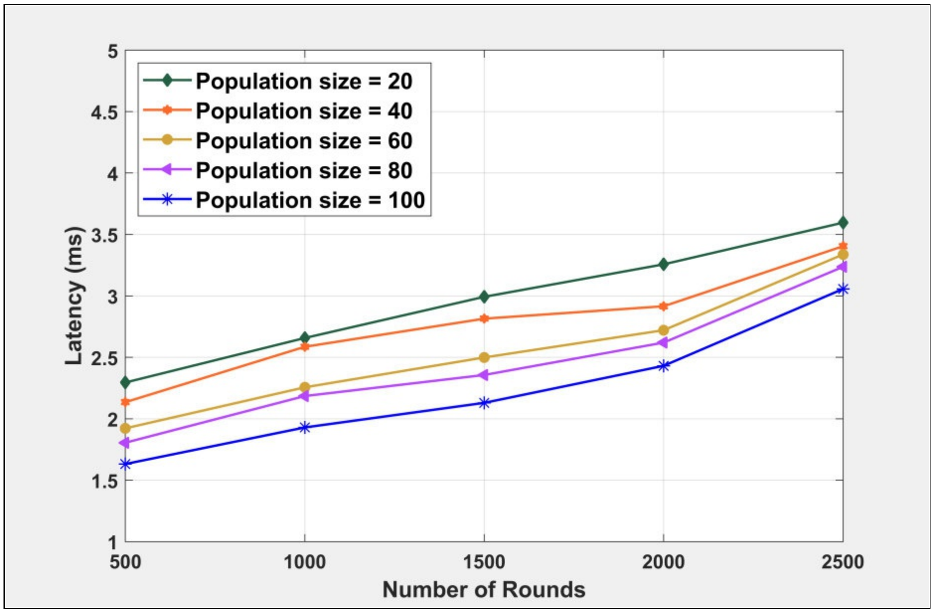


Figure 5.22: Latency based on Population size with 50 users

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.

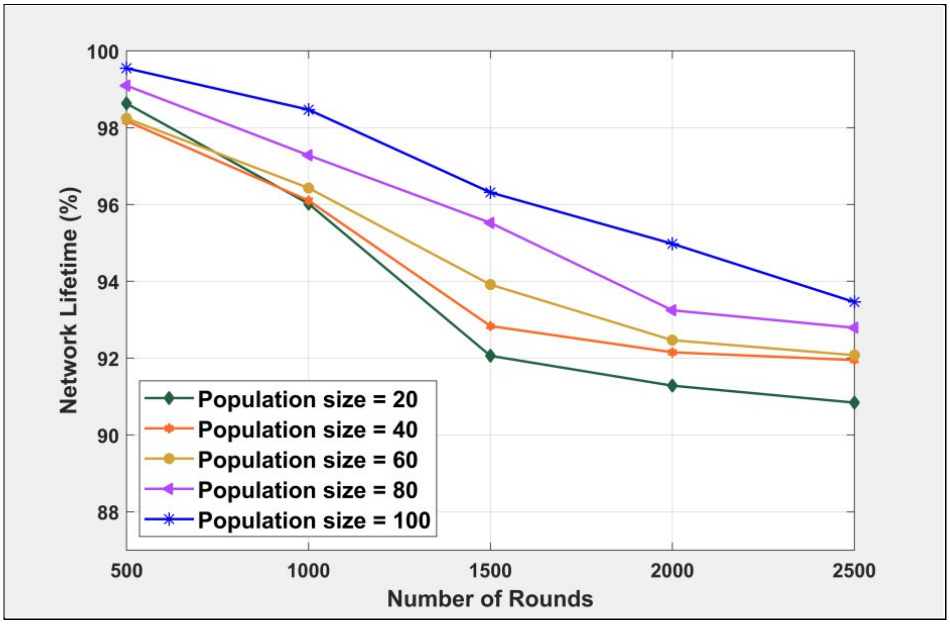


Figure 5.23: Network Life Time based on Population size with 50 users

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.

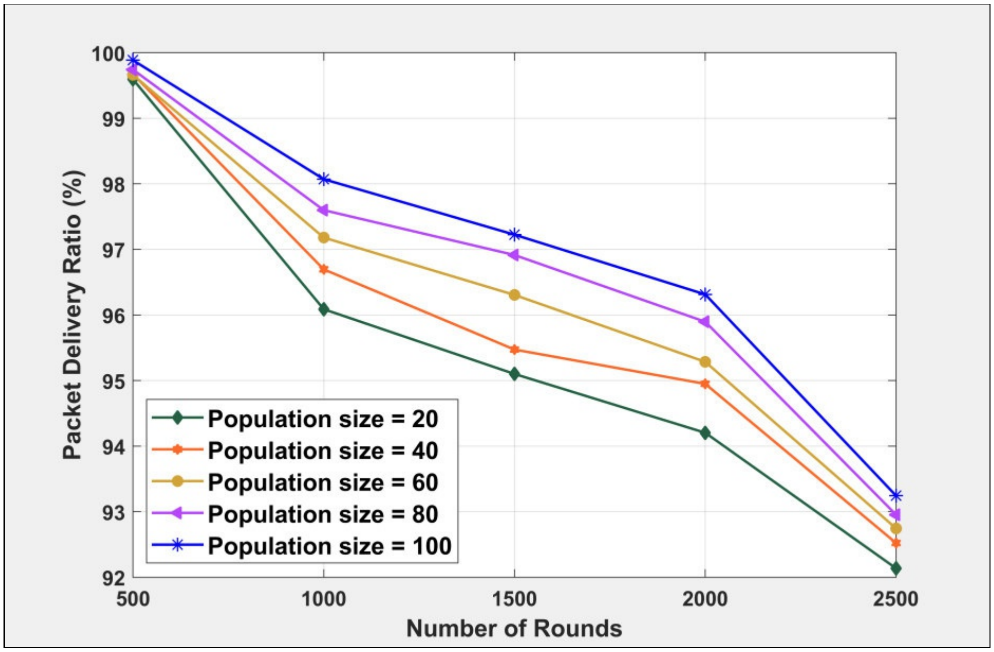


Figure 5.24: Packet Delivery Ratio based on Population size with 50 users

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.

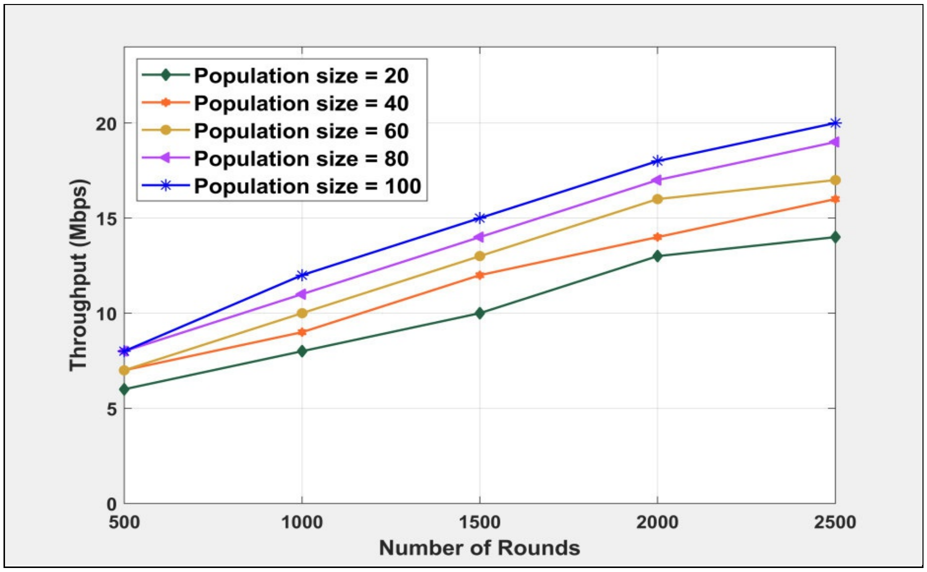


Figure 5.25: Throughput based on Population size with 50 users

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.

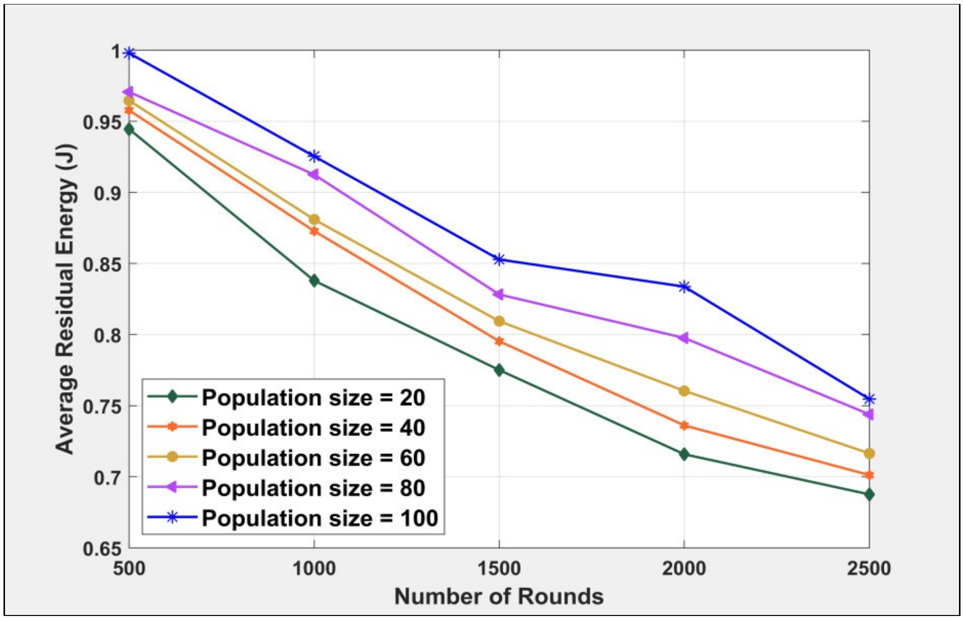


Figure 5.26: Average Residual Energy based on Population size with 100 users

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.

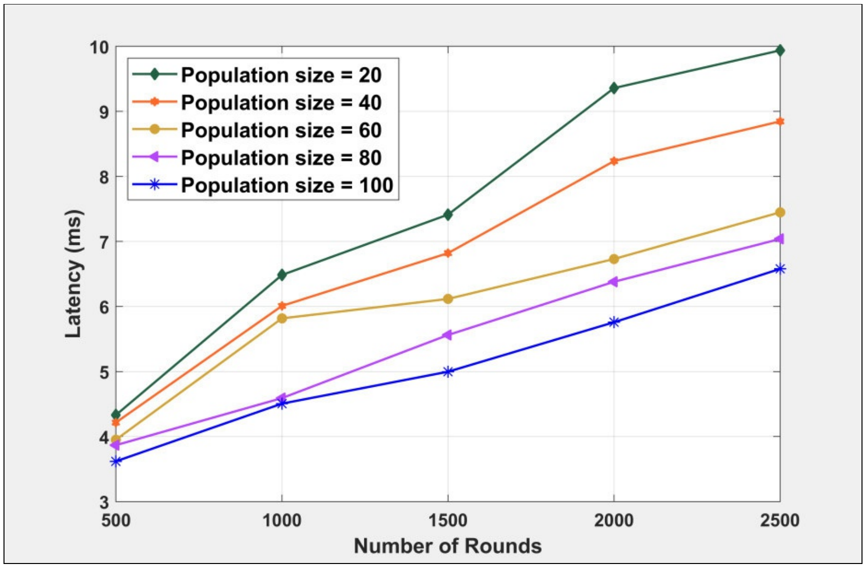


Figure 5.27: Latency based on Population size with 100 users

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.

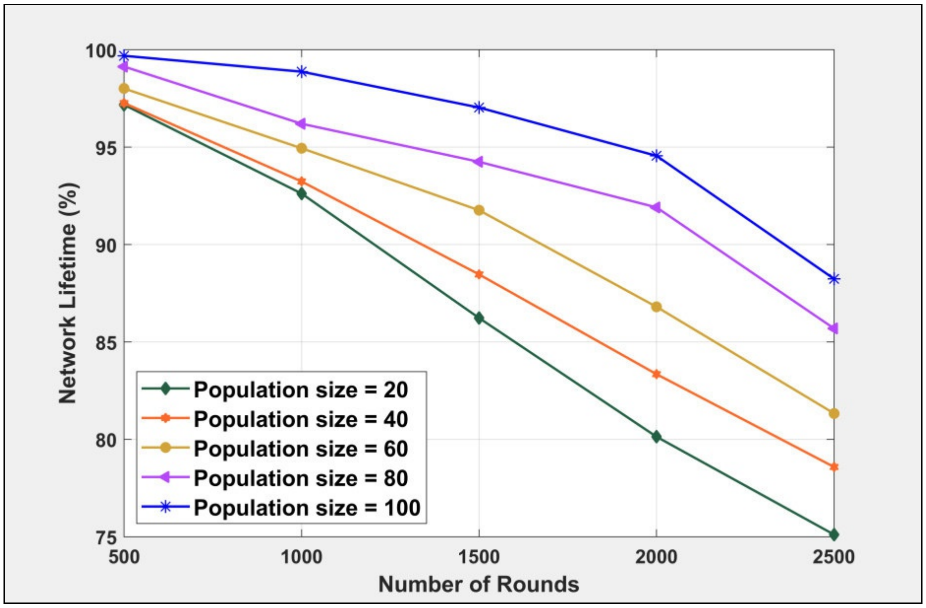


Figure 5.28: Network Life Time based on Population size with 100 users

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.

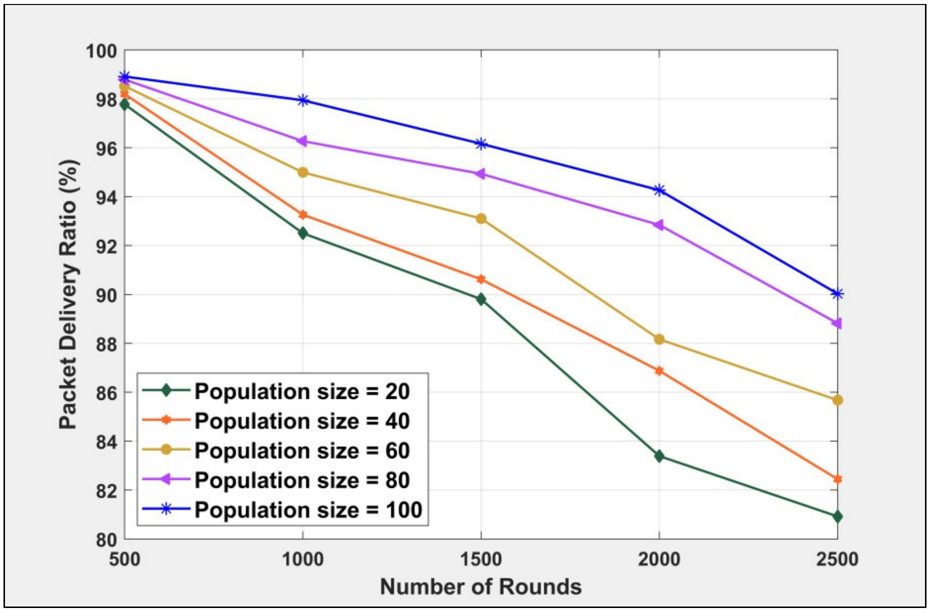


Figure 5.29: Packet Delivery Ratio based on Population size with 100 users

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.

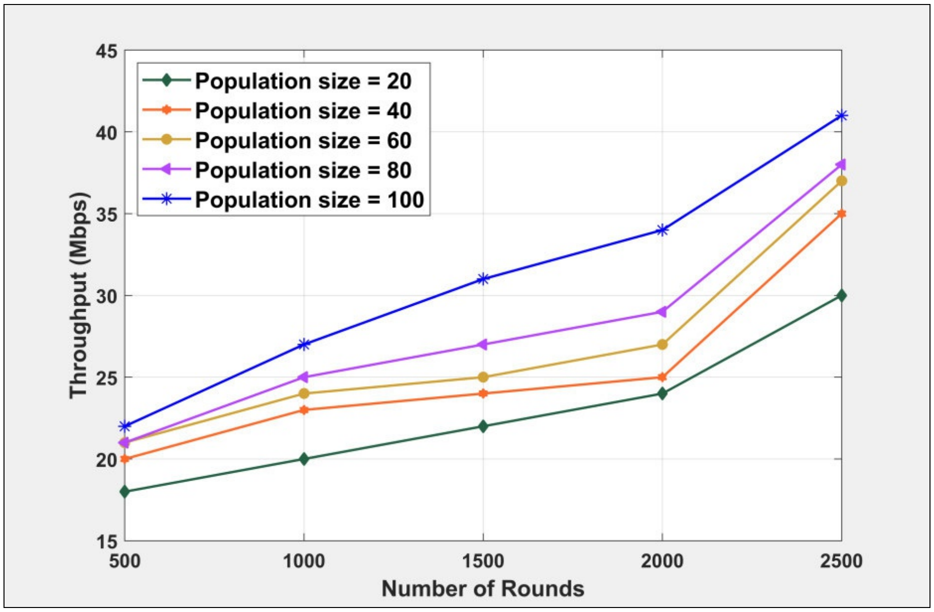


Figure 5.30: Throughput based on Population size with 100 users

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.

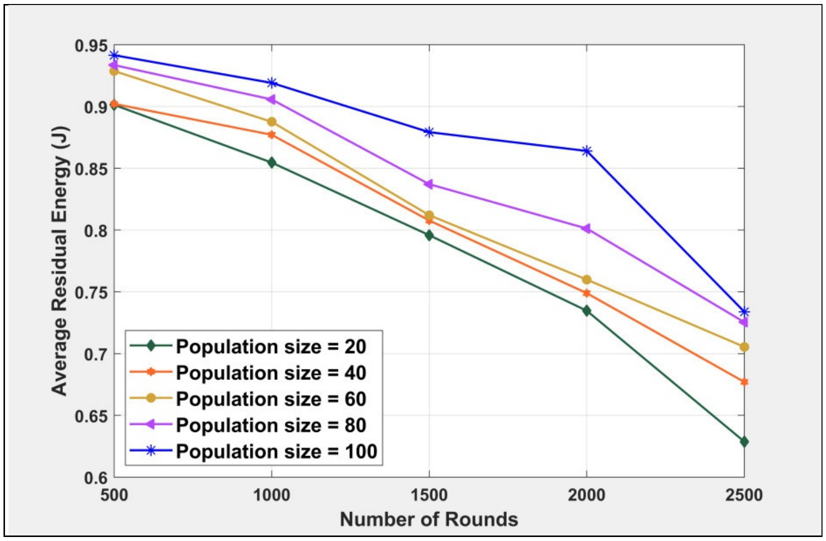


Figure 5.31: Average Residual Energy based on Population size with 150 users

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.

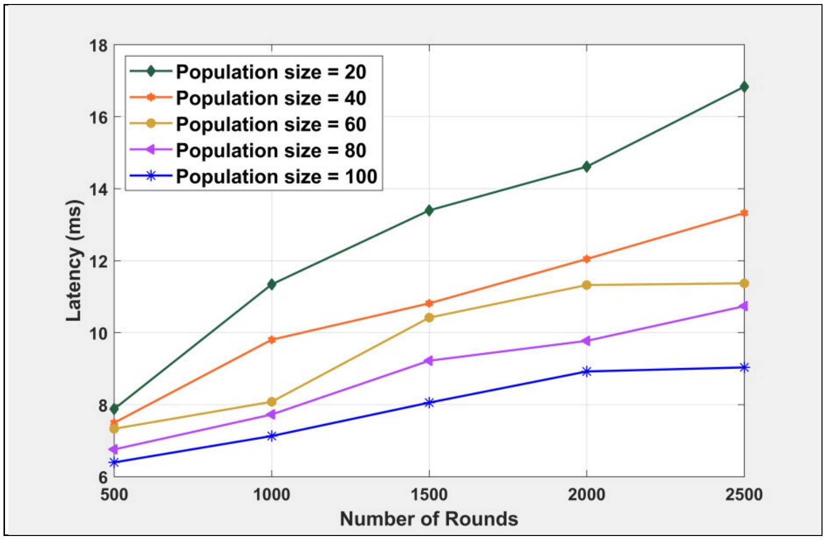


Figure 5.32: Latency based on Population size with 150 users

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.

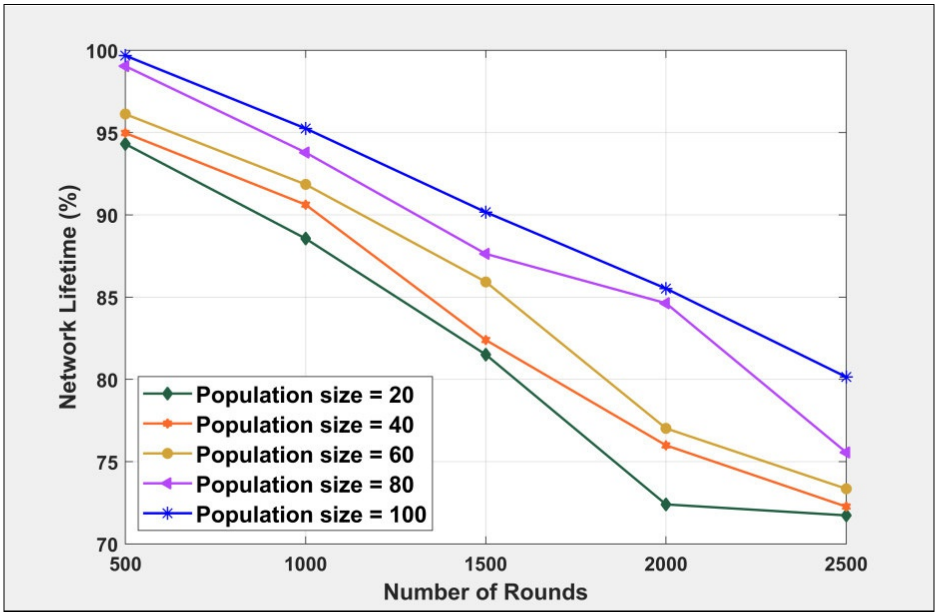


Figure 5.33: Network Life Time based on Population size with 150 users

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.

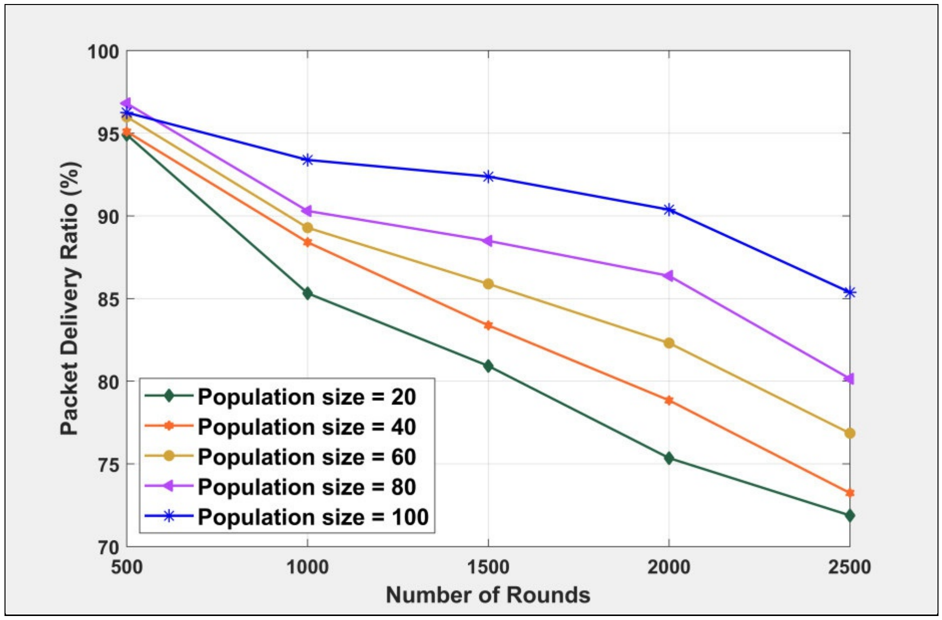


Figure 5.34: Packet Delivery Ratio based on Population size with 150 users

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.

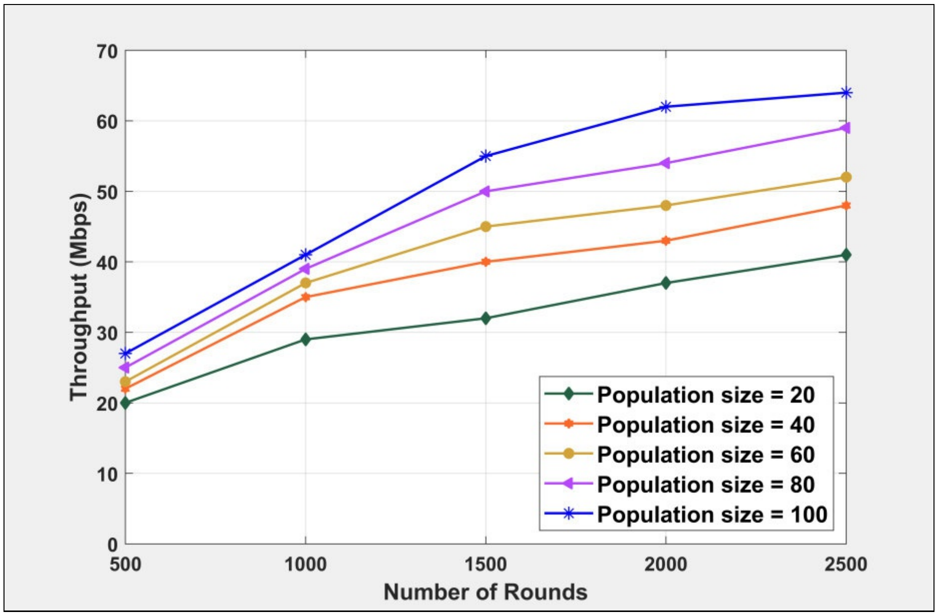


Figure 5.35: Throughput based on Population size with 150 users

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.

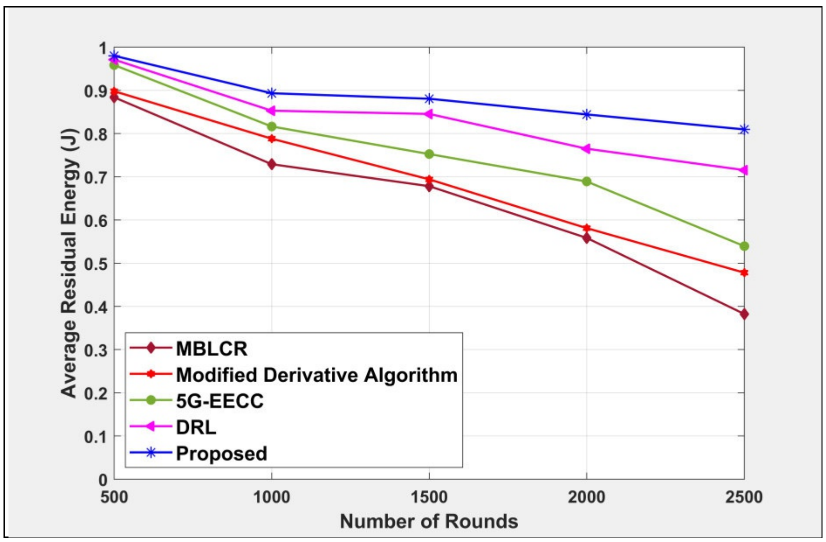


Figure 5.36: Average Residual Energy with 50 users

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.

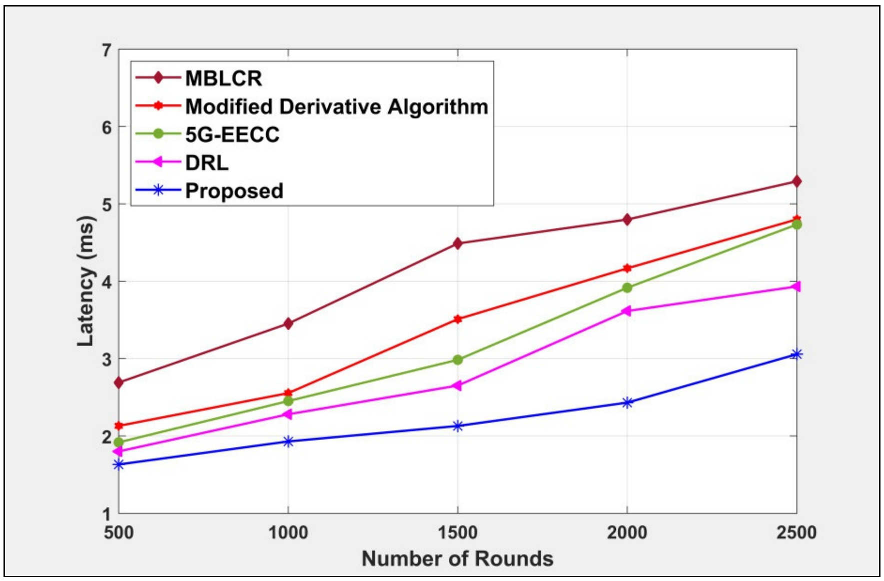


Figure 5.37: Latency with 50 users

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.

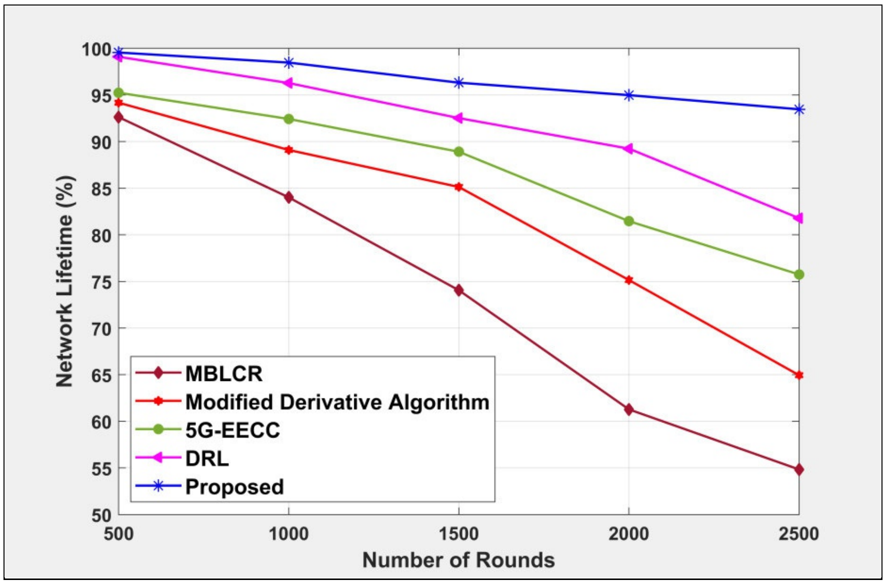


Figure 5.38: Network Life Time with 50 users

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.

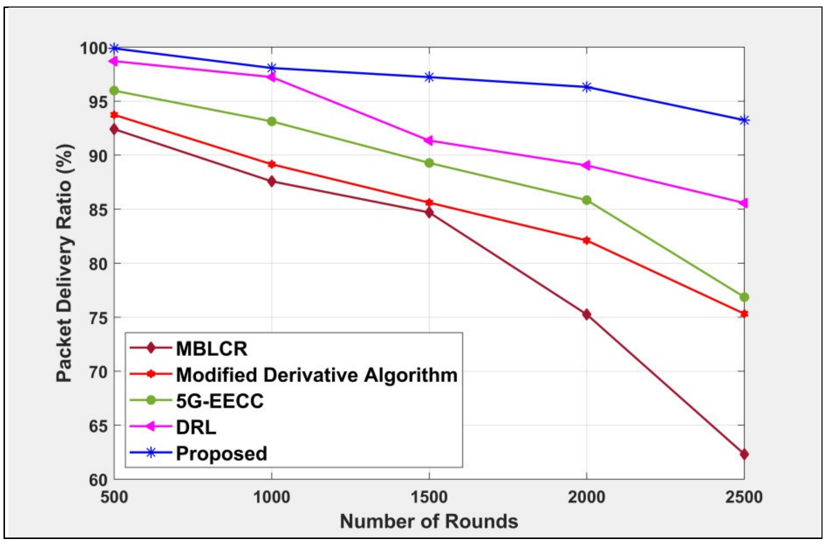


Figure 5.39: Packet Delivery Ratio with 50 users

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.

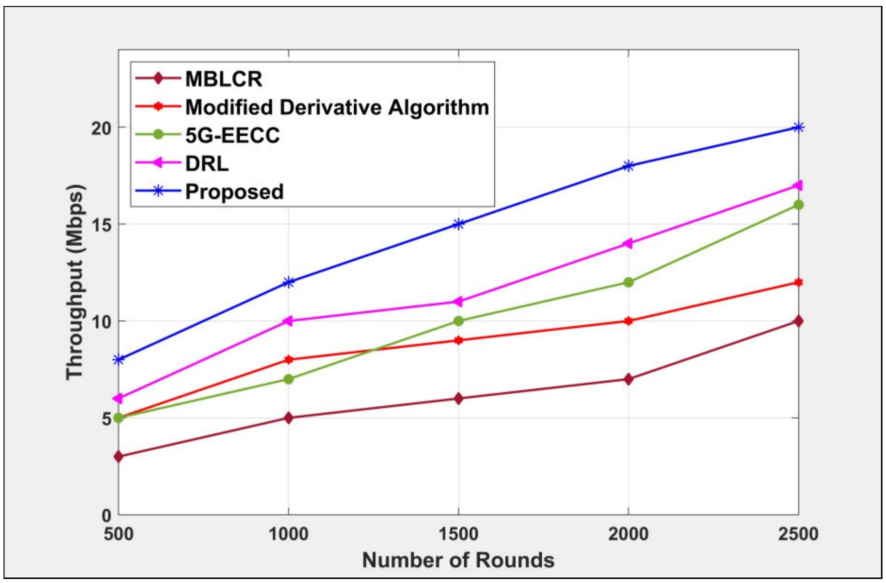


Figure 5.40: Throughput with 50 users

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.

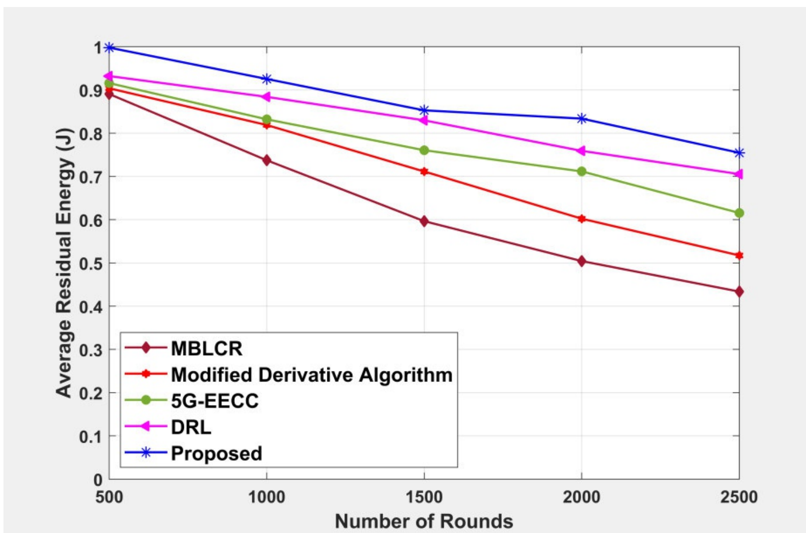


Figure 5.41: Average Residual Energy with 100 users

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.

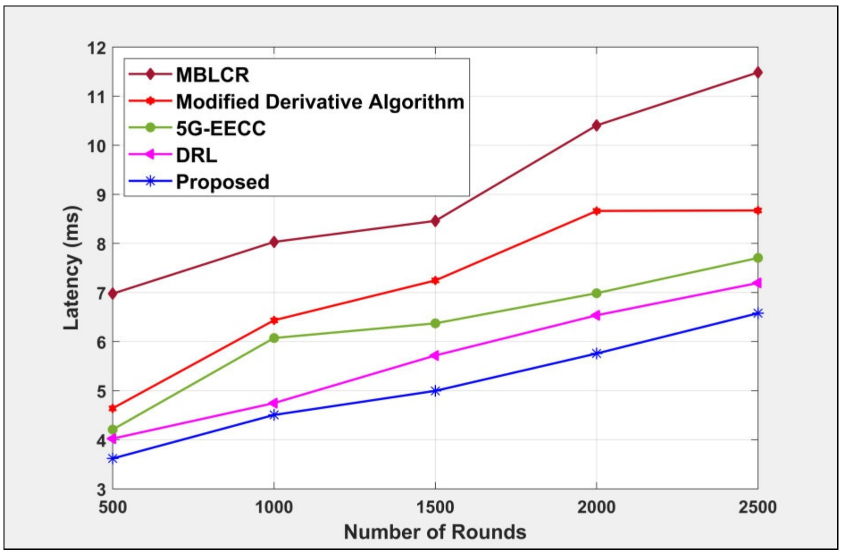


Figure 5.42: Latency with 100 users

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.

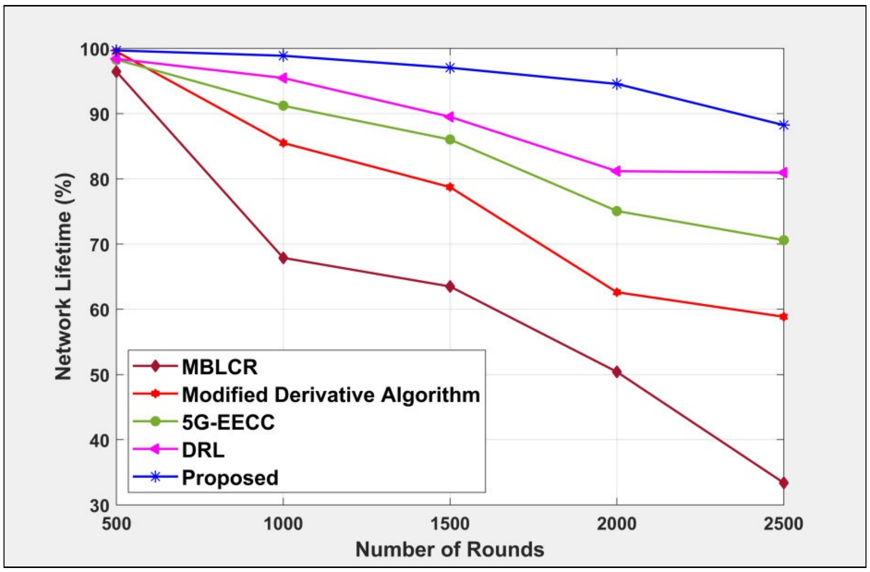


Figure 5.43: Network Life Time with 100 users

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.

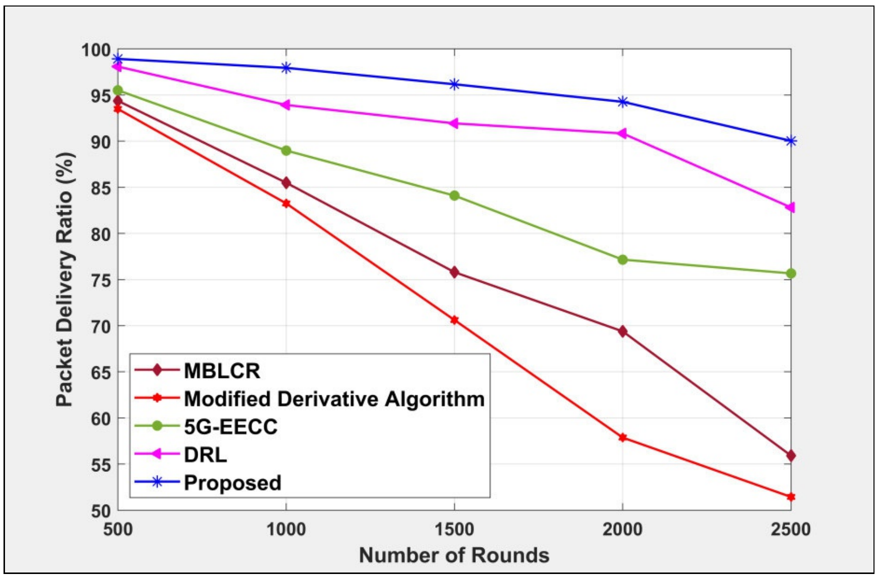


Figure 5.44: Packet Delivery Ratio with 100 users

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.

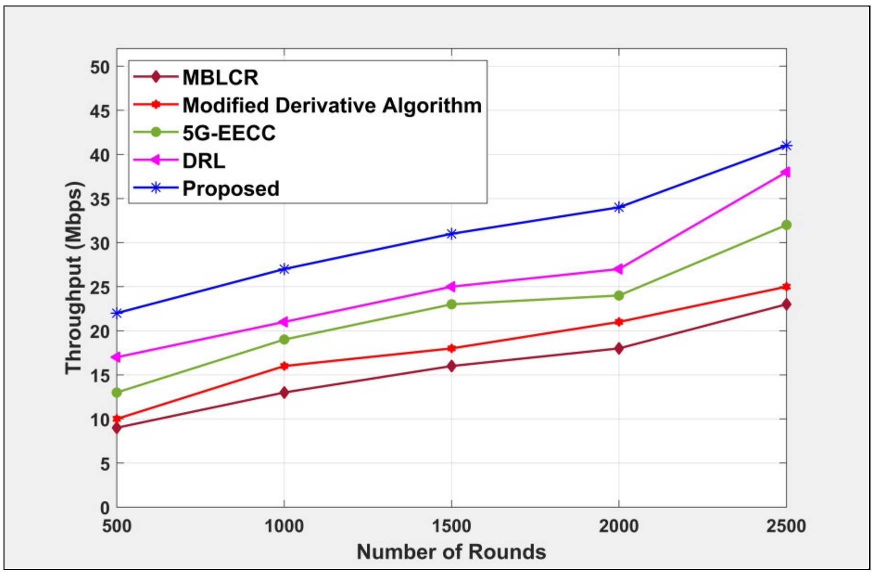


Figure 5.45: Throughput with 100 users

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.

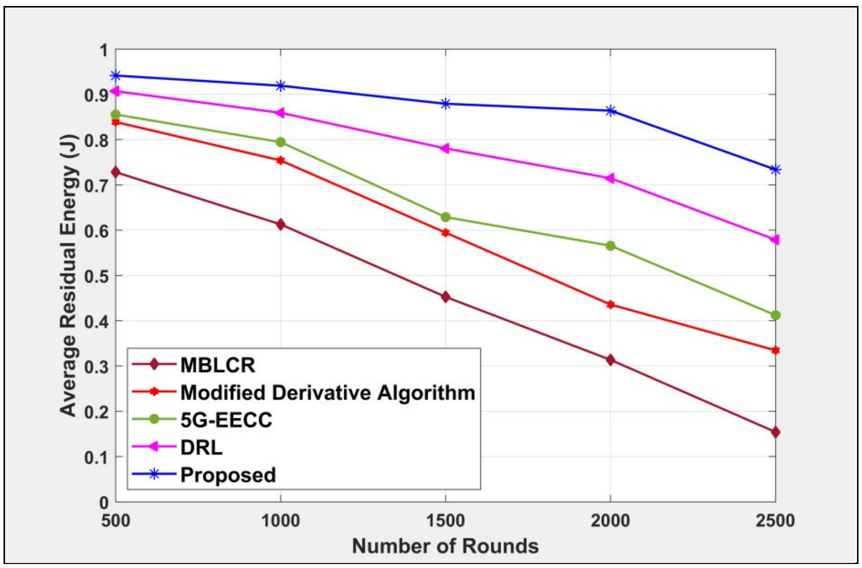


Figure 5.46: Average Residual Energy with 150 users

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.

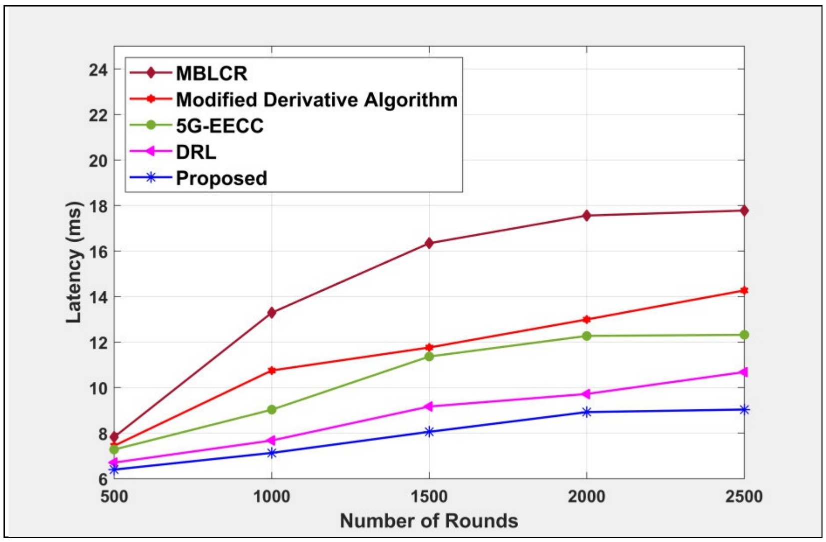


Figure 5.47: Latency based on Iteration with 150 users

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.

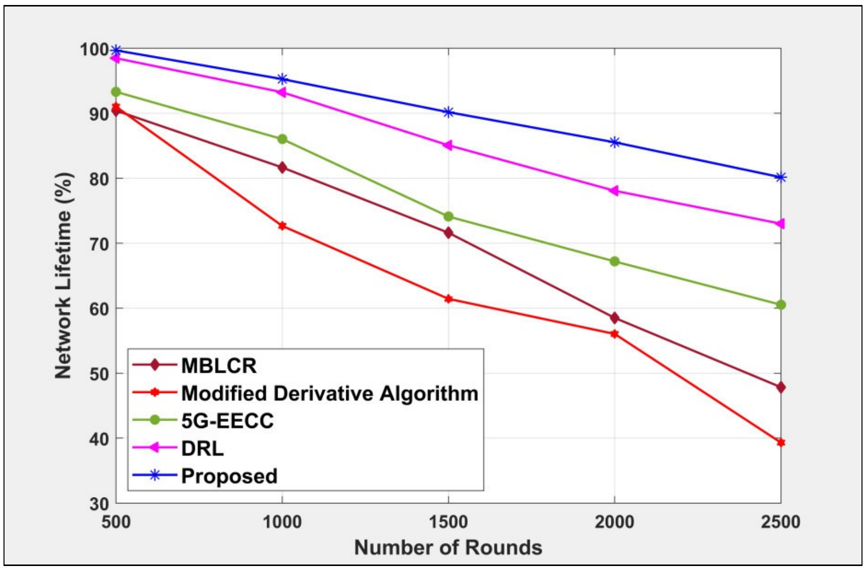


Figure 5.48: Network Life Time with 150 users

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.

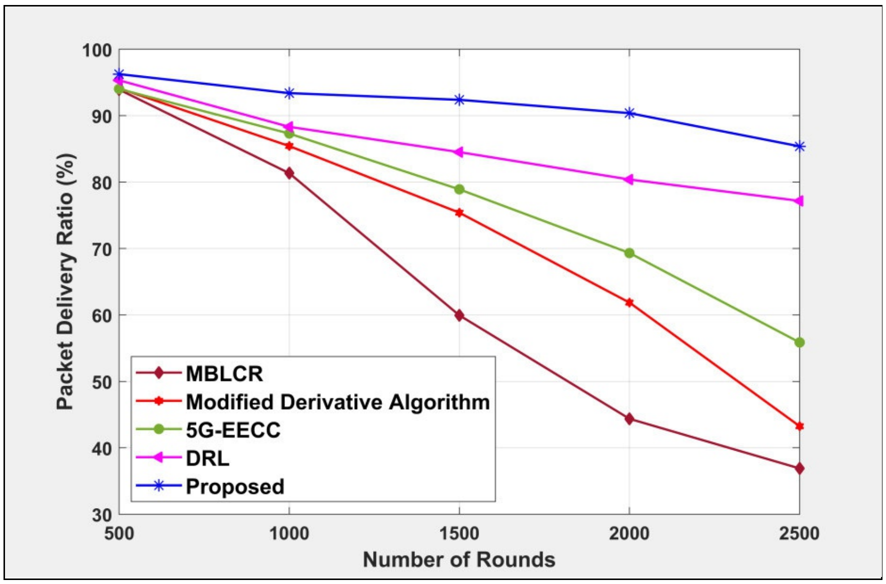


Figure 5.49: Packet Delivery Ratio with 150 users

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.

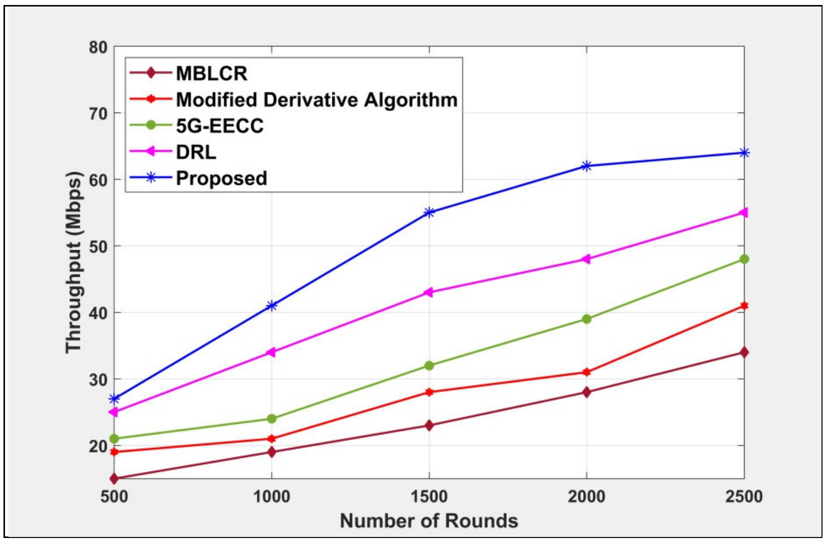


Figure 5.50: Throughput with 150 users

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.