CHAPTER 1
INTRODUCTION

1.1 Background

One of the enablers keys to the success of 5G technology is massive Machine Type Communication (mMTC), which has a tremendous development impact in terms of applications and services. Examples are smart houses, smart cities, smart agriculture, smart building, and smart automobile. This progression is always associated with increases in demand for high data rates, low latency, and regulated Quality of Service [1]. This growth, however, is not equivalent to the availability of frequency as a resource in communication [2]. As a result, the system needs a solution to optimize the available frequencies to provide the various services.

Device-to-Device (D2D) communication is one technology that facilitates 5G as mMTC. D2D technology enables users to send data directly without going via a base station. D2D technology is classified into two forms based on frequency: overlaying and underlying. In overlaying, D2D users utilize a distinct frequency, but in underlaying, D2D users reuse the frequency maintained by the cellular user equipment (CUE). The D2D underlying technology outperforms spectrum efficiency and network capacity due to its ability to reuse CUE's frequencies. However, the use of frequencies in several devices causes interference problems. Therefore, one solution to mitigate interference problems is to use a power allocation scheme to adjust the power transmit level between CUE and D2D to reduce the interference effect due to the same resource. Furthermore, IoT is frequently used on wearable devices or devices with limited power sources, such as batteries. Hence, besides interference problems, energy efficiency is considered due to the energy limitations of each device. As a result, the problem formulation of this thesis is to solve the interference problem by using a power allocation scheme that maximizes the system's energy efficiency [3].

In several works of literature, power allocation optimization problems are solved by utilizing an iterative Algorithm, for the examples such as Convex Approximation (CA) based algorithm [4] and Weighted Minimum Mean Square Error (WMMSE) [5]. This conventional technique employs a large number of Transmission Time intervals (TTI), which can impact performance if the system requires a real-time operation. Furthermore, iterative algorithm utilization depends on the number of devices and the size of the network [6].

Because of the limitations of traditional methods for operating in real-time systems, machine learning has emerged as the most appropriate way to overcome the limitations of real-time operation. Machine learning is described as the capacity to extract information from data and then utilize it as knowledge to adapt to the system's environment. In general, IoT devices create massive amounts of data. Machine learning can use the data to provide automated solutions for IoT services. Furthermore, Deep Learning (DL) can be employed for feature extraction and meaningful categorization. At the same time, the data availability is large and multidimensional. [7]. Therefore, Convolution Neural Network (CNN), as part of Deep Learning (DL), is utilized to replace (CA)-based algorithm for generating power allocation policies. However, the conventional method of CNN has limitations in accepting arbitrary input size. Accordingly, to the limitation of CNN, the combination of CNN with Spatial Pyramid Pooling (SPP) is used to overcome the limitation of the input size of conventional CNN [8].

This thesis utilizes deep learning to approximate iterative algorithms for generating power allocation policies. The Deep Learning method used in this thesis combines a Convolution Neural Network with Spatial Pyramid Pooling (CNN-SPP). The proposed method consists of convolutional layers, spatial pyramid pooling, and fully connected layers. To produce power control policies, CNN-SPP needs to train using datasets. The datasets utilized in this thesis are divided into two parts: channel gain as the input and power control policies as the output. In addition, the CA-based algorithm is used to create the output of the datasets. However, the datasets consist of several scenarios. Each scenario has a distinct input and output size due to varying the number of CUEs and D2D pairs, restricting the CNN from producing output efficiently. Spatial Pyramid Pooling is used to overcome the limitation of CNN to accept arbitrary input size. By placing SPP before the fully connected layer, SPP can produce a fixed size to the output of the last convolution layer, which leads to a fixed input size to the fully connected layer.

To examine the performance of proposed methods, simulation is done repeatedly to see how well all methods conduct optimal power policies. The simulation is performed by evaluating the tendency of data rate, energy efficiency, and time consumption to the number of users. Through simulation, CNN-SPP can approximate the performance of the traditional method up to 95% accuracy. Furthermore, by combining CNN with SPP, CNN's input size constraints are solved, reducing the number of models to just one. The author used CNN because CNN is a special type of neural network with powerful learning capability achieved using multi-stage feature extractions such as the Convolutional Layer, as illustrated in [9]. Compared with Deep Neural Network (DNN), which has no feature extraction, CNN is better due to the multi-stage feature extraction.

1.2 Problems Definition

In this research, the problem formulation is defined as follows:

1. In the D2D underlying communication system, interference is a very important problem to solve. The use of a power control scheme can overcome the problem of underlying D2D communication system interference. Besides power control, energy efficiency is also the main focus of this research due to the limited battery power of each device. How CNN-SPP methods approximate the CA-based algorithm method to generate power control policies for maximizing system energy efficiency in D2D underlaying with the cellular network.
2. The traditional optimization approaches, such as the CA-based algorithm, have large time consumption due to the multiple iterations used to generate power control policies that cover optimal energy efficiency. How does the performance of the CNN-SPP model in terms of data rate, energy efficiency and time consumption to the number of devices.
3. Before CNN-SPP can be used in generating power control policies, CNN-SPP must be trained using datasets. How the impact of the number of datasets used in training on the Mean Square Error of the models.
4. To see the impact of computational complexity from adding SPP modules to the CNN architecture, the Big O method is used to test the computational complexity of the CNN-SPP architectures. How the CNN-SPP architecture's computational complexity.

1.3 Releated Research

In the study [10], a channel allocation technique based on weighted bipartite matching is used to solve the interference problem. The goal of the study is to raise the system's data rate. D2D users will be assigned to the channel to boost the system's data rate. The results reveal that the system's interference level may be lowered, increasing the total rate. In research [11], the objective is to solve interference concerns by integrating channel allocation and power allocation systems. Earlier, the author defined channel allocation and power allocation as Mixed-Integer non-linear programming (MIP) problems. Then divide the problem formulation into two stages: the greedy heuristic method handling channel allocation and the dual Lagrangian method managing power allocation. The total rate has increased. However, the time complexity is significantly high as the trade-off.

In the study [12], channel allocation and power allocation strategies are combined to boost the system's energy efficiency. The author began by converting the problem formulation to a MIP problem formulation. Then, the author developed a two-layer Convex Approximation Iteration Algorithm (CAIA) to give a feasible solution. The simulation findings reveal that CAIA's performance improves the system's energy efficiency while increasing its time complexity. Research [13] solves interference with channel allocation and power control schemes with the same goal in mind. The problem formulation, a non-convex problem, is first modified into a tractable convex optimization problem. The author then devises a two-stage technique for resolving the problem. The Dinkelbach method is utilized to channel allocation, and then Lagrangian is used to handle power allocation. In general, research [10],[11], [12] and [13] are the conventional method that employ large number of iteration, hence this method is not suitable to the system with real-time operation.

Deep Learning, as part of Machine Learning, has become a popular study topic in a variety of fields due to its significant advantages over traditional approaches. For example, [14], [15], and [16] are examples of Deep Learning applications in real-time face recognition, agriculture, and healthcare, respectively. Although Deep Learning has been widely used in the computer science arena, its deployment has started to overcome various problems in wireless communication systems. Such as channel estimation, data detection, and signal classification [17].

Deep Neural Network (DNN) is utilized in research [18] to solve interference problems with the power allocation scheme. The goal of the research is to maximize the system's energy efficiency. The model of DNN consists of two modules, namely total transmit power network (Tnet) and the power allocation network (Pnet). The Pnet module determines the proportion of transmit power allocated to each user. While the Tnet module ensures that the power allocation does not exceed the maximum transmit power. DNN-based power allocation can attain near-optimal performance with a short calculation time. The research [19] employed a Convolution Neural Network (CNN) with the same goal. The CNN model consists of convolutional layers, pooling layers and fully connected layers. The CNN method outperforms the other benchmark methods and achieves similar performance to the traditional method. On the other hand, research [20] tries to overcome the problem of CNN in accepting arbitrary input size by combining CNN with Spatial Pyramid Pooling (SPP). However, the method is used for hand gesture recognition.

Several studies have been carried out to improve the system's throughput, energy efficiency, and fairness using D2D underlaying. On the other hand, interference has become the most important element affecting system performance. Interference can arise from both outside and inside the site, known as Inter-cell interference and Intra-cell interference. Some research employs a large number of Transmission Time Intervals, which is difficult to implement in a real-time system. According to the explanation, this thesis approximates the traditional iterative algorithm to produce the power allocation policies by combining the Convolution Neural Network (CNN) with Spatial Pyramid Pooling.

1.4 Research Purposes

The research objectve on this thesis are defined as:

1. Solve interference problem by using power control scheme to maximize the system's energy efficiency.
2. Design a modification architecture of CNN-SPP to overcome the limitation on input size of CNN, in order to approximate CA-based algorithm to produce power control policies.
3. Evaluate and analyze the performance of CNN-SPP in approaching the performance of CA-based algorithms to generate power control policies in parameters of:
   (a) Average system datarate.
   (b) Average system energy efficiency.
   (c) Average time consumption.
   (d) Mean Square Error (MSE).
   (e) computational complexity.

1.5 Scope of Work

The goal of this thesis is to provide an allocation technique for maximizing system energy efficiency in a D2D underlay with a multi-cell cellular network. The following are some of the areas of research that will be pursued:

1. Produce a power control policeis that maximizes system energy efficiency in the D2D underlay with a multi-cell cellular network.
2. Convolutional Neural Network as part of Deep Learning is ultilized to approach iterative method to produce power control polices

3. Put the suggested resource allocation algorithm through its paces while keeping the following constraints in mind:
   (a) Multi-cell system
   (b) The user is presumed to be stationary, therefore no handover is required.
   (c) Observation is carried out through uplink transmission.
   (d) The uplink resource block has been orthogonally preassigned to all CUE.
   (e) The power control management is focused on D2D and CUE side.
   (f) Resources owned by CUE can be utilized by several D2D pairs.
4. The proposed CNN-SPP method is compared to the conventional CNN.

1.6 Research Methodology

This work's research is separated into various phases, which are as follows:

1. Problem Formulation
   In this study, the problem formulation is done by a review of works of literature. The results of current investigations, either papers or journals from an international conference and a relevant textbook are used to create works of literature.
2. System Environment Design
   The system model is created during this stage. The system model is made up of two cells, each of which has same number of CUE and D2D pairs that are placed randomly throughout the cell and contain one Base Station. D2D pair consist of one D2D receiver and D2D transmitter. Moreover the maximum distance between the D2D transmitter and the D2D receiver is defined in order to sustain D2D connection.
3. Algorithm Design
   This stage involves creating the Convex Approximation (CA) based algorithm, CNN-SPP architecture and models in order to solve problem formulation. Furthermore, at this step, a dataset is created with channel gain as the input and power policies as the output.
4. Simulation
   The simulation will be done using computer software. All algorithms will be simulated in several scenarios to see how it performs.
5. Analysis and Conclusion
   The simulation's outcomes will be examined and discussed. CNN-SPP model is examined and compared to the CA-based algorithm as a benchmark to see if CNN-SPP can approach the performance of CA-based algorithm. Moreover, the

conclusion will be drawn based on the simulation and examination of the data. The final conclusion must address the research goals.

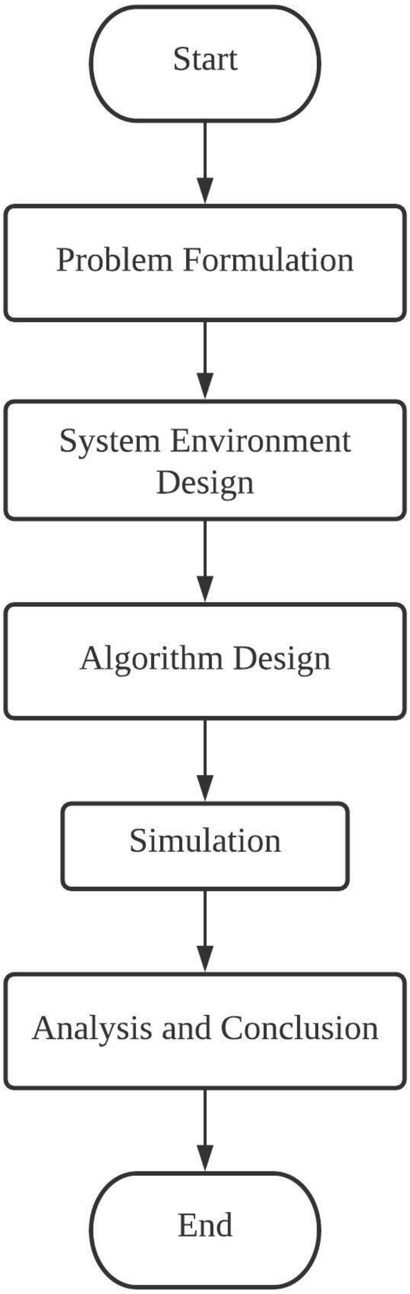

FIGURE 1.1: Reseach methodology