Thesis for the Degree of Master of Engineering

# Adaptive Deep Learning Approaches for Power Control and Modulation Recognition in Dynamic Wireless Networks

by

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적응형 딥러닝을 활용한 동적 무선 네트워크에서의 전력 제어 및 변조 분류

Advisor: Prof. Jun-Pyo Hong

by

Lưu Văn Chung

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## List of Abbreviation

| | |
|---|---|
| ADC | Analog Digital Converter |
| DNN | Deep neural network |
| D2D | Device-to-device |
| CU | Central unit |
| CSI | Channel state information |
| CNN | Convolutional neural network |
| FFN | Feed-forward neural network |
| GNN | Graph neural network |
| LSTM | Long-short term memory |
| WMMSE | Weighted sum mean-square error minimization |
| QoS | Quality of service |
| MPNN | Message passing neural network |
| MC | Modulation classification |

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The best part of graduate school at Pukyong has been the opportunity to meet and collaborate with many amazing people. Firstly, I would like to express my sincere gratitude to my advisor Professor Jun-Pyo Hong for his inspiration in our meetings, his extreme patience in guiding me in the research, and his countless hours devoted to helping me improve my writing and thinking. This thesis owes much to his contributions. I am deeply grateful to my committee for their valuable suggestions and contributions: Professor Sang-Seok Yun; to Professor Hoon Lee for his interesting courses on Linear Algebra and Optimization Theory.

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## Abstract

With a high and diverse demand for wireless communications, the optimization of communication systems became more complicated, so that the convex optimization-based traditional communication techniques are hard to satisfy the performance requirements of next-generation communication networks. To mitigate such limitations, the introduction of machine learning algorithms has received great attention. In other words, it leverages vast amounts of data to learn and adapt to optimization problems, meeting high requirements for data rate, latency, and energy consumption. However, deep learning-based approaches in modern systems have challenges with adaptability, scalability, potential inaccuracies, and suboptimal performance. To improve real-time applications, researchers and engineers must address these limitations and develop robust wireless communication systems. To this end, in this thesis, we propose a new deep learning-based power control method for maximizing the sum rate subject to rate requirements in the interference-limited device-to-device (D2D) communications and Bayesian learning approach for the modulation classification problem. For the first problem, based on the dynamic nature of D2D communications, we consider the environment where system parameters, such as the number of devices, rate requirements, and deployment area, unpredictably change over time. To deal with the low adaptability and scalability problems of the conventional deep learning-based approaches in dynamic environments, we develop an environment-adaptive power control method by leveraging graph neural network (GNN) architecture and meta-learning approach. In the developed method, we design the node feature and message update rule for GNN by taking into account the characteristics of power optimization problem and meta-train model by treating some past environments as meta-tasks. Simulation results verify that the developed method outperforms the conventional GNN-based power control methods in terms of the average sum-throughput achievement ratio by facilitating the model adaptation to new unseen environments. For the second problem, we aim to quantify the uncertainty of predictions of the deep learning model while maintain a high classification performance. Specifically, we propose a framework based on Long Short-Term Memory (LSTM) modules and Laplace approximation. The introduction of LSTM architecture into Bayesian learning not only improves the classification accuracy by effectively exploiting the temporal features but also enables to perform an uncertainty-aware incremental modulation classification. In our approach, we first pre-train the LSTM model and then use Laplace approximation on its last layer to create a lightweight model that is aware of uncertainty. Simulation results demonstrate that our method is superior to frequentist methods in terms of predicting uncertainty and classification accuracy.

# Chapter 1 Introduction

Communication systems have undergone significant transformations, transitioning from traditional methods to modern wireless technologies. Traditional communication systems relied on mathematical models to design and optimize their operations, while modern wireless communication systems leverage data-driven approaches to directly learn solutions for optimization problems. This introduction explores the characteristics of both traditional and modern communication systems, highlighting their strengths and limitations.

In traditional communication systems, the process begins with the development of a mathematical model that represents the communication system's behavior. Engineers would then design and optimize the system based on this model. However, the optimization problems associated with traditional systems are typically nonconvex, meaning they lack a simple and straightforward solution. As a result, effectively solving these optimization problems can be challenging and require sophisticated techniques.

On the other hand, modern communication systems adopt data-driven methods to address the limitations of traditional approaches. By leveraging vast amounts of data, these systems can directly learn and adapt to the optimization problems they encounter. This data-driven approach enables modern communication systems to meet high requirements for data rate, latency, and energy consumption. By learning directly from the data, these systems can achieve optimal solutions without relying solely on mathematical models.

However, conventional deep learning-based approaches in modern communication systems also have their own set of challenges. These approaches may exhibit low adaptability and scalability, making it difficult to handle dynamic environments and changing requirements effectively. Additionally, they can sometimes be overconfident in their predictions, leading to potential inaccuracies or suboptimal performance.

To enhance system performance and reliability for real-time applications, it becomes crucial to explore and address the limitations of modern wireless communication systems. By understanding the strengths and weaknesses of both traditional and modern approaches, researchers and engineers can work towards developing robust and efficient wireless communication systems that meet the demands of contemporary applications.

In the following sections, we will delve deeper into the intricacies of traditional and modern wireless communication systems, analyzing their advantages and challenges. By doing so, we aim to shed light on the potential avenues for improving system performance and reliability in real-time applications.

# Chapter 2 : GNN-Based Meta-Learning Approach for Adaptive Power Control in Dynamic D2D

## 2.1 Motivation

Device-to-device (D2D) communication is considered as one of key enabling technologies for supporting high requirements on data rate, latency, and energy consumption in 5G and beyond [1]. The main technical challenge hindering the implementation of D2D communication is the inter-device interference management. In interference channels with multiple transmitter-receiver pairs, wireless resource management problems for maximizing system performance are generally non-convex and computationally prohibitive to derive their optimal solutions [2]. To circumvent this challenge, many practical approaches have been proposed to derive satisfactory solution, ranging from traditional optimization techniques to modern data-driven ones.

The conventional optimization approaches have exploited exhaustive search with the reduced search space [3] and iterative algorithm [4]-[6] to derive satisfactory power control solution for maximizing sum-rate or guaranteeing minimum rate requirements. Nevertheless, their computational complexities are still high to derive the solution in real-time.

To overcome the limitations of the optimization approaches, the machine learning-based data-driven approaches have recently attracted great attention for the resource management. For the computational complexity reduction, the supervised learning has been adopted to mimic popular power control algorithm named weighted sum mean-square error minimization (WMMSE) [5], [7].

Although the supervised learning-based power control methods have shown to achieve the sum-rate comparable to WMMSE with the reduced complexity, they require considerable amount of WMMSE results for various channel realizations in the model training phase and cannot outperform WMMSE in terms of the sum-rate.

To remove the dependency on the traditional method, the unsupervised learning has been adapted in [8]-[11]. In [8], the primal-dual method has been exploited to train a deep neural network (DNN) without the labeled training data. In [10], [11], the unsupervised learning-based power control has additionally taken into account the energy harvesting constraint in the power-limited wireless networks. In [9], the ensemble learning method has been adopted to further improve the sum-rate performance of the unsupervised learning approach. For the interference management in a decentralized network where only the local state information is available at each device, reinforcement learning has been adopted to derive the power control method maximizing sum-rate in a distributed manner [12], [13].

Although the aforementioned deep learning-based approaches have shown to derive effective power allocation with a low computation complexity for given scenarios, they have some practical limitations in common: low scalability and low adaptability. First, the aforementioned works have the scalability problems caused by the feed-forward model architecture with fixed input and output sizes. Specifically, the feed-forward neural network (FFN) designed for a given network topology cannot utilize anymore when the network topology changes with the arrivals and departures of devices. Second, due to the low adaptability of typical training algorithm, the trained model does not work well in dynamic environments. In other words, the typical training algorithm requires significant amount of time and additional data samples for the pre-trained model to adapt to a new environment with different system parameters. In order to overcome such limitations, graph neural network (GNN) and meta-learning have recently been adopted in deep learning-based power control problems. In the GNN-based approaches [14], [15], the power control problems are translated into the parameter optimizations of GNN that is designed upon the network topology. Then, the optimized power control policies are derived by solving parameter optimization with the algorithms built on primal-dual method [14] and message passing technique [15]. Since the input and output sizes of GNN are invariant to the number of devices, the trained GNN is applicable to wireless networks of various sizes. In addition, for the rapid adaptation of GNN-based power control to time-varying network topology, the generalized model has been trained with meta-learning in [16].

In dynamic environments, not only the number of devices but also other system parameters, such as the quality-of-service (QoS) requirement and locations of devices, can change over time. Nonetheless, there has been no work on the deep learning-based power control that deals with time-varying system parameters except the number of devices [16]. Motivated by this, we propose a learning-based power control method for maximizing sum-rate subject to individual rate requirements in dynamic environments where system parameters are different between training and application phases. For the rapid adaptation of the model to a new environment with just a few samples in the application phase, we exploit GNN architecture and meta-learning approach to develop the power control method. Although the proposed method has some similarities to [16] in that both exploit GNN architecture and meta-learning, the model adopted in [16], named random edge graph neural network (REGNN), is unable to handle variant rate constraints and has a limited expressive power due to its simple node states generated by linear shift invariant filter. To deal with such limitations of REGNN in our problem, we adopt a message passing neural network (MPNN) that exploits the node states generated with expressive DNN by incorporating the node feature as well as the structural information on graph. In other words, to effectively deal with variant rate requirements, we incorporate it into the node state of wireless channel graph by means of DNN and re-design the update rule of MPNN. Through numerical simulations, we demonstrate that the proposed method outperforms the conventional learning-based power control methods in terms of the adaptability to diverse environments.

The contributions of this work can be summarized as follows:

1. We propose a deep learning-based power control method for maximizing sum-rate subject to the rate requirement in dynamic environments where system parameters are different between the training and application phases.
2. We exploit GNN architecture and meta-learning approach for the environment-adaptive and scalable power control.
3. Through numerical simulations in various environments with different network sizes, rate requirements, and deployment areas, we validated that the proposed method outperforms the conventional GNN-based power control methods in terms of the adaptability to new environments.

## 2.2 Problem Description

As We consider the indoor Internet of things (IoT) scenarios where multiple devices communicate with each other within a limited deployment area, $a \times a$. The network consists of $K$ single-antenna transmitter-receiver pairs interfering with each other and a single central unit (CU) coordinating D2D communications. With the concurrent transmission of $K$ transmitters, the received signal of the receiver $i$ is represented

$$y_i = h_{i,i}x_i + \sum_{j \in \mathcal{N}_i} h_{i,j}x_j + n_i \tag{1}$$

where $\mathcal{N}_i$ denotes a set of all transmitters except the transmitter $i$, $x_i$ denotes a symbol of transmitter $i$, $n_i \sim \mathcal{CN}(0,\ \sigma^2)$ denotes the additive noise at receiver $i$, and $h_{i,j} \sim \mathcal{CN}(0, (1 + d_{i,j}^{\alpha})^{-1/2})$ denotes channel gain of the link from transmitter $i$ to receiver $i$ for link distance $d_{i,j}$ and path loss exponent $\alpha$. We consider the block fading channel where the channel gain $h_{i,j}$ remains constant within a transmission interval and changes independently from one interval to another. With the periodic channel state information (CSI) feedback from devices, CU is assumed to have global CSI. Define $\mathbf{H}$ as global channel gain matrix where the entry in row $i$ and column $j$ is $h_{i,j}$.

Due to the low computing power of edge devices, the interference from other communication pairs is treated as additive noise. Then, the signal-to-interference-plus-noise ratio (SINR) of receiver $i$ is given by

$$\gamma_i = \frac{\left|h_{i,i}\right|^2 p_i}{\sigma^2 + \sum_{j \in \mathcal{N}_i} \left|h_{i,j}\right|^2 p_i} \tag{2}$$

where $0 \leq p_i \leq p_{max}$ denotes the transmit power of transmitter.

Each communication pair $i$ is assumed to have its individual rate requirement $r_{min,i}$ to guarantee a minimum QoS. Based on the rate requirements and global CSI, CU optimizes the powers of transmitters by solving the problem as

$$\max_{\mathbf{p}} \sum_{i=1}^{K} \log_2(1+\gamma_i) \tag{3}$$

$$\text{subject to } \log_2(1+\gamma_i) \geq r_{min,i}, \text{for i} \in \{1,2,..,\text{K}\}$$

$$0 \leq p_i \leq p_{max}$$

Where $\boldsymbol{p} = [p_1, p_2, \dots, p_K]$.

Note that we consider dynamic environments where the system parameters are time-variant. The number of devices K, the rate requirements $r_{min,i}$, and deployment area $a \times a$ can arbitrarily change after several transmission intervals. It is assumed that the transmission interval is much shorter than the environment change period. For example, Bluetooth v4.0/v4.1 and 5G for ultra-reliable low latency communications (URLLC) have the transmission intervals of 700μs and 125μs, respectively [17], [18]. If the environment is assumed to change every 0.5s, there would be 714 and 4,000 transmission intervals, respectively, before another environment change.

**Algorithm 1** MPNN-based meta-training algorithm

**Input:** node feature $\mathbf{v}_i$, for all $i \in \{1, 2, ..., K\}$;
edge feature $e_{i,j}$, for all $(i, j) \in \mathcal{E}$

Initialize model parameters $\boldsymbol{\theta}$
**repeat**
  $\mathbf{s}_i^{(0)} = \mathbf{v}_i$, for all $i \in \{1, ..., K\}$
  Randomly sample a task $\tau \in \mathcal{T}$ and set $\boldsymbol{\theta}_\tau = \boldsymbol{\theta}$
  **for** $m = 1, 2, ..., M$ **do**
    **for** $l = 1, 2, ..., L$ **do**
      Compute $\mathbf{s}_i^{(l)}$ according to (6), for all $i \in \{1, ..., K\}$
    **end for**
    Compute $L(\boldsymbol{\theta}_\tau)$ according to (7)
    Update $\boldsymbol{\theta}_\tau$ by performing one step of Adam on $L(\boldsymbol{\theta}_\tau)$
  **end for**
  Update $\boldsymbol{\theta} = \boldsymbol{\theta} + \epsilon(\boldsymbol{\theta}_\tau - \boldsymbol{\theta})$
**until** convergence
**return** $\boldsymbol{\theta}$

### 2.3 GNN-based meta-learning for environment adaptive power control

The problem (3) can be dealt with existing FFN-based learning method [9] if the system parameters are invariant. However, if the system parameters are different between training and application phases with their time-varying nature, the conventional FFN-based method may not work well in the new environment due to its poor scalability and adaptability. Especially, in case of topology change with different K, the model trained with [9] cannot even apply to the new environment due to the mismatched input and output sizes. In order to resolve such limitations, we exploit GNN architecture and meta-learning approach to develop the power control method that enables the model to rapidly adapt to a new environment with a few channel data samples.

At the beginning of the training phase, the CU is assumed to have some training data samples obtained from past transmissions. The training data samples are partitioned into some subsets, or meta-tasks, depending on which environment they come from. Specifically, a meta-task $\tau_{(K,\{r_{min,i}\}_{i=1}^{K},a)}$ is defined as a set of channel samples that come from the environment with K communications pairs, rate requirements $\{r_{min,i}\}_{i=1}^{K}$, and deployment area $a \times a$. We also define $\mathcal{T}$ as a set of meta-tasks.

Based on the mutual influence between the communication pairs, we can model wireless network as a directed graph $G = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of edges. We treat a transmitter-receiver pair $i$ as a node $i$ and a channel from transmitter $j$ to receiver $i$ as an edge $(i,j) \in \mathcal{E}$. By taking into account our optimization problem (3), we define the feature of node $i$ and the feature of edge $(i,j) \in \mathcal{E}$, respectively, as

$$v_i = \left[h_{i,i}, r_{min,i}, p_i\right]^T \tag{4}$$

$$e_{i,j} = h_{i,j} \tag{5}$$

Based on our wireless channel graph, we exploit MPNN to deal with the dynamic topology in solving the problem (3). We consider MPNN with $L$ message passing layers. In layer $l \in \{1,2,\dots,L\}$, each node $i \in \{1,2,..,K\}$ updates its internal state $s_i^{(l-1)}$ by aggregating its neighboring nodes' internal states as follows

$$s_{i,3}^{(l)} = sig\left(\phi_2\left(s_i^{(l-1)}, max\left(\phi_1\left(s_i^{(l-1)}, s_j^{(l-1)}, e_{i,j}, e_{j,i}\right)\right)\right)\right) \tag{6}$$

$$s_i^{(l)} = \left[h_{i,i}, r_{min,i}, s_{i,3}^{(l)}\right]^T \tag{7}$$

where the initial state $s_i^{(0)} = v_i$ is the feature of node $i$, $max(\cdot)$ denotes an entry-wise maximum function, $sig(\cdot)$ denotes a sigmoid function, and $\phi_1: \mathbb{R}^8 \mapsto \mathbb{R}^N$ and $\phi_2: \mathbb{R}^{N+3} \mapsto \mathbb{R}$ are multi-layer perceptrons (MLPs) that play roles of aggregation function and combination function, respectively.

Note that the aggregation function $\phi_1$ is different from its conventional definition in that the proposed aggregation function additionally takes the information of node $i$ to consider the influence on its neighboring nodes $j \in \mathcal{N}_i$.

We define a loss function for training MPNN by applying penalty method to the optimization problem (3) as follows

$$L(\boldsymbol{\theta}) = \mathbb{E}_H\left[-\sum_{i=1}^{K}\left[log_2(1+\gamma_i(\boldsymbol{\theta})) - \lambda max\{0, r_{min,i} - log_2(1+\gamma_i(\boldsymbol{\theta}))\}\right]\right] \tag{8}$$

Where $\boldsymbol{\theta}$ denotes parameters of MLPs $\phi_1$ and $\phi_1$, $\lambda > 0$ denotes a penalty coefficient, and

$$\gamma_i(\boldsymbol{\theta}) = \frac{\left|h_{i,i}\right|^2 s_{i,3}^{(L)} P_{max}}{\sigma^2 + \sum_{j\in\mathcal{N}_i}\left|h_{i,j}\right|^2 s_{i,3}^{(L)} P_{max}} \tag{9}$$

Based on the MPNN update rule (6) and loss function (8), the CU trains the model to learn a common initialization across multiple meta-tasks according to Algorithm 1 in the training phase. In Algorithm 1, $\epsilon$ denotes a learning rate and we exploit a first-order meta-learning algorithm, called reptile algorithm [19]. In the application phase, the trained model with Algorithm 1 is utilized as an initial model. At the beginning of each transmission interval, the CU collects the environment information $\left(K, \{r_{min,i}\}_{i=1}^{K}, a\right)$ and global CSI $\mathbf{H}$ from the devices. Then, the CU makes the inferences on power control, $\left\{s_{i,3}^{(L)}\right\}_{i=1}^{K}$, with the collected information and distributes the inferred power values to the respective transmitters. In the meantime, the CU fine-tunes the model with the accumulated channel samples every T transmission intervals. Eventually, when the application phase ends with another environment change, the CU treats the accumulated channel samples during the application phase as an additional meta-task for further meta-training the model.

## 2.4 Simulation

Table I: Simulation Parameters for MPNN-based meta-training algorithm

| **Parameters** | **Value** [unit] |
|---|---|
| Number of communication pairs, $K$ | 4 [pairs] |
| Path loss exponent, $\alpha$ | 3 |
| Maximum transmit SNR, $p_{max}/\sigma^2$ | 50 [dB] |
| Rate requirement, $r_{min,i} = r_{min}$ | 0.3 [bps/Hz] |
| Area of device deployment, $a \times a$ | $15 \times 15$ $[m^2]$ |
| Fine-tuning period on application phase, $T$ | 20 [transmission intervals] |
| Penalty coefficient, $\lambda$ | 200 |
| Number of iterations, $M$ | 10 |
| Learning rate, $\epsilon$ | 0.008 |
| Number of message passing layers, $L$ | 3[layers] |

The simulation parameters are set as Table I unless otherwise stated. In the meta-training phase with Algorithm 1, we exploit 27 different meta-tasks that are defined as the combinations of system parameters in Table II.

Table II: System Parameters for Meta-Tasks

| **Parameters** | **Value** [unit] |
|---|---|
| Device deployment area, $a \times a$ | $10\times 10, 15 \times 15, 20 \times 20$ $[m^2]$ |
| Number of communication pairs, $K$ | 2, 4, or 6 [pairs] |
| Rate requirement, $r_{min,i} = r_{min}$ | 0.2, 0.3, or 0.4 [bps/Hz] |

In this section, we present several simulation results to verify the adaptability of our proposed method to dynamic environments where the number of devices, rate requirements, or deployment area in application phase can be different from those in meta-training phase. Note that CU obtains a channel sample **H** of the new environment every transmission interval in the application phase. All transmitters and receivers are assumed to be deployed uniformly at random in $a \times a$ squared area. The simulations are performed under feasible channel conditions where there exists a power control vector p for satisfying the power and rate constraints. The feasible channel samples are generated in the same way as [3].

The simulation parameters are set as Table I unless otherwise stated. In the meta-training phase with Algorithm 1, we exploit 27 different meta-tasks that are defined as the combinations of system parameters in Table II. The aggregation function $\phi_1(\cdot)$ is a three-layer MLP comprising 8 input nodes, 128 hidden nodes, and 64 output nodes. The combination function $\phi_2($ $(\cdot)$ is a four-layer MLP comprising 67 input nodes, {32, 16} hidden nodes, and a single output node.

We define sum-throughput as the sum-rate that is achieved without violating the rate constraints. Hence, if any of communication pairs does not satisfy the rate constraint with the inferred power vector $\boldsymbol{p} = [s_{1,3}^{(L)} P_{max}, s_{2,3}^{(L)} P_{max}, \dots, s_{K,3}^{(L)} P_{max}]$, the sum-throughput becomes zero regardless of the sum-rate. As performance metrics, we consider the average sum-throughput achievement ratio against the genie-aided scheme that pre-trains MPNN with prior knowledge on the new environment and the probability of outage that is the event of violating the rate constraints. In simulation results, each curve is obtained by averaging out the achievement ratios of 5 different environments with 100 independent trials.

For performance comparison, we consider the benchmark methods as follows:

- Joint trained: It pre-trains MPNN with the proposed wireless channel graph according to the proposed update rule (6) with channel samples obtained from various meta-tasks belonging to $\mathcal{T}$ . However, it follows typical training method without meta-learning.
- WCGCN [15] with meta-learning: It meta-trains MPNN in the same way as the proposed method except that it adopts the wireless channel graph and update rule developed in [15].
- REGNN [16] with meta-learning: It meta-trains REGNN in the same way as the proposed method except that it adopts the wireless channel graph and update rule developed in [16].
- Fine-tuned (single env.): It pre-trains MPNN with the proposed wireless channel graph according to the proposed update rule (6) with channel samples come from a single environment.

Note that the rate requirement $r_{min,i}$ is considered in the training processes of all benchmark methods by evaluating their inferences with (7).

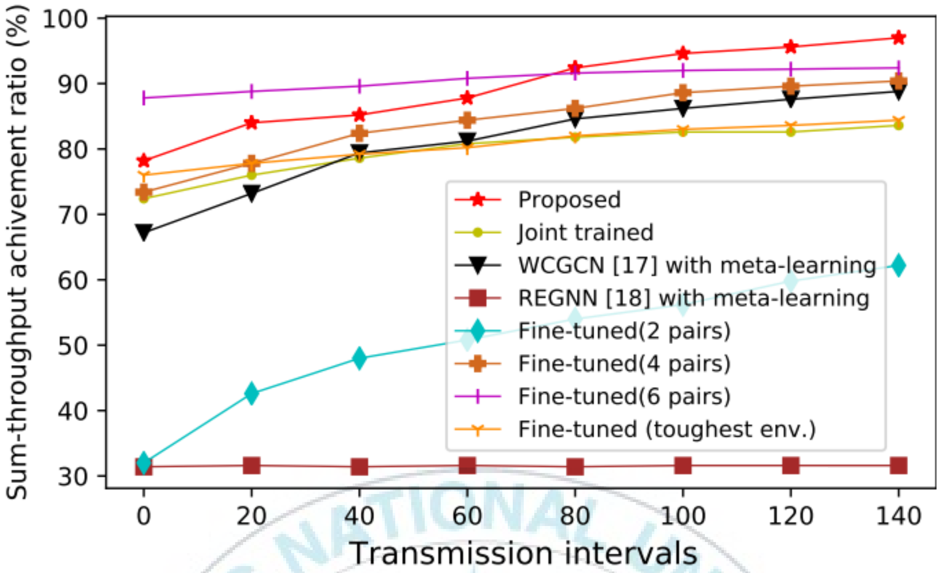


Figure 1: Sum-throughput ratio in dynamic network topology

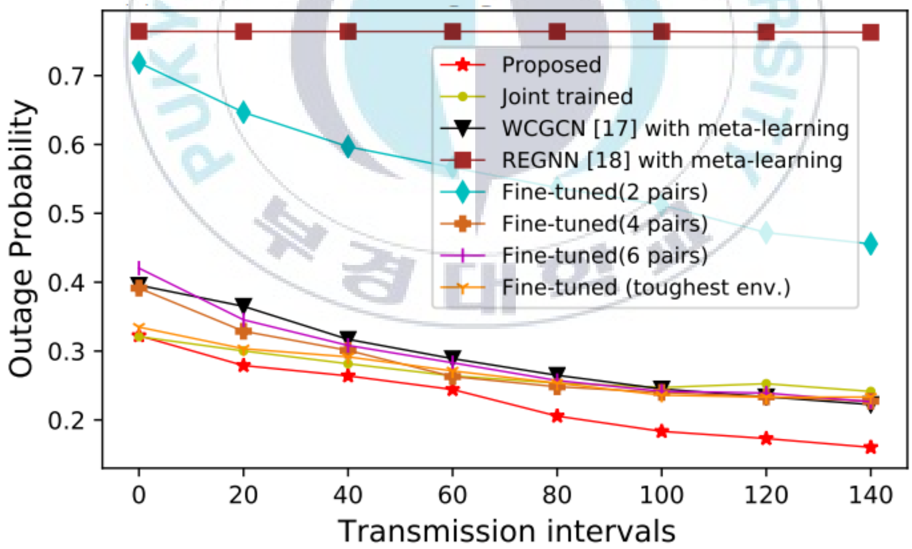


Figure 2: Outage Probability in dynamic network topology

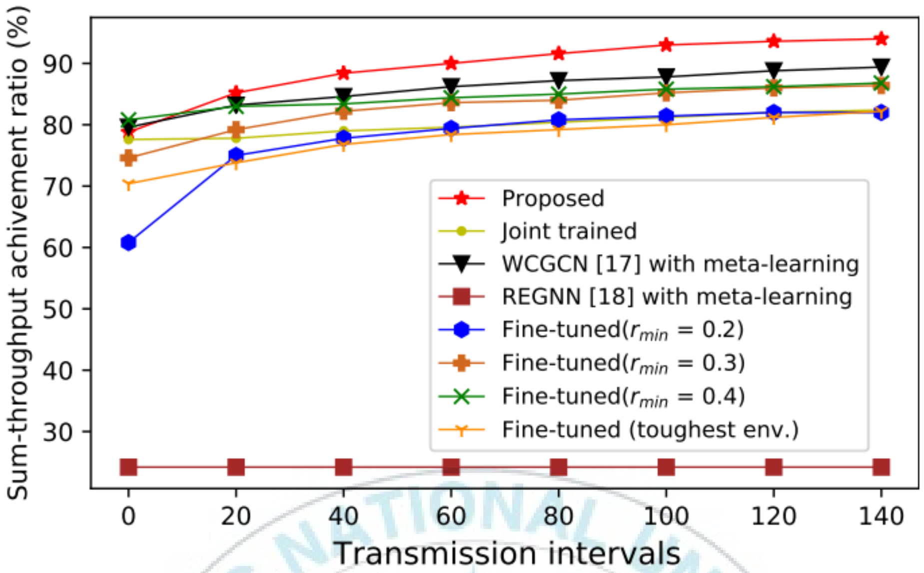


Figure 3: Sum-throughput ratio in dynamic rate requirements

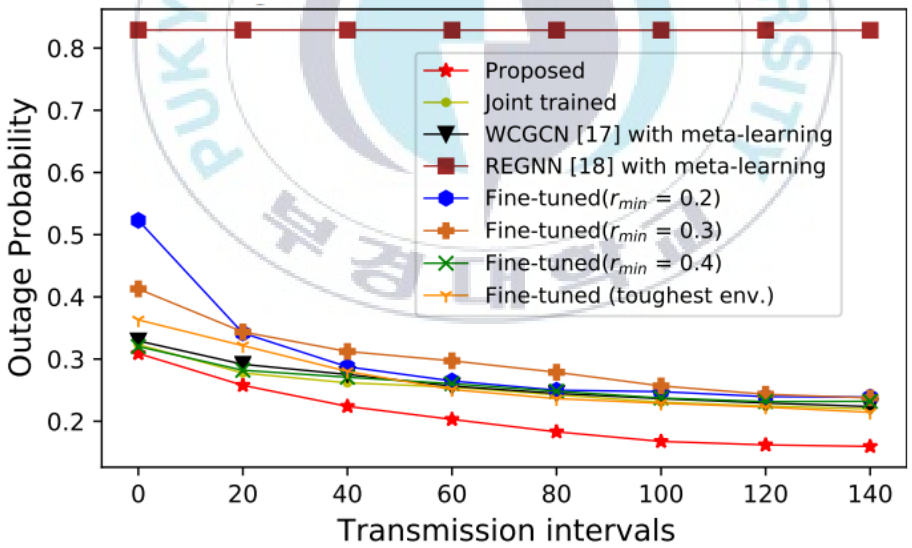


Figure 4: Outage Probability in dynamic rate requirements

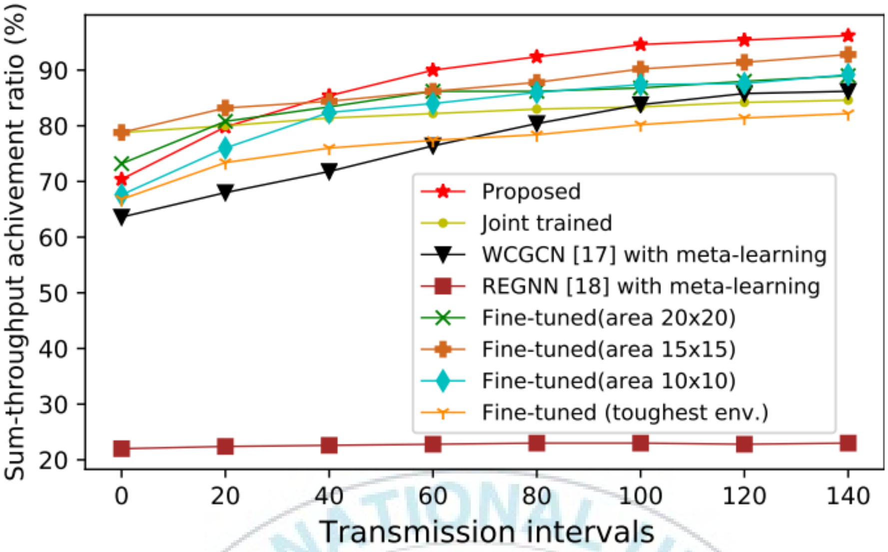


Figure 5: Sum-throughput ratio in dynamic deployment area

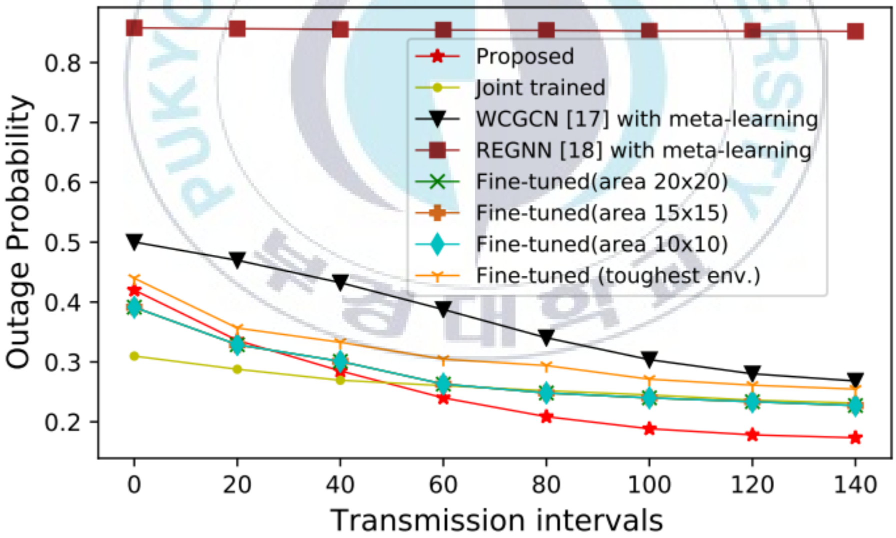


Figure 6: Outage Probability in dynamic deployment area

Figs. 1, 2, 3, 4, 5 and 6 show the adaptation progresses of the pretrained models to the environments with various number of communication pairs $K \in \{2, 3, 4, 5, 6\}$, rate requirements $r_{min} \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$, and deployment areas $a \times a \in \{5 \times 5, 10 \times 10, 15 \times 15, 20 \times 20, 25 \times 25\}$, respectively. For all types of environment changes, the proposed method is shown to outperform the benchmark methods in terms of the average sum-throughput after 80 transmission intervals. Even though the fine-tuned models for a single environment are shown to achieve relatively higher sum-throughput than the proposed method in the initial stage of the adaptation, they are outperformed by the proposed method due to their low adaptability to new environments. From the observation that the proposed method achieves higher increasing rate than the joint trained model, we can see that meta-training steps of the proposed training algorithm makes it possible to learn common initialization across multiple environments. It is interesting to note that the model fine-tuned to a tough environment with a high rate requirement ($r_{min}$ = 0.4), a large number of devices ($K = 6$), or a large deployment area ($a = 20$) is shown to achieve near-best performance in all simulation results. This is because the model fine-tuned to the tough environment can easily learn conservative power control strategy to avoid the outage event. However, as we can see from the performance of the model fine-tuned to the toughest environment (e.g. with the largest $K$, $r_{min}$, and $a$) among test environments, the training in tough environment does not always guarantee a high transferability to relatively favorable environment if there is a big difference in characteristics between those two environments. This implies that it is hard to obtain the model applicable to diverse types of environments with the conventional training method. On the other hand, the model trained with the proposed method is shown to perform well in any types of environments in virtue of meta-learning.

## 2.5 Summary

In this work, we have proposed a deep learning-based power control method for maximizing sum-rate subject to the rate requirements in dynamic environments where system parameters are different between the training and application phases. For the environment-adaptive and scalable power control, the proposed method has exploited GNN architecture and meta-learning approach. Through numerical simulations in various environments with different network sizes, rate requirements, and deployment areas, we have validated that the proposed method outperforms the conventional GNN-based power control methods in term of the adaptability to new environments.

# Chapter 3 : Reliable Modulation Classification: Laplace Approximation LSTM-Based Approach

## 3.1 Motivation

Modulation classification (MC) is the process of recognizing the modulation types at the receiver based on the received signals. It is crucial for both civilian and military applications on achieving automatic receiver configuration, interference mitigation, and spectrum management.

Traditionally, there are two types of modulation classification approaches, namely likelihood-based and feature-based techniques. The likelihood-based method [20] calculates the likelihood function of the received signal for each modulation type by constructing multiple hypothesis testing problems. Although this approach provides the optimal solution, it suffers from expensive computation costs or even mathematic intractability. Additionally, it is not effective when dealing with channel impairments like phase or frequency offset and channel fading. The feature-based techniques have lower computational complexity than the likelihood-based ones. Many kinds of features have been exploited for MC, such as the higher-order moments and higher-order cumulants of the received signal [21], cyclo-stationarity [22]. In addition, there are many other features such as instantaneous amplitude, phase, and frequency [23].

These above model-driven methods extract the key information of the various modulation types such as structure or underlying statistics to define rules for MC. This manual selection of features is less flexible and is not robust to fading, path loss, time shift, and sample rate variations.

Recently, deep learning (DL) has emerged as a promising technique for MC. This is because it has the ability to directly extract important features from the raw input data and has less complexity in the interference phase. There are a variety of applications of DL for MC. In [24], the one-dimensional convolutional layers and baseline models such as VGG and ResNet were used to handle the modulation classification task of radio signals. Other works like [25], [26] tried different convolutional neural network (CNN) architectures with the aim of reducing the size of the model and training complexity. However, due to the fixing of input, the CNN model is not suitable for input data with unknown sampling rates. This motivated authors of [27], [28] to utilize Long Short-Term Memory (LSTM).

All mentioned DL approaches above can be categorized as frequentist learning methods that output a fixed model. Frequentist models might achieve good classification accuracy but they do not have the ability to measure the uncertainty of the models. This could lead to over-confident results. More concretely, the frequentist models produce the maximum predictive probability that might not match the true accuracy. For deep learning models to be employed in real-world safety-critical applications such as healthcare or autonomous driving, they are not required to provide correct predictions, but also produce reliable confidence estimates in their predictions. For MC problem, it is desirable to assign high confidence score to modulation schemes that are adequately explained by the training data and low confidence for ones that was not presented during the training phase. Therefore, incorporating uncertainty quantification techniques is critical to enhance the robustness of DL models for MC tasks. To this end, probabilistic methods, in particular Bayesian learning, can empirically help to improve the predictive uncertainty estimates since they learn a distribution over the model parameter space. However, there is only work [30] that proposed a CNN-based Bayesian framework to deal with model misspecification and noisy training data for MC. Motivated by this, we propose an efficient learning-based MC method that can provide reliable predictions for both in-domain and out-of-domain samples with variable input data that the framework proposed in [30] is unable to handle. Specifically, we pre-train an LSTM architecture then apply the Laplace approximation [31] on its last layer. The Laplace approximation can help with increasing the uncertainty-aware ability of predictions and only constructing a Gaussian distribution over the weights of the last layer can help reduce the training cost. The simulation results reveal that the proposed approach can effectively measure uncertainty compared to the frequentist model.

### 3.2 System Model

We consider single-input single-output communication systems. The $n$-th complex baseband sample of the received signal is represented as

$$r[n] = \mathcal{H}(n, (s[n])_{n=1}^{n}) \tag{10}$$

where $s[i]$ denotes $i$-th baseband sample of the transmitted signal, $\mathcal{H}$ represents the relationship between transmitted and received sample sequences, and $N$ denotes the length of the received sample sequence for AMC. In addition to multi-path fading and additive white Gaussian noise, the channel $\mathcal{H}(\cdot)$ can encompass practical factors whose effects on the received signal are complicated to be mathematically formulated, such as pulse shaping, oscillator drift, timing offsets, carrier frequency offset, and phase difference. The sample sequence $(s[n])_{n=1}^{N}$ transmitted with the modulation scheme $c \in \mathcal{C}$, where $\mathcal{C}$ denotes a set of all possible modulation schemes. The modulation scheme is assumed to be not changed at least for $N$ samples. Due to the complicated channel model in practical scenarios, it is favorable to derive AMC method from received signal data instead of analytical information on channel $\mathcal{H}(\cdot)$. Training dataset $D_{train}$ consists of pairs of received sample sequence and corresponding modulation label, $\left((s[n])_{n=1}^{N_{train}}, c_{train}\right)$, where $N_{train}$ denotes the received sequence length of the training data. Note that the dataset may not contain the data points of all modulation schemes. According to data availability, the set $\mathcal{C}$ is partitioned into two sets, $\mathcal{C}_{in}$ and $\mathcal{C}_{out}$. In other words, the dataset $D_{train}$ consists of data points for modulation schemes $c_{train} \in \mathcal{C}_{in}$, so that the modulation classifier may receive the signal of unknown modulation $c_{train} \in \mathcal{C}_{out}$ , or out-domain data, in the test phase.

### 3.3 Bayesian Learning via Laplace Approximation

Frequentist learning aims at finding $\theta$ that minimizes the training loss:

$$\theta^* = \underset{\theta}{argmin} \sum_{r[n] \in D} \mathcal{L}(f_\theta(r[n]), c) \tag{11}$$

where $\mathcal{L}(f_\theta(r[n]), c)$ is the loss function of model $f_\theta$ evaluated at $r[n]$. The frequentist models for classification tasks provide a probability distribution is overconfident and cannot be used for predictive uncertainty quantification [31]. Therefore, Bayesian learning has been investigated to address the shortcomings of the frequentist models. Conventional Bayesian learning framework formulates an approximate distribution to the posterior and optimizes the variational lower bound with respect to the model's parameters. However, this approach often makes the model underestimate the uncertainty about the parameters [32]. In addition, deriving the distribution of parameters in all layers is expensive. To overcome this, we propose a framework based on the last layer Laplace approximation technique.

Bayesian neural networks aim at creating a probabilistic model to learn a distribution over model parameter space. In the inference phase, the model has to compute the entire posterior distribution $P(\theta|D)$. Therefore, the predictive distribution is given as

$$P(c|r[n]) = \int \phi\big(f_\theta(r[n])\big)P(\theta|D)d\theta \tag{12}$$

Where $\phi()$ is the softmax function. By applying Bayes' rule, and assuming independence between the model parameters, the posterior probability of $\theta$ given data D can be expressed as follows:

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)} = \frac{P(D|\theta)P(\theta)}{\int P(D|\theta)P(\theta)d\theta} \tag{13}$$

Where $P(\theta)$ is the prior probability on $\theta$, $P(D|\theta)$ denotes likelihood of model parameters.

In practice, calculating the posterior is computationally prohibitive or even intractable. Therefore, it is necessary to approximate the posterior. To this end, we use the Laplace approximation for approximating the posterior. In Laplace, we can approximate the posterior by Gaussian approximation as $P(\theta|D) \approx \mathcal{N}(\mu, \Sigma)$ with $\mu = \theta_{MAP}$(we first train the model $f_\theta$ by classical backpropagation) and $\Sigma = (-\nabla^2 \log P(\theta|D)|_{\theta_{MAP}})^{-1}$, the inverse Hessian of the negative log-posterior at the mode. Yet, an approximation with full Hessian is still computationally expensive. A faster wat is to fix all but the last layer of $f_\theta$ and only apply the Laplace approximation on the last layer $\theta^{(L)}$

$$P\big(\theta^{(L)}\big|D\big) \approx \mathcal{MN}\Big(\theta^{(L)}\Big|\theta_{MAP}^{(L)}, U^{(L)}, V^{(L)}\Big) \tag{14}$$

Where $\mathcal{MN}$ is the Matrix Normal distribution; $U^{(L)}, V^{(L)}$ are the Kronecker factorization of the Hessian matrix $\Sigma \approx U^{(L)} \otimes V^{(L)}$. Specifically, they are given as

$$U^{(L)} = \left(\sqrt{|D|}\boldsymbol{K_1} + 1/\sigma_0^2\boldsymbol{I}\right)^{-1} \tag{15}$$

$$V^{(L)} = \left(\sqrt{|D|}\boldsymbol{K_2} + 1/\sigma_0^2\boldsymbol{I}\right)^{-1} \tag{16}$$

Where $\boldsymbol{K_1}, \boldsymbol{K_2}$ are obtained via KFAC algorithm [33] which approximates the curvature by Kronecker, $\boldsymbol{I}$ is the identity matrix, and $\sigma_0^2$ is prior variance and is treated as a hyperparameter [32].

Let $\Phi$ be the first L-1 layers of $f_\theta$, seen as a feature map. The distribution over $z = \theta^{(L)}\Phi(r[n])$ is given as

$$P(z|r) = \mathcal{N}\left(z\middle|\theta_{MAP}^{(L)}, \Phi(r), \left(\Phi(r)^T V^{(L)} \Phi(r)\right) U^{(L)}\right) \tag{17}$$

Then, the predictive distribution is calculated as

$$P(c|r, D) = \int \phi(z)\, \mathcal{N}\left(z\middle|\theta_{MAP}^{(L)}, \Phi(r), \left(\Phi(r)^T V^{(L)} \Phi(r)\right) U^{(L)}\right) d(z) \tag{18}$$

Which can be approximated by the Monte-Carlo integral. The summary is in Algorithm 2.

**Algorithm 2** LSTM-based Laplace approximation algorithm

**Input:** A pre-trained LSTM network $f_{\boldsymbol{\theta}}$, $\boldsymbol{\theta}_{MAP}$ is the weights in the last layer of $f_{\boldsymbol{\theta}}$, cross-entropy loss $\mathcal{L}$, training dataset $D_{train}$, mini-batch size $b$, prior variance $\sigma_0^2$

**for** $i = 1, 2, ..., |D_{train}|/b$ **do**
    Sample a mini-batch $(\boldsymbol{x}_i, \boldsymbol{c}_i)$ of size $b$ from $D_{train}$
    $\boldsymbol{K}_1^{(i)}, \boldsymbol{K}_2^{(i)} = KFCA\Big(\mathcal{L}(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i)), \boldsymbol{C}_i\Big)$
    $\rho = min(1/(i+1), 0.95)$
    $\boldsymbol{K}_1 = \rho \boldsymbol{K}_1 + (1-\rho)\boldsymbol{K}_1^{(i)}$
    $\boldsymbol{K}_2 = \rho \boldsymbol{K}_2 + (1-\rho)\boldsymbol{K}_2^{(i)}$
**end for**
$\boldsymbol{U}^{(L)} = (\sqrt{|D_{train}|}\boldsymbol{K}_1 + 1/\sigma_0^2 \boldsymbol{I})^{-1}$
$\boldsymbol{V}^{(L)} = (\sqrt{|D_{train}|}\boldsymbol{K}_2 + 1/\sigma_0^2 \boldsymbol{I})^{-1}$
$\Sigma = \boldsymbol{U}^{(L)} \otimes \boldsymbol{V}^{(L)}$
**return** $\Sigma$

## 3.4 Simulation

Table III: Simulation Parameters for modulation classification

| **Parameters** | **Value** [unit] |
|---|---|
| Signal-to-noise ratio, $SNR$ | 10 [dB] |
| Input sequence length | 128 |
| Number of LSTM layer | 2 |
| Prior variance, $\sigma_0^2$ | 0.0005 |

This section presents a comparison of the proposed framework and the Frequentist methods in terms of classification accuracy and the average confidence score of output predictions. The evaluation involves two experiments: in-domain and out-of-domain testing data samples. In the in-domain setting, the testing data has the same distribution as the training data and the objective is to compare the accuracy and confidence of the proposed and Frequentist models. In the out-of-domain setting, both models are trained using the same data and then tested on unseen data samples. Overall, the evaluation aims to provide a comprehensive analysis of the proposed framework's effectiveness and compare it against a standard method. We use the RadioML2016.10a dataset [34]. This dataset contains 220K vectors of IQ samples of signals comprising 11 modulation schemes (BPSK, AM-DSB, AM-SSB, QPSK, 8PSK, 16QAM, 64QAM, BFSK, CPFSK, WB-FM). In addition, this dataset has many realistic channel imperfections such as channel frequency offset, sample rate offset, and additive white Gaussian noise along with multiple paths.

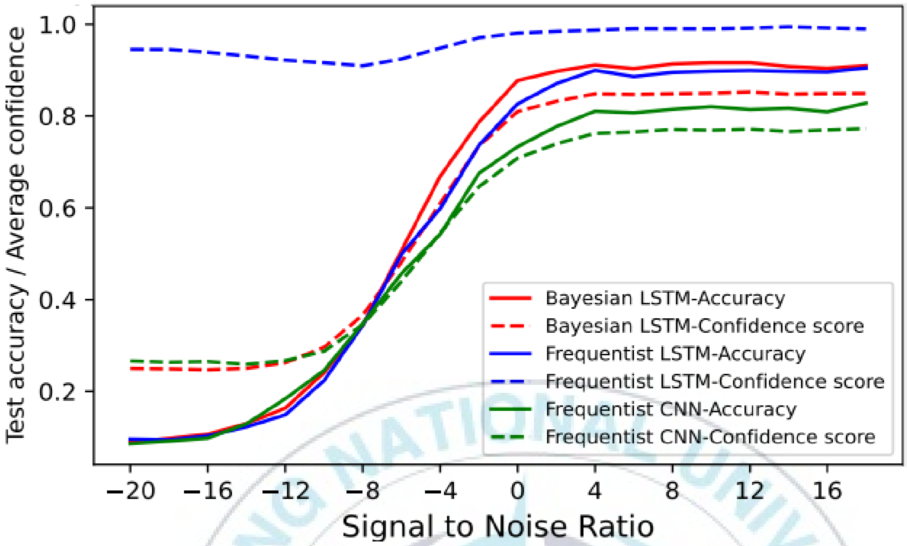


Figure 7: Accuracy and confidence versus SNR on in-domain data

The initial simulation aims to evaluate the accuracy and uncertainty of the frequentist and proposed models under varying signal-to-noise ratio (SNR) and input sequence lengths. Both models are trained on all 11 classes, and the test data follows the same distribution as the training data. Figure 7 shows the classification results and average confidence score for the three methods across different SNR on the test data. SNR ranges from -20 dB to 18 dB with a step size of 2 dB. The results indicate that LSTM architecture achieves a high classification accuracy of approximately 90% in the high SNR regime while CNN architecture shows a lower accuracy at around 80%. In terms of confidence score, at low SNR levels, both the frequentist and Bayesian models produce highly confident outputs. However, as the SNR increases, the Bayesian model becomes better calibrated, with the confidence score more closely matching the accuracy. In contrast, the frequentist LSTM model produces consistently overconfident outputs with an average score of nearly 1 across all SNR regimes, which significantly exceeds the actual accuracy. This disparity underscores the importance of uncertainty quantification in improving model calibration and reliability. It is interesting that the frequentist CNN has a good calibration.

Figure 8 presents the classification accuracy and average confidence score under the variable input sequence data samples setting. The input sequence length varies from 8 to 128 with a step size of 8. Note that during the training phase, the input sequence is 128. In terms of accuracy, the performance of both LSTM approaches grows as the input sequence increases. For the quantifying uncertainty purpose, the same behavior as in the varying SNR experiment is observed. The Frequentist LSTM model consistently produces over-confident predictions, while the Bayesian model is slightly confident when the input sequence length is below 40 but becomes increasingly less confident as the sequence length increases. In this setting, CNN model does not work because it can only handle a fixing input data.

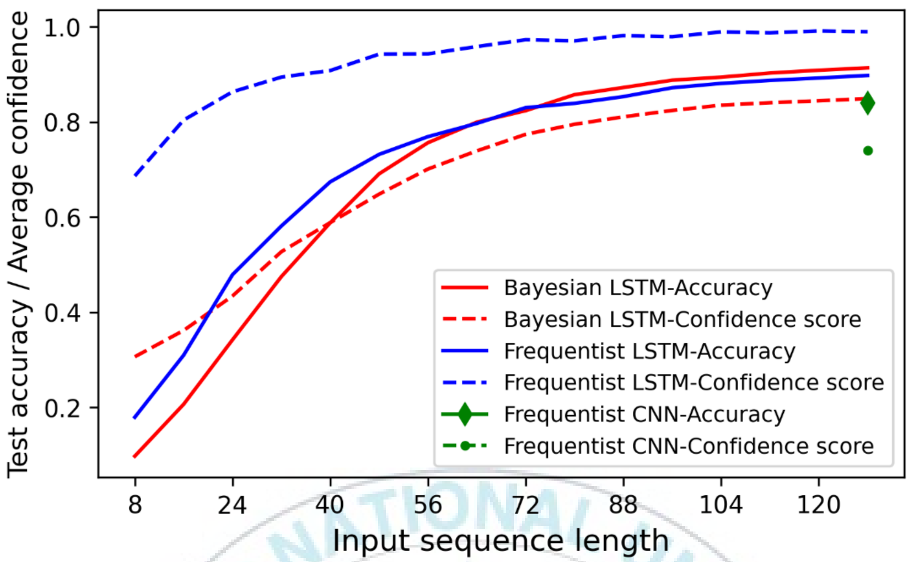


Figure 8: The accuracy and confidence versus input sequence length on in-domain data

In the second simulation, we investigate the ability to measure the uncertainty for out-of-domain data samples of the frequentist and the proposed models. Particularly, we use 10 classes for training, and modulation type PAM4 is left for testing. In Figure 9, we show the average confidence versus modulation types for 1000 input samples. It is clear that the frequentist models are too confident and mostly predicts the input sequence as BPSK or QAM64 with a confidence score of around 0.8 and 1.0, respectively. The proposed approach performs better than the frequentist ones since its predictions are diverse with the highest confidence score for BPSK at only 0.25.

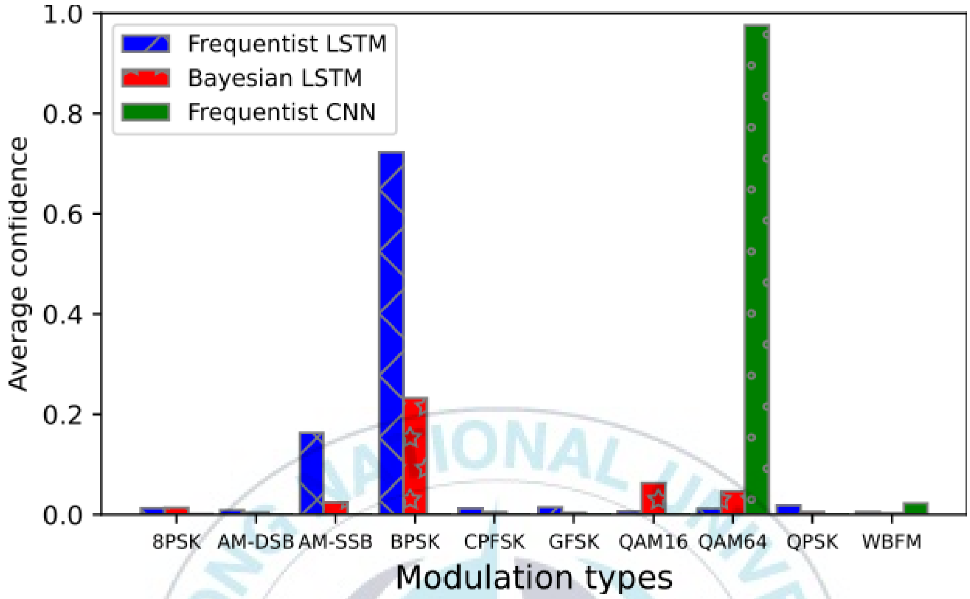


Figure 9: The average confidence score on out-of-domain data PAM4

Figure 10 and 11 show the average confidence score at varying input sequence length and SNR, respectively, when the input samples are out-of-domain data PAM4. In both cases, the frequentist models produces highly confident predictions with a score of 1.0. The proposed framework, on the other hand, has less confidence compared to the frequentist model. For variable input sequence length, as the sequence length grows, the confidence score increases but it keeps unchanged at 0.4 when the sample length reaches 128. For varying SNR setups, the confidence is always around low, at around 0.4.

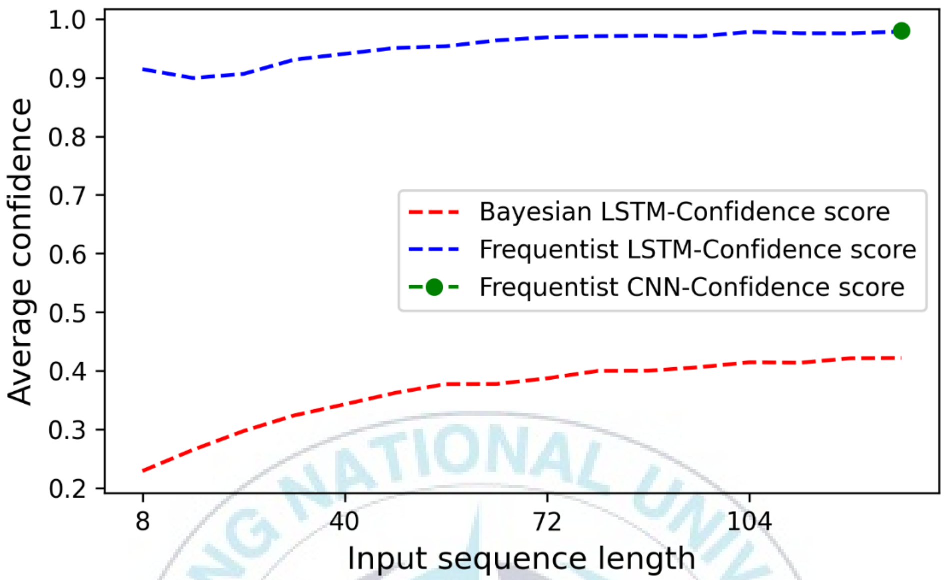


Figure 10: The average confidence score on out-of-domain data PAM4

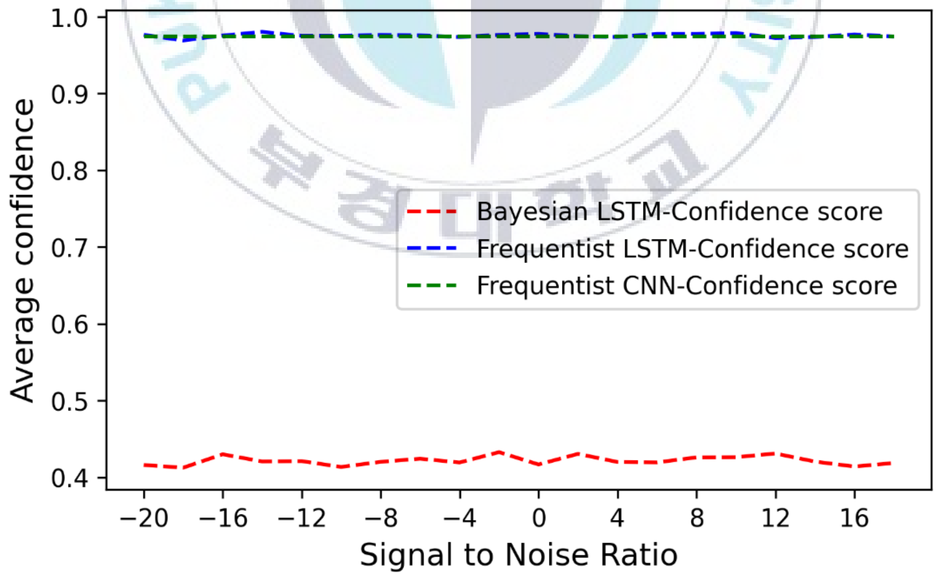


Figure 11: The average confidence score on out-of-domain data PAM4

## 3.5 Summary

This chapter has proposed a last-layer Laplace approximation method for quantifying the uncertainty of predictions of deep learning models for modulation classification. Specifically, we use an LSTM module as a pre-trained model, then we apply Laplace approximation on its last layer to reduce the training complexity and increase the ability to quantify the uncertainty of predictions. Simulation results on RadioML2016.10a dataset have validated the effectiveness of the proposed framework in terms of accuracy and ensuring the calibration of the predictions, especially when dealing with out-of-domain data samples.

# Chapter 4 Conclusion

In conclusion, this thesis presented two significant contributions to the field of wireless communications. The first work focused on adaptive power control for device-to-device (D2D) communications in dynamic environments with changing system parameters. To enhance adaptability and scalability, a novel approach using a Graph Neural Network (GNN)-based meta-learning method was proposed. This method leveraged the power of meta-learning to adapt to varying conditions, enabling efficient power control in dynamic D2D communication scenarios. The results demonstrated improved adaptability and scalability compared to traditional approaches, highlighting the potential of GNN-based meta-learning in optimizing power control strategies. The second work addressed the challenge of reliable modulation classification, a vital task in wireless communication systems. Recognizing the variability in input sequence length and the need to quantify prediction uncertainties, a Bayesian-based Long Short-Term Memory (LSTM) framework was proposed. This framework combined the strengths of Bayesian inference and LSTM networks to accurately classify modulation schemes while providing uncertainty estimates for the predictions. The experimental results validated the effectiveness of the proposed framework in achieving reliable and robust modulation classification, even in scenarios with varying input sequence lengths. Both works demonstrated the potential of advanced techniques in enhancing the performance and reliability of wireless communication systems. The application of a GNN-based meta-learning method in adaptive power control for D2D communications provided a flexible and scalable solution to cope with changing environmental conditions. Similarly, the Bayesian-based LSTM framework for reliable modulation classification offered a reliable and uncertainty-aware approach to accurately classify modulation schemes. Overall, these contributions contribute to the body of knowledge in wireless communications by addressing key challenges in dynamic environments and modulation classification. The proposed methods provide valuable insights and foundations for future research and development in these areas. By continuously exploring and improving adaptive techniques and uncertainty quantification methods, we can strive towards more efficient, reliable, and resilient wireless communication systems in various real-world applications.

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