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].

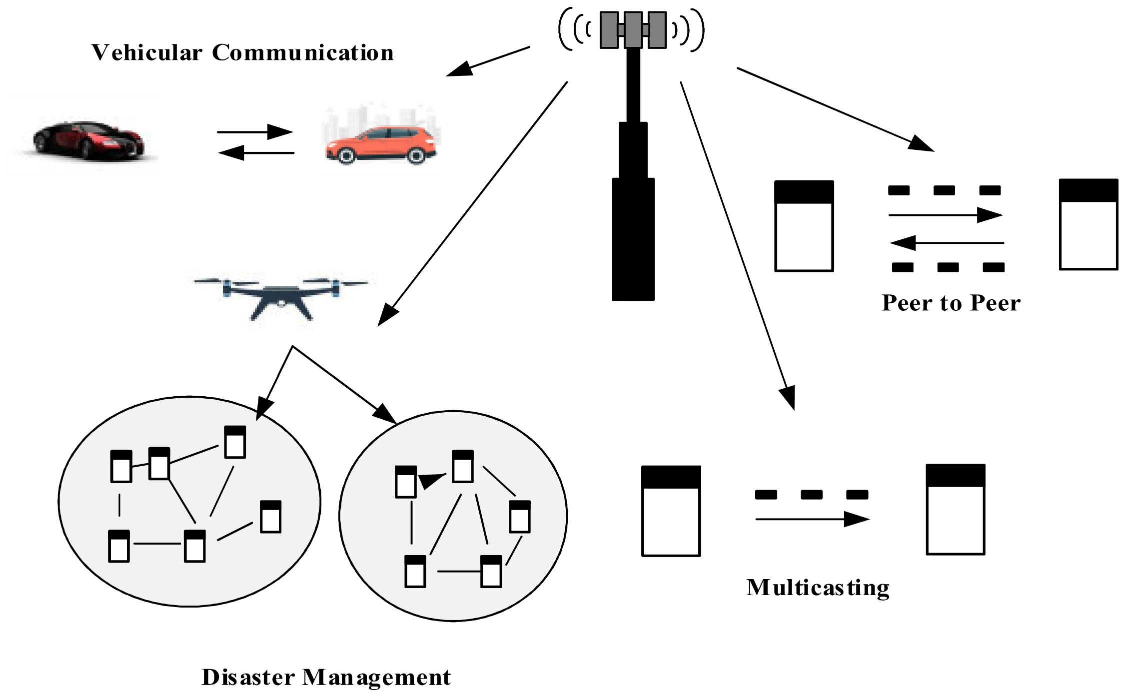

Figure 3.1: Architecture of D2D Communication

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.