AI for Link Adaptation and Energy Prediction in Realistic 5G Networks

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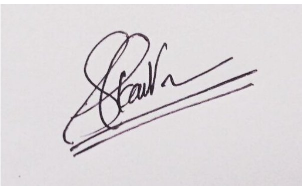
Declaration

I hereby declare that this dissertation entitled *"AI for Link Adaptation and Energy Prediction in Realistic 5G Networks"* is the result of my own independent work, carried out under the supervision of Professor Evgeny Osipov.

All sources of information used in this work have been duly acknowledged and referenced in the text and bibliography. No part of this dissertation has been submitted for a degree or diploma at any other university or institution of higher learning.

I understand that any form of plagiarism or academic dishonesty will be treated as a serious offence in accordance with the regulations of the Erasmus Mundus Green Networking and Cloud Computing program.

Signature



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Abstract

As 5G networks grow in complexity, ensuring efficient spectrum use and energy consumption has become a critical challenge—one where AI offers significant promise. This paper explores AI-driven optimization of link adaptation in 5G standalone networks, focusing on MCS prediction using SINR and CQI as input. With more than 20,000 samples generated through 5G-LENA simulations, several supervised models, including CNN, LSTM, and contextual variants, were evaluated. While overall classification accuracy remained modest (52–55%), recurrent models outperformed others, aligning with prior research on temporal dependencies in wireless channels.

Parallel efforts in energy modeling used a public dataset of 5G base station activity. Traditional regressors struggled with high error, but a neural model inspired by Chen et al. (2024). achieved a MAPE of 5.5%, underscoring the importance of temporal and contextual features in forecasting energy use.

Together, these results highlight the practical potential of AI in 5G network optimization while emphasizing the need for richer datasets and more temporally expressive models.

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1 INTRODUCTION

The transition to fifth-generation (5G) networks has unlocked new capabilities in mobile communication, from enhanced mobile broadband to ultra-reliable low-latency services. As this infrastructure matures, its optimization is guided by a dual imperative: achieving ever-higher levels of performance and reliability while ensuring the network's long-term environmental and economic sustainability. Balancing these often-competing objectives is a central challenge in modern network engineering.

On the performance front, a central mechanism is link adaptation, where the network adjusts transmission parameters to match fluctuating channel conditions. The key decision in this process is the selection of the Modulation and Coding Scheme (MCS), which directly dictates the trade-off between data throughput and reliability. Traditional methods rely on reactive feedback from the user, but this feedback is often delayed, causing the network to use an MCS that is mismatched to the real, instantaneous channel state. This inefficiency—leading to either underutilized capacity or wasteful retransmissions—highlights a clear opportunity for a more proactive approach, where future channel conditions are predicted to select the optimal MCS in advance.

In parallel, on the sustainability front, the energy consumption of the Radio Access Network (RAN) has become a critical concern for operators due to its significant operational cost and environmental impact. The majority of this energy is consumed by base stations, whose power draw fluctuates based on traffic load, hardware state, and transmission parameters like the MCS. To implement effective energy-saving strategies, such as intelligent sleep modes or load balancing, operators require granular and accurate energy forecasts. Simple historical averaging is insufficient for dynamic 5G environments. This creates a need for sophisticated modeling techniques that can predict a base station's future energy consumption based on its specific operational context.

The primary research challenge impeding this goal lies in the transition from conventional reactive network control to proactive, AI-driven optimization. Traditional systems are designed to react to network events based on feedback that is often delayed and imperfect. For example, by the time a base station receives a channel quality report and adjusts the MCS, the actual channel conditions may have already changed, leading to a persistently suboptimal configuration. A proactive paradigm, in contrast, aims to overcome this inherent latency by forecasting future network states. By predicting what the channel will be like in the next moments, the network can make optimal decisions in advance, leading to higher spectral efficiency, improved reliability, and reduced resource wastage.

The need for both proactive link adaptation and predictive energy forecasts points directly toward solutions based on Artificial Intelligence (AI). However, the implementation of effective AI in the 5G RAN is fraught with well-known research challenges. A persistent data problem is foremost among them: the scarcity of real-world, high-resolution data necessitates the use of simulators for performance models, which introduces a "sim-to-real" gap. This data issue is compounded by the inherent complexity and speed of the 5G environment. AI models must learn from a non-stationary wireless channel that changes rapidly. This task requires the capture of intricate, non-linear temporal dependencies that are simply too difficult for conventional methods to handle.

The aforementioned challenges lead to the central research problem of this work: how can proactive AI models be effectively developed for the distinct yet interconnected tasks of 5G link adaptation and energy forecasting? Due to disparate data sources—simulated for the former, real-world for the latter—these tasks are rarely studied in conjunction, creating a research gap. The consequence of this separation is a limited understanding of how AI-driven performance optimization might impact real-world energy consumption, and vice-versa. Therefore, this thesis addresses this problem by systematically developing and analyzing AI models for each task on its own terms, providing critical insights into their individual efficacy and paving the way for their future integration.

This thesis addresses the research problem by seeking to answer the following key questions:

RQ1: How effectively can an AI model learn to predict the optimal MCS from simulated, time-series data, and what are the limitations imposed by a realistic, imbalanced dataset?

RQ2: How precisely can the energy consumption of 5G base stations be forecasted using real-world operational logs, and what are the most influential predictive features?

RQ3: What foundational insights do these separate modeling efforts provide for the future development of a unified, dual-objective optimization framework for 5G networks?

To answer these key questions, the following four research objectives were defined and pursued:

RQ1: RO1: Develop and evaluate a temporal AI model for proactive MCS prediction. This objective involved using a custom-generated, realistic dataset from the 5G-LENA simulator to investigate the impact of inherent data imbalance on model performance.

RQ2: RO2: Design and assess an AI model for granular energy forecasting. This was accomplished using a real-world operational dataset, with a specific focus on identifying the most influential features for predicting energy consumption.

RQ3: RO3: Synthesize findings and formulate practical recommendations. This objective involved analyzing the results from both predictive models to provide foundational insights for a future strategy that balances network performance with sustainability.

RO4: Investigate the industrial relevance of the proposed techniques. This involved collaborating with our industry partner, Effnet AB, to identify the practical utility and potential integration pathways of the AI-driven models.

This work is situated at the intersection of technological advancement and sustainable development. By creating AI-driven tools to enhance the efficiency of 5G networks, this research contributes directly to the goals of building more innovative and sustainable infrastructure (SDG 9). As 5G becomes the foundation for smart cities (SDG 11), managing its energy footprint becomes a crucial form of climate action (SDG 13). The models developed in this thesis provide a tangible method for operators to understand and manage this footprint, supporting a more sustainable digital future.

The remainder of this thesis is structured to systematically fulfill these objectives and answer the guiding research questions. Section 2 provides a comprehensive review of the relevant academic literature, situating this work within the current state of the art. Section 3 briefly discusses the institutional and foundational context relevant to the study. Section 4 details the research methodology, outlining the distinct modeling approaches for link adaptation and energy forecasting, and includes the critical steps of data acquisition and preprocessing. Section 5 presents a comprehensive evaluation of the developed models' performance. Section 6 then analyzes these results, discussing their implications in the context of the research questions and highlighting key trade-offs. Finally, Section 7 summarizes the key contributions of this thesis and proposes directions for future research.

2 LITERATURE

This chapter reviews the existing body of research relevant to this thesis, establishing the context and identifying the specific gaps that this work aims to address. The review begins by examining traditional, heuristic-based methods for 5G link adaptation and their inherent limitations. It then traces the evolution of Artificial Intelligence (AI) and Machine Learning (ML) solutions developed to overcome these shortcomings, categorizing them by methodology and data requirements. Finally, it explores the parallel challenge of energy consumption modeling and synthesizes these findings to define the precise research gap and outline the contributions of this thesis.

2.1 Traditional Link Adaptation and Its Limitations

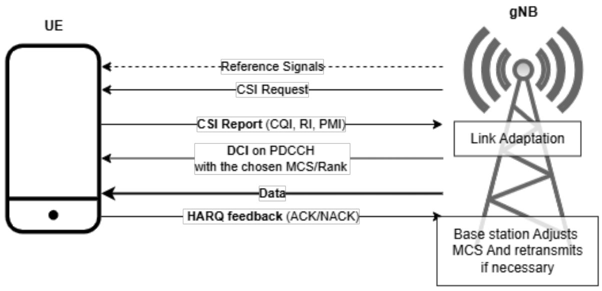


Figure 1: Traditional Link adaptation

Link adaptation is a fundamental mechanism in 5G networks, responsible for dynamically adjusting transmission parameters to match real-time channel conditions to maximize throughput while maintaining a target level of reliability Gigayasa Wireless (2025).The conventional approach to this task is a layered, feedback-driven control system composed of Inner Loop Link Adaptation (ILLA) and Outer Loop Link Adaptation (OLLA), as depicted in Figure 1.

ILLA operates on the fastest timescale, selecting a Modulation and Coding Scheme (MCS) from a predefined lookup table based on instantaneous channel quality indicators (CQI) reported by the user equipment (UE) Gigayasa Wireless (2025). While effective in stable channel conditions, the performance of ILLA is highly dependent on the accuracy and timeliness of this feedback. In high-mobility scenarios or congested networks, this feedback can be delayed or outdated, leading to a misestimation of the true channel state Sahu and Sahu (2024).

To correct for these misestimations, OLLA operates on a slower timescale. It adjusts a SINR correction offset based on the ACK/NACK feedback from Hybrid Automatic Repeat Request (HARQ)Cruz et al. (2022) transmissions, gradually steering the system toward a target Block Error Rate (BLER), typically around 10% Lee et al. (2021). Effnet's internal logs confirm this behavior, where HARQ feedback directly influences the Link Adaptation Mechanism (LAM) to adjust the MCS.

While this two-loop system is robust, its core design is fundamentally reactive. Both ILLA and OLLA make decisions based on past information. The inherent latency in the feedback loops means the system is always playing catch-up, a significant limitation in highly dynamic 5G environments that demand proactive control for low-latency applications and optimal resource utilization. This reactive nature motivates the exploration of predictive models that can anticipate channel changes and select an optimal MCS in advance.

2.2 AI-Driven Link Adaptation: A Paradigm Shift

To break the dependency on delayed feedback, research has increasingly turned to Artificial Intelligence (AI) to bring proactive capabilities to link adaptation. The core principle of these AI-driven methods is to move beyond simple, reactive lookups and instead learn a predictive model of the wireless channel. By training on historical network data, these models learn to forecast the likely future state of the channel, allowing for more timely and accurate MCS selection. This predictive capability is key to unlocking higher throughput and more robust connections in demanding 5G environments. These approaches generally follow one of two main strategies: direct MCS classification or indirect channel metric prediction.

2.2.1 Direct vs. Indirect Prediction Models

One major category of AI models employs direct prediction, an end-to-end learning approach. These models are trained to directly output an MCS class based on a vector of network state indicators. The goal is to let the model itself discover the complex, non-linear function that links channel history to the optimal MCS. This has been successfully implemented using various architectures. For example, Tsipi et al. (2024) showed that a standard ANN could effectively learn this mapping and outperform other machine learning methods. Other research has leveraged the feature extraction capabilities of Convolutional Neural Networks (CNNs) to process raw sequences of channel measurements (Oh et al. (2023)). The main appeal of the direct method is its conceptual simplicity; it allows the model to learn the entire decision-making process from input to output, potentially discovering patterns that a human-designed, two-step process might miss.

Table 1: AI Models and Data Sources in Related Studies

Study (Citation)	**AI Model Used**	**Prediction Task**	**Data Source**
Tsipi et al. (2024)	LSTM (2-layer)	Direct MCS	Ray-tracing
Varshney et al. (2023)	LSTM	CIR Prediction	NYUSIM
Oh et al. (2023)	CNN/MLP	Direct MCS	MATLAB (Stepwise SINR)
Elgabroun (2019)	RL	Direct MCS	Ericsson Sim
This Study	LSTM, CNN	Direct MCS	5G-LENA (3GPP-compliant)

The second major approach uses an indirect prediction strategy, which breaks the problem into a two-step process. Instead of directly classifying the MCS, the model first performs a regression task to predict a fundamental channel quality metric, such as the future SINR or the Channel Impulse Response (CIR). In the second step, this predicted metric is then mapped to an MCS value using a conventional, often deterministic, method like a lookup table or a threshold function (Kojima et al. (2019)). This approach is valued for its modularity and interpretability. By forecasting an understandable physical metric like SNR, the system's decisions are easier to debug and validate. Furthermore, as shown by Stenhammar et al. (2024), the predicted channel metric can be repurposed to inform other network control decisions, making the model more versatile than a single-task MCS classifier.

Table 2: Key Limitations and Contributions of Related Studies

Study (Citation)	**Key Limitation / Contribution**
Tsipi et al. (2024)	Achieved high accuracy but ray-tracing is computationally heavy.
Varshney et al. (2023)	Realistic mmWave traces but not fully 3GPP-compliant.
Oh et al. (2023)	Controlled environment, lacks real-world channel noise/dynamics.
Elgabroun (2019)	High realism but proprietary and non-reproducible.
This Study	Balances realism and reproducibility; addresses data imbalance.

2.2.2 Temporal Models for Link Adaptation

While the choice between direct and indirect prediction defines the model's overall strategy, at its core, proactive link adaptation is a time-series forecasting problem. The goal is to predict a future value (MCS or a channel metric) based on a sequence of past observations. While simple machine learning models can be applied, they often fail to capture the auto-correlations and sequential patterns inherent in the data. This has led to the widespread adoption of models specifically designed for sequential data, namely recurrent neural networks (RNNs). Architectures like LSTMs and GRUs are purpose-built to maintain an internal state or "memory" that allows them to learn dependencies across time steps (Stenhammar et al. (2024)). The high performance reported in studies using LSTMs, such as the 98% accuracy achieved by Tsipi et al. (2024) for MCS selection and the channel prediction work by Varshney et al. (2023), confirms the importance of treating link adaptation as a time-series task. The consensus in the literature is that models that ignore the temporal dimension are unlikely to perform well in realistic, dynamic 5G environments.

2.3 The Data Challenge: Simulation vs. Reality

The effectiveness of any deep learning model is fundamentally determined by the quality and realism of its training data. In the context of 5G link adaptation, this presents a significant challenge, as the logistical and commercial barriers to obtaining live, high-resolution RAN data are immense (Qureshi et al. (2023)). Consequently, the majority of academic research, including the studies previously mentioned, relies on simulated datasets. However, the level of realism across these simulations varies widely(Salvato et al. (2021)), which has a direct impact on the universality of the resulting models.

Some studies utilize simplified, synthetic datasets, such as the stepwise SINR inputs used by Oh et al. (2023). While this approach creates clean, easily trainable data, it fails to capture the stochastic noise and volatility of real-world wireless channels. Other researchers aim for higher fidelity using specialized simulators. For example, Varshney et al. (2023) employed NYUSIM to generate realistic mmWave traces, though the simulator does not fully implement the 3GPP protocol stack(Rappaport et al. (2017)). Conversely, studies like Elgabroun (2019) have leveraged proprietary commercial simulators which, while highly realistic, are not publicly available, hindering the reproducibility and validation of their findings.

The 5G-LENA simulation framework, used in this thesis, was chosen specifically to navigate this trade-off between simplicity and proprietary realism. Built on the well-established ns-3 platform, 5G-LENA integrates key 3GPP-compliant features such as HARQ retransmissions, CQI feedback mechanisms, and realistic urban macrocell propagation models(Bojovic et al. (2022)). This configuration enables the generation of datasets that reflect the spatio-temporal complexity of a real deployment while ensuring the entire research pipeline remains transparent and reproducible—addressing a key limitation in prior work.

2.4 The Energy Dimension: A Parallel Challenge

Beyond link performance, energy efficiency has emerged as a critical research area for sustainable 5G networks (Wu et al. (2017)). The ultimate goal in this field is the joint optimization of performance and power, where every network decision, including MCS selection, is power-aware (Parsa et al. (2022); Norolahi and Azmi (2023)). However, a significant gap currently exists between the high-fidelity link-level simulators used for performance studies and the often-simplified power models they employUsama and Erol-Kantarci (2019). Open-source tools like 5G-LENA, for instance, do not include empirically validated energy consumption profiles, making a truly realistic joint simulation impossible at present(Koutlia et al. (2022)).

To bridge this gap, this study takes a foundational, two-part approach. First, it models link adaptation with the highest possible realism using 5G-LENA. Second, it separately develops a high-fidelity energy model using a dataset from real-world 5G hardware. By developing state-of-the-art predictive models in both domains independently, this work provides two essential, realistically-grounded components. While not yet integrated, these parallel investigations offer a more robust starting point for future research aiming to combine them, for example, by integrating empirical power profiles into next-generation simulation frameworks.

2.5 Research Gap and Contributions

Based on the reviewed literature, this thesis identifies an opportunity to build upon the state of the art in two key areas. While the superiority of temporal models for link adaptation is established, there is a clear need to apply these models within more realistic and reproducible simulation environments. Furthermore, the prevailing separation between performance modeling and empirical energy analysis limits a holistic understanding of network efficiency. This thesis aims to address these gaps through the following key contributions:

- Applying a temporal deep learning model to the MCS prediction task within a realistic, 3GPP-compliant simulator (5G-LENA).
- Developing a high-accuracy energy forecasting model from a large, real-world operational dataset.
- Providing a foundational, dual-pronged analysis that bridges the gap between simulated performance and empirical sustainability, offering a basis for future integrated optimization.

3 BACKGROUND

The research presented in this thesis was performed within a collaborative framework with Effnet AB, a provider of 3GPP-compliant 5G network technologies. The objective of this collaboration was to explore the application of AI-driven techniques to enhance their existing 5G network solutions. Effnet provided essential guidance during the problem identification phase, highlighting scheduler optimization for eMBB traffic in urban macro and micro scenarios as a key area of commercial interest. This industry perspective was instrumental in focusing the research on the specific task of predictive MCS selection. Although this project represented an early exploration of AI within the company, the collaboration furnished important contextual understanding of real-world link adaptation behavior and provided access to internal datasets that, while not ultimately used for training, aided in the initial analysis.

4 METHODOLOGY

This chapter details the research methodology employed to answer the guiding research questions of the thesis. The work is organized into two distinct but complementary parts, each addressing one of the core predictive tasks. Part I describes the methodology for predictive link adaptation, which involved generating a custom dataset via the 5G-LENA network simulator. Part II details the methodology for energy consumption forecasting, which utilized a large-scale, real-world operational dataset. For each part, the following sections will systematically describe the data source and preprocessing steps, the AI modeling architecture, and the metrics used for evaluation.

4.1 Part I: Predictive Link Adaptation

This first part of the methodology details the end-to-end process for developing a proactive link adaptation model. The core objective was to train a model capable of predicting the optimal Modulation and Coding Scheme (MCS) based on a recent history of channel conditions. This required three main steps, detailed in the following subsections: first, generating a high-fidelity, time-series dataset using a custom 5G-LENA simulation; second, preprocessing this data into a format suitable for deep learning models; and third, designing and training several AI architectures to perform the time-series classification task.

4.1.1 Dataset Generation: 5G-LENA Simulation

To generate a suitable training dataset for the MCS prediction task, we employed the 5G-LENA simulation framework. The scenario was designed to produce a realistic, dynamic dataset reflecting a challenging urban eMBB use case. A single gNB and four UEs were simulated, with UE mobility governed by a Random Walk model to ensure the channel conditions were not static. The choice of gaming traffic over UDP was made to introduce bursty, latency-sensitive traffic, which places significant stress on the link adaptation algorithm.

The physical layer configuration was chosen to represent a standard 5G mmWave deployment, with the specific parameters detailed in Table 3. Of particular importance was the use of the 3GPP Urban Macro (UMa) channel model, which ensures the simulated

Parameter	**Description**
Simulator	5G-LENA (NR-v4.0)
ns-3 Version	ns-3.44
Channel Model	3GPP Urban Macro (TR 38.901), NLOS condition
Frequency	30.5 GHz
Bandwidth	100MHz
Number of gNBs	1 (center of hexagonal layout)
Number of UEs	4
Mobility Model	Random Walk with variable speed (UEs repositioned randomly for each run)
Traffic Type	Gaming traffic over UDP
Scheduling Algorithm	Default PDSCH RR Scheduler
CQI Reporting	Event-driven
MAC Stats Logging Interval	0.01 seconds
Output Files	NrDlMacStats.txt,DlDataSinr.txt, RxedGnbMacCtrlMsgsTrace.txt
Simulation Duration	2̃00 seconds (real time per run)
Simulation Runs	10 different seeds × 3 runs = 30 runs total
Automation	bash script
OS & Toolchain	Ubuntu 20.04 LTS, g++-11.4.0

Table 3: Simulation Configuration

propagation environment is consistent with industry standards. To capture a wide range of channel behaviors, the simulation was executed 30 times with randomized seeds. The raw data for the study was then extracted from the key log files generated by 5G-LENA, including those for MAC statistics and SINR events.

4.1.2 Data Preprocessing and Feature Engineering

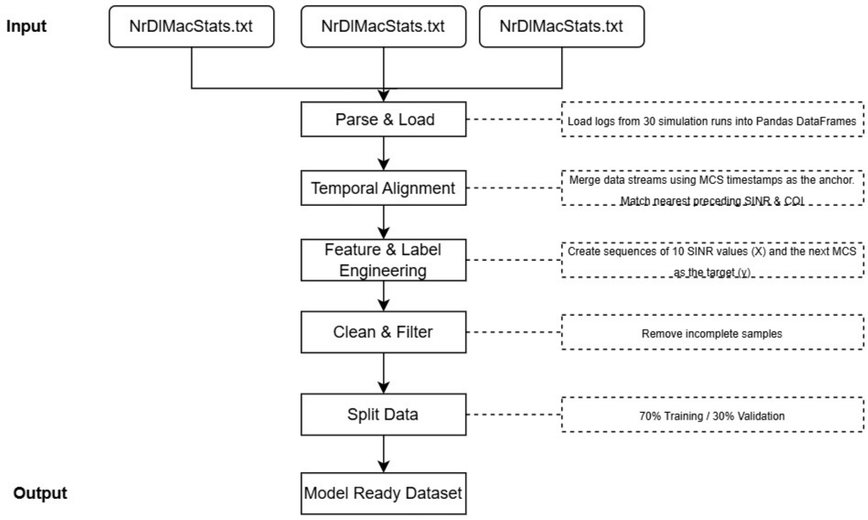


Figure 2: Preprocessing pipline

Preprocessing of the raw simulation logs was conducted in Python using the Pandas and NumPy libraries as illustrated in Figure 2. The workflow consisted of three main steps. First, the log files for MAC statistics, SINR, and CQI from all 30 runs were loaded and parsed.

Second, a temporal alignment was performed to create a unified dataset. Since the data sources were logged at different cadences (fixed-interval vs. event-driven), the MCS assignment timestamps from the MAC statistics file were used as the primary reference points. The corresponding SINR and CQI values were then merged based on the closest preceding timestamp.

Finally, the aligned data was transformed into a supervised learning format. Feature sequences were constructed by taking a sliding window of 10 historical SINR values, and the target label was set as the MCS value immediately following that window. After removing any incomplete samples, this resulted in a final dataset of approximately 21,000 instances, which was then split into 70% for training and 30% for validation.

4.1.3 AI Modeling Approach

The predictive link adaptation task was formally framed as a supervised, multiclass time-series classification problem. The primary objective was to train a model that could accurately predict the optimal MCS for a future transmission slot based on a recent sequence of channel state indicators. Specifically, the model's input was defined as a sequence of the 10 most recent SINR measurements, and its output was the single MCS class to be used in the subsequent time slot. All models for this task were developed and implemented using the PyTorch deep learning framework, chosen for its flexibility in building custom neural network architectures.

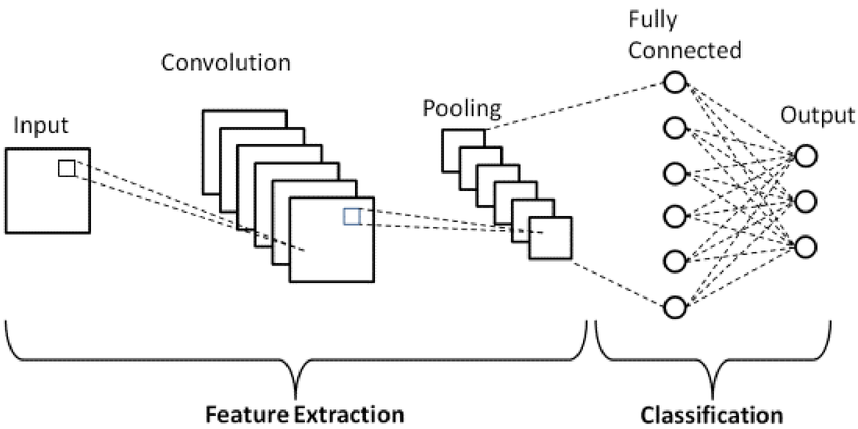


Figure 3: CNN visual representation [taken from source : He (2024)]

The primary architecture investigated was a one-dimensional Convolutional Neural Network (1D-CNN). This model was selected as a strong baseline due to its proven effectiveness in automatically extracting hierarchical features from sequential data, a technique shown to be successful for link adaptation tasks in studies such as Oh et al. (2023). As depicted in Figure **??**, the model's architecture begins with an input layer that accepts the sequence of 10 SINR values. This is followed by a 1D convolutional layer with 128 filters and a ReLU activation function, designed to identify local patterns and motifs in the channel data. The resulting feature maps are then downsampled by a max-pooling layer before being flattened into a one-dimensional vector. Finally, this vector is passed through a fully-connected dense layer which outputs logits for each of the 29 possible MCS classes, followed by a softmax activation to produce the final probability distribution.

Table 4: Distribution of MCS Classes in the Generated Dataset, Highlighting Severe Class Imbalance

MCS	0	2	4	6	8	11	13	15	18	20	22	24	26	28
Count	1143	436	439	658	577	529	880	610	1030	674	968	1677	6965	4132

A critical characteristic of the generated dataset, as detailed in table 4, is a severe class imbalance. Certain MCS values corresponding to favorable channel conditions are heavily represented, while MCS values for poor or intermediate conditions are rare. If left unaddressed, this imbalance would cause the model to develop a strong bias toward predicting the majority classes, leading to a high but misleading overall accuracy while failing on the infrequent but critical edge cases. To mitigate this, a WeightedRandomSampler was implemented within the PyTorch data loading pipeline. For each sample in the dataset, a weight is calculated that is inversely proportional to its class frequency. The sampler then uses these weights to draw samples for each training batch, effectively oversampling instances from minority classes. This ensures that the model is trained on a more balanced distribution of MCS classes in each epoch, encouraging it to learn more robust and generalizable decision boundaries. In addition to this baseline configuration, variations were also tested, including a model that incorporated CQI reports as a second input channel alongside the SINR sequence to assess the value of explicit channel feedback.

An alternative model was developed using Long Short-Term Memory (LSTM) networks to explicitly model the sequential nature of the SINR data. Unlike a CNN, which processes the entire 10-step sequence in parallel to find spatial patterns, an LSTM processes the sequence one step at a time, updating its internal hidden state at each step. This allows the LSTM to build a rich, contextual understanding of the sequence's evolution. The model was constructed with two sequential LSTM layers, followed by a final dense layer for classification. The goal of this design was to determine if this step-by-step, memory-based processing offered any performance advantage over the parallel feature extraction of the CNN for the task of MCS prediction.

All models were trained within a consistent framework to ensure a fair comparison. The training process was run for 50 epochs using the Adagrad optimizer and a Cross-Entropy Loss function, which is the standard objective function for multiclass classification problems. A basic hyperparameter sweep was conducted on a subset of the data to identify an effective set of parameters for the main experiments. This sweep explored variations in learning rate, the number of convolutional filters, and the inclusion of dropout for regularization. The final, best-performing configuration, which is summarized in Table 5, utilized a learning rate of 0.005 and a batch size of 64. To investigate if the models could learn user-specific channel patterns, an 8-dimensional embedding for each UE's RNTI was also tested as an additional input feature.

Table 5: Final Hyperparameters Used for Model Training

Hyperparameter	**Value**
Optimizer	Adagrad
Loss Function	Cross-Entropy
Learning Rate	0.005
Epochs	50
Batch Size	64
Class Imbalance Strategy	WeightedRandomSampler

4.2 Part II: Energy Consumption Forecasting

This part of the study addresses the second research objective: energy consumption forecasting. The methodology is entirely data-driven, based on a publicly available dataset of 5G base station operational logs. The following subsections describe the dataset, the preprocessing steps, the modeling approach, and the evaluation metric.

4.2.1 Dataset and Preprocessing

Table 6: Key Features of the 5G Energy Consumption Dataset

Feature	**Description**
Timestamp	Hourly timestamp of the log entry (YYYYMMDDHHMMSS)
BS	Unique identifier for the base station (e.g., B_0)
Energy	Energy consumption in Watt-hours (Wh) - Target Variable
Load	Normalized traffic load on the base station (0-1)
ESMODE	Indicator for an active energy-saving mode (0 or 1)
TXpower	Transmission power level of the base station

The energy forecasting task is based on the "5G-Energy Consumption Dataset", a publicly available resource first provided as part of a global ITU challenge Nadia Triki (2025). This large-scale, real-world dataset provides an invaluable empirical basis for this study. It contains 92,629 hourly log entries spanning a period of several months for a total of 1,019 unique base stations (BS). The key attributes of the dataset, which form the basis of the predictive models, are summarized in Table 6.

Preprocessing was performed using Python with the pandas and NumPy libraries. The Timestamp field, initially in a string format, was converted to a datetime object. This enabled the feature engineering of several time-based cyclical features, specifically the hour of the day (0-23) and the day of the week (0-6), as well as a binary weekend flag. These features were designed to capture the daily and weekly traffic patterns that strongly influence energy consumption. The categorical BS identifiers were transformed into a numerical format using one-hot encoding for use in the baseline regression models. An initial data quality check confirmed that there were no missing values in the critical Energy, Load, and TXpower columns.

4.2.2 AI Modeling Approach

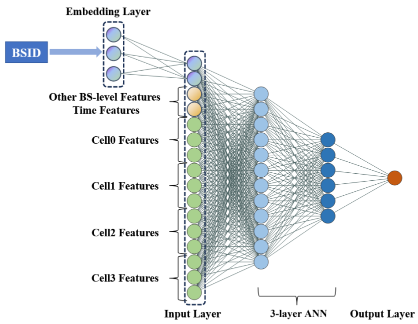
The modeling strategy for the energy forecasting task was designed to benchmark a state-of-the-art methodology on the publicly available subset of the ITU challenge data. The approach progresses from a simple baseline to a more sophisticated neural network, inspired by the second-place winning solution detailed by Chen et al. (2024).

1. *Baseline Model*: A **Linear Regression** model was first implemented to serve as a performance baseline. This model establishes a benchmark by quantifying the purely linear relationships between the available features (Load, TXpower, etc.) and the target Energy variable. Its performance provides a clear reference point against which the benefits of more complex, non-linear models can be measured.

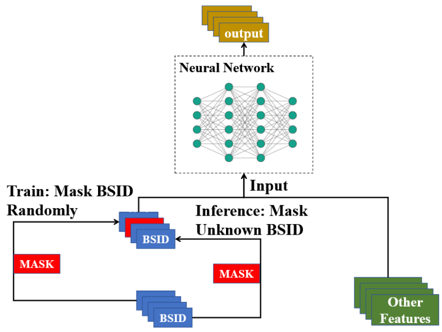
2. *Core Architecture*: Feed-Forward Neural Network with BSID Embedding: The primary model was a **multi-layer feed-forward neural network (NN)**. A key limitation of prior methods, as noted by Chen et al., is the failure to properly incorporate the Base Station Identifier (BSID), which is critical for capturing the unique "energy fingerprint" of each station. To address this, our model incorporates the BSID not as a simple one-hot vector, but through a learned **embedding layer**. This technique, adopted from \cite{chen2024modelling}, transforms each of the 1,019 unique BSIDs into a dense, low-dimensional vector. This is far more efficient than one-hot encoding and allows the model to learn relationships between similar base stations in the embedding space.

3. *Advanced Technique*: Masked Training for Generalization: The most critical technique replicated from \cite{chen2024modelling} was the **masked training strategy**, designed to improve the model's ability to generalize to base stations not seen during training. During each training epoch, the BSID for a random subset of the training data (e.g., 30%) is deliberately hidden or "masked." This forces the model

to learn to predict energy consumption based solely on the operational features (load, time, etc.) for those samples. By doing so, the model learns a general "energy fingerprint" from operational patterns, which it can then apply during inference when it encounters a completely unknown BSID.



(a) Simplified Model Architecture



(b) Masked Training and Inference Phase

Figure 4: The energy forecasting model architecture and training strategy, adapted from Chen et al. (2024). (a) Our simplified feed-forward network with a BSID embedding layer. (b) The conceptual diagram of the masked training process used to improve generalization to unknown base stations.

4.2.3 Evaluation Metrics

To evaluate and compare the performance of the Linear Regression, standard Neural Network, and Masked Neural Network models, the primary evaluation metric was the Mean Absolute Percentage Error (MAPE), as defined in the benchmark study Chen et al. (2024). This metric calculates the sum of absolute errors divided by the sum of actual values, providing a robust measure of overall prediction accuracy. It is defined by the following equation:

$$MAPE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{\sum_{i=1}^{n} |y_i|}, \tag{1}$$

where yi is the actual energy value and $(\hat{y}_i)$ is the predicted value for the i-th sample. This specific formulation was selected to ensure a direct and fair comparison with the results reported by Chen et al. (2024).

5 RESULTS

This chapter details the empirical findings from the two main experimental branches of this study. The first subsection, Part I, reports the performance results for the link adaptation models. The second subsection, Part II, reports the performance results for the energy forecasting models. All results are presented objectively, with interpretation reserved for the Discussion chapter.

5.1 Part I: Predictive Link Adaptation Performance

Model	Input Features	Accuracy
CNN (baseline)	SINR	52.3%
CNN + CQI	SINR + CQI	53.71%
CNN + Masking	SINR + CQI + Masking	54.11%
LSTM (best)	SINR + CQI	55.15%

Table 7: Link Adaptation Model Comparison

The overall classification accuracy for the four developed link adaptation models is summarized in Table 7. The baseline CNN model, trained only on SINR sequences, achieved an accuracy of 52.3%. Incorporating CQI values as an additional input feature provided a notable improvement, with the CNN + CQI model reaching 53.7%. The addition of an input masking strategy yielded a further small gain to 54.1%. The best performance was achieved by the LSTM model, which reached a final validation accuracy of 55.1%, indicating its superior ability to capture the temporal dynamics of the channel.

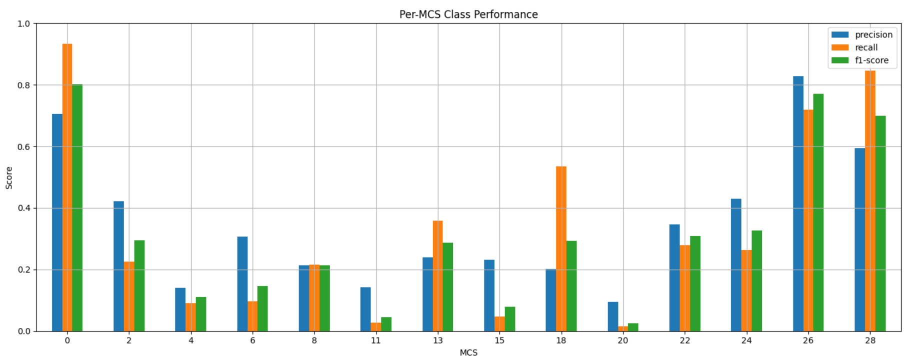


Figure 5: per MCS accuracy metric of MCS

To gain a deeper insight beyond the single accuracy metric, a more granular analysis is required to understand the model's behavior under the severe class imbalance present in the data. Adopting the multi-metric evaluation framework used in comparable link adaptation studies such as Tsipi et al. (2024), this analysis, visualized for the LSTM model in Figure **??**, reveals the model's true behavior. . The chart clearly shows a performance skew: the model demonstrates significantly higher F1-scores for the most frequently occurring MCS classes (e.g., 0, 24, 26, 28), while performance on rare, intermediate classes is markedly lower, with some exhibiting F1-scores near zero. This detailed analysis, which is essential for a complete performance picture, reveals nuances that a single accuracy metric would otherwise obscure.

A confusion matrix was generated to provide a detailed view of the LSTM model's classification errors and is shown in Appendix **??** (Figure B4). The vertical axis represents the true MCS labels and the horizontal axis represents the predicted labels. The values on the main diagonal are the counts of correct predictions. The brightest cells on the diagonal occur at MCS 0, 26, and 28, corresponding to the classes with the highest F1-scores. The off-diagonal cells show the misclassification counts. A clear pattern is visible where these non-zero counts are concentrated in the cells neighboring the main diagonal.

5.2 Part II: Energy Consumption Forecasting Performance

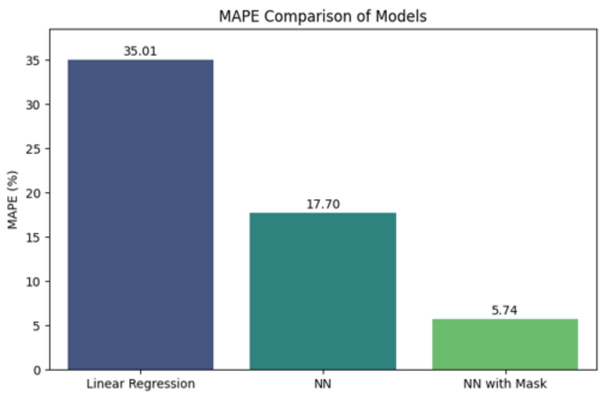


Figure 6: Mape Comparision over different models

The performance of the three models developed for the energy forecasting task is presented in Figure 6. The models were evaluated using the Mean Absolute Percentage Error (MAPE) on the held-out test set, where a lower value indicates a more accurate model. The baseline Linear Regression model performed poorly, resulting in a high MAPE of 35.01%. A substantial improvement was achieved by introducing a non-linear 3-layer Neural Network, which reduced the MAPE to 17.70%. The most significant performance gain came from implementing the masking strategy, with the Masked Neural Network achieving the lowest error and demonstrating the best performance with a final MAPE of 5.74%.

Table 8: Comparison of Energy Prediction Models

Model	**Key Feature / Strategy**	**MAPE (% ↓)**
Masked NN	BSID Masking	5.74
Chen et al. (2024)	BSID Masking + Attention	4.98

The strong performance of the Masked Neural Network is further validated by a benchmark comparison with the state-of-the-art results from Chen et al. (2024). As shown in Table 8, our final MAPE of 5.74% is highly competitive with the 4.98% MAPE they reported. This consistency in performance, despite our model being trained on a less feature-rich public dataset, confirms that the BSID embedding and masking strategy is a robust and highly effective technique for 5G energy forecasting.

6 DISCUSSION

This chapter discusses the results presented in the previous section. The first subsection interprets the findings from the predictive link adaptation experiments. The second subsection analyzes the performance of the energy forecasting models. The final subsection synthesizes the insights from both parts, discusses the study's limitations, and considers the broader implications of the work for 5G network optimization.

6.1 Interpretation of Link Adaptation Results (Answering RQ1)

The results from the link adaptation experiments, while numerically modest, provide several key insights into the challenges and opportunities of applying AI to this real-time control problem. The peak validation accuracy of 55.1% achieved by the LSTM model,

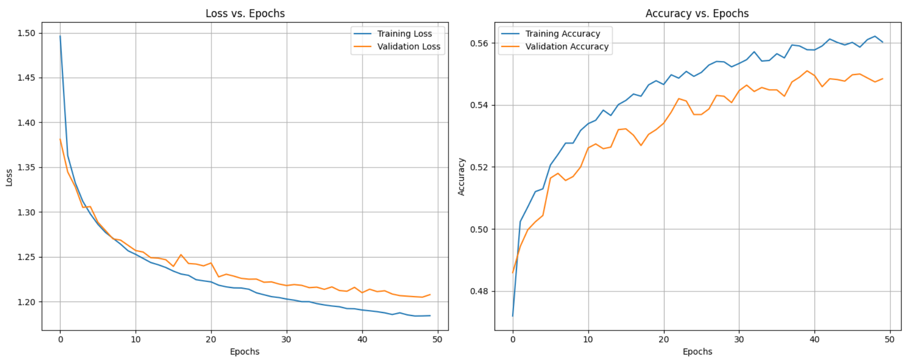


Figure 7: Graphs depicting training and validation curves of LSTM

while seemingly modest, should be interpreted in the context of the problem's inherent difficulty. The task is a multiclass classification problem with 29 distinct MCS classes. This high cardinality means that a model making a purely random guess would achieve an accuracy of only 3.4% (1 out of 29). A more informative, non-learning baseline is a majority-class classifier, which would always predict the single most frequent class in the dataset (MCS 26). Based on the data distribution shown in Table 4, such a naive model would yield an accuracy of approximately 33%. The fact that our 55.1% result significantly outperforms both of these trivial baselines demonstrates that the model successfully learned meaningful predictive patterns from the SINR sequences. This successful learning process, confirmed by the rising validation accuracy during training (Figure 7) validates the foundational hypothesis that the 5G channel possesses a learnable structure and establishes a strong proof-of-concept for the viability of this AI-driven approach.

The skewed per-class performance, where the model excels at predicting frequent MCS classes but fails on rare ones (as shown in Figure ??), is a direct consequence of the dataset's severe class imbalance. While a WeightedRandomSampler was used to mitigate this during training, its effectiveness is limited when a class has extremely few samples from which to learn robust patterns. The model's strong performance on high MCS indices (like 26 and 28) and the lowest index (0) simply reflects the greater volume of training data available for those common network states. Crucially, this is not merely a simulation artifact but is representative of real-world network behavior. Operational 5G networks are engineered to maximize throughput, meaning they spend the majority of their time in favorable channel conditions using high-order modulation schemes. The imbalanced dataset is therefore a feature of a realistic simulation, not a bug, and the model's performance accurately mirrors this operational reality.

An analysis of the confusion matrix (Figure B4) is essential for interpreting the model's error profile. The strong clustering of predictions around the diagonal demonstrates that the model's errors are not random. When the model misclassifies a sample, it overwhelmingly predicts a neighboring MCS index. This pattern is significant because it implies that the feature representations learned by the LSTM have successfully captured the continuous, ordered nature of the underlying signal quality. While the model may struggle with the precise classification boundary between, for example, MCS 25 and 26, its internal representation correctly identifies them as being very similar. This is a much more sophisticated form of learning than simple classification and points to the model's robust understanding of the data.

The link adaptation experiments provide two key insights that directly address our first research question. First, this study demonstrates that an LSTM-based model can effectively learn to predict MCS values from temporal data. The model's final accuracy, its successful learning curves, and the ordinal nature of its errors collectively show that the proactive, AI-driven approach is viable. Second, the analysis reveals that the primary limitation on this effectiveness is the realism of the dataset itself. The severe class imbalance, which mirrors real-world network behavior, is the main barrier to achieving uniformly high performance across all MCS classes. Therefore, the answer to RQ1 is that the model learns effectively, but its performance is ultimately constrained by the statistical properties of the realistic data it is trained on.

6.2 Interpretation of Energy Forecasting Results (Answering RQ2)

The results from the energy forecasting experiments were markedly different from the link adaptation task, demonstrating a high degree of predictability and highlighting the profound impact of the chosen modeling strategy.

The substantial reduction in MAPE from 17.70% to 5.74% can be directly attributed to the effectiveness of the masked training technique. This strategy acts as a powerful form of regularization specifically tailored to this problem. A standard neural network is prone to overfitting to the 1,019 specific base stations in the training set, essentially learning a lookup table of their average behaviors. The masking process disrupts this overfitting by periodically hiding the station's identity. This forces the model to create a more robust and generalizable function that maps operational features (load, time of day, etc.) to energy consumption, a function that works even when the BSID is unknown. The success of this technique demonstrates that the most important predictive information is contained within the operational patterns, and that forcing the model to rely on them leads to superior performance.

The 5.74% MAPE achieved by our Masked NN aligns closely with and confirms the state-of-the-art results presented by Chen et al. Chen et al. (2024), who reported a 4.98% MAPE. The minor difference in performance is well within the expected range, given that our study was conducted on a public version of the dataset with a more limited feature set. The strong performance of our replicated model validates their central conclusion: that a neural network with BSID embedding and a masked training strategy is a highly effective approach for accurately forecasting 5G energy consumption.

The energy forecasting experiments lead to two key conclusions that directly answer our second research question. First, this work concludes that the hourly energy consumption of 5G base stations is highly predictable from operational data, with our best model achieving a low MAPE of 5.74%. Second, the study concludes that the most influential predictive information is not just the immediate traffic load, but the unique energy profile of the base station itself. The success of the BSID embedding and masking technique demonstrates that learning a latent representation of this "energy fingerprint" is the critical factor in achieving high accuracy, far outweighing the contribution of any single input feature alone.

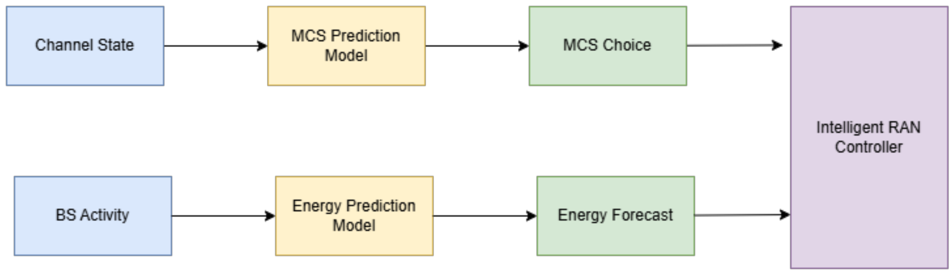


Figure 8: Conceptual diagram of a future Intelligent RAN Controller that utilizes the two models developed in this thesis. The MCS Prediction Model informs real-time performance decisions, while the Energy Prediction Model provides sustainability forecasts, enabling a dual-objective optimization strategy.

Although the link adaptation and energy forecasting models were developed independently, they represent two halves of the same coin: the dual objective of a performance-driven and sustainable 5G network. The findings from this thesis highlight their inherent interdependence. The MCS selection, which was the focus of Part I, is a primary driver of a base station's transmission power (TXpower), one of the key features in the energy model of Part II. An aggressive link adaptation strategy that consistently chooses high-order MCS to maximize throughput will inevitably lead to higher energy consumption. By developing realistic, data-driven models for both domains, this thesis provides the foundational components required to analyze this critical trade-off. For the first time, we have a realistic model of performance alongside a realistic model of energy, which is the necessary first step before a truly integrated, dual-objective control system can be designed, as conceptually illustrated in Figure 8.

Despite the promising results, it is important to acknowledge the limitations of this study. The predictive link adaptation model (Part I) was developed and evaluated exclusively on simulated data. While the 5G-LENA framework was chosen for its high fidelity and 3GPP compliance, a "sim-to-real" gap will always exist. The model's true performance on a live, operational 5G network remains untested and would require further validation.

For the energy forecasting model (Part II), the primary limitation was the granularity of the public dataset. The real-world data, while extensive, lacked specific RAN configuration details (e.g., number of active antennas, specific scheduling decisions, MIMO layers) that are known to influence power consumption. The model's high accuracy was achieved using only high-level operational metrics.

Finally, the overarching limitation of the thesis is that the two models were not integrated. The analysis of the trade-off between performance and sustainability was therefore conceptual. A full understanding of their dynamic interplay would require a co-simulation environment or a live testbed where both models can operate and influence each other in real time.

In response to the third research question, "what foundational insights this work provides for a unified framework?", this study offers two key conclusions. First, it reveals that data realism is the most critical factor. The challenges of class imbalance and the "sim-to-real" gap in the link adaptation task, combined with the power of the "energy fingerprint" in the real-world energy data, strongly suggest that future efforts must prioritize the acquisition and generation of high-fidelity, representative data. Second, this thesis validates the feasibility of creating powerful, specialized AI components for distinct network tasks.

These insights have direct practical implications, particularly for our industry partner, Effnet AB. The proof-of-concept for the proactive MCS prediction model provides a clear pathway for enhancing their 5G scheduler. Furthermore, the high accuracy of the energy forecasting model offers a tangible method for developing new "green" network features. A key observation from this work is that the development of these AI components would have been significantly streamlined by a simulation environment tailored specifically to Effnet's own scheduler logic and target use cases. Such a custom environment would allow for rapid, offline training and validation of AI models before their integration into a live product. Ultimately, this thesis provides Effnet with not only two validated foundational models but also a strategic recommendation for accelerating their future AI development cycle.

7 CONCLUSION

This thesis was motivated by the central challenge of balancing performance and sustainability in modern 5G networks. It aimed to bridge the gap between traditional, performance-focused link adaptation and the growing need for energy-efficient operations. The research objective was to investigate the feasibility of applying specialized AI models to both domains in parallel: a predictive model for MCS selection trained on high-fidelity simulation data, and an energy forecasting model trained on real-world operational data. The ultimate goal was to establish a robust, evidence-based foundation for future energy-aware performance optimization.

To achieve this, a two-pronged methodology was employed. For link adaptation, a custom dataset was generated using the 3GPP-compliant 5G-LENA simulator, which was then used to train and evaluate several temporal deep learning architectures. For energy forecasting, a large-scale, real-world operational dataset was used to train and benchmark a state-of-the-art Masked Neural Network against simpler models. The key findings of this research were twofold. First, it was demonstrated that an LSTM model can successfully learn the predictive structure of the wireless channel, achieving a validation accuracy of 55.1% in a challenging, imbalanced scenario. Second, it was confirmed that a Masked Neural Network can forecast base station energy consumption with high precision, achieving a final MAPE of 5.74%.

The findings of this thesis provide clear answers to the guiding research questions. In response to RQ1, this work established that temporal AI models are effective for proactive MCS prediction, but that their performance in realistic scenarios is fundamentally limited by data imbalance. In response to RQ2, this work demonstrated that energy consumption can be forecasted with high precision, and that the key to this is a model that learns the unique "energy fingerprint" of a base station. Finally, in response to RQ3, the primary contribution of this work is the establishment of a foundational, dual-pronged analysis. It provides two realistically-modeled components that bridge the gap between simulated performance and empirical sustainability, offering a more robust basis for future integrated research than has been previously shown.

In conclusion, this thesis successfully bridges the gap between performance-centric and sustainability-focused research in 5G networks, providing two validated, data-driven components that pave the way for a truly unified approach to energy-aware network management.

7.1 Future Work

The findings of this thesis pave the way for future work across three distinct horizons. The first is the immediate refinement of the models themselves. The link adaptation model, for instance, could be enhanced through more sophisticated feature engineering, such as using CQI deltas to capture the rate of channel change, or by evaluating computationally efficient recurrent architectures like the Gated Recurrent Unit (GRU). Similarly, the energy model would benefit from more systematic hyperparameter tuning to further optimize its performance. A second, more ambitious horizon is the design of a truly integrated, dual-objective framework. This would involve using the two models developed in this thesis as core components in a larger system, perhaps leveraging Reinforcement Learning to train an agent that learns a dynamic policy to balance the trade-off between throughput and energy in real time. Finally, the third and broadest horizon addresses the overarching challenge highlighted by this research: the critical need for richer, more accessible public datasets. Overcoming the ”sim-to-real” gap and providing empirical data that jointly captures link-level dynamics and energy consumption is a community-wide challenge, and progress in this area will be the most significant enabler for the future of deployable, AI-driven 5G optimization.

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Appendix A: Code

All code for this thesis can be found in : https://github.com/Alka-vn/Master_Thesis.git

Appendix B: Supplemental Figures for Link Adaptation Results

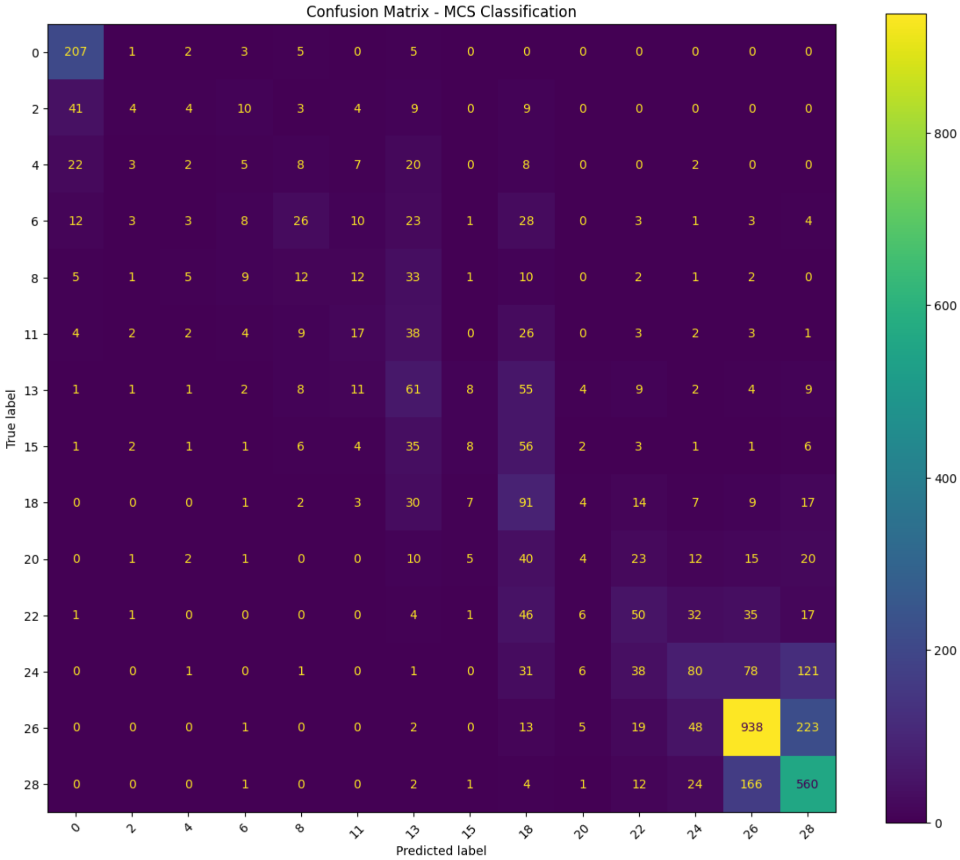

Figure B1: Confusion Matrix for the CNN Model on the Validation Set. The vertical axis represents the true MCS labels, and the horizontal axis represents the predicted labels. The strong diagonal and clustering of errors indicate successful learning of the MCS scale's ordinal nature.

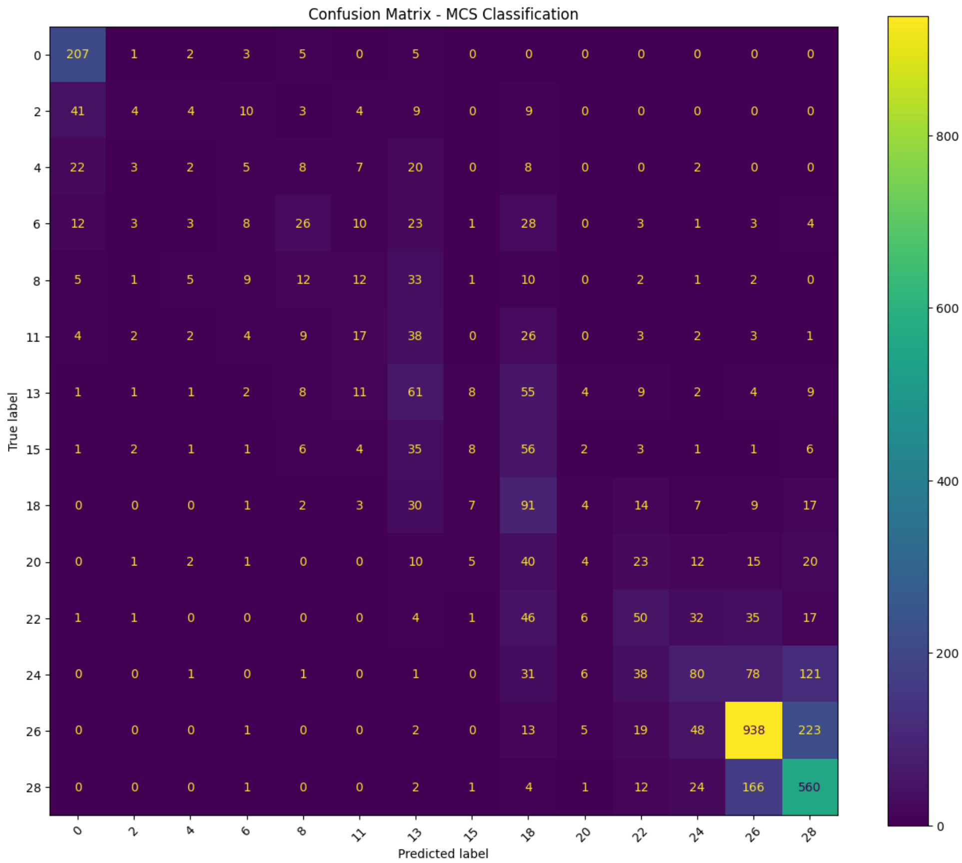

Figure B2: Confusion Matrix for the CNN CQI Model on the Validation Set. The vertical axis represents the true MCS labels, and the horizontal axis represents the predicted labels. The strong diagonal and clustering of errors indicate successful learning of the MCS scale's ordinal nature.

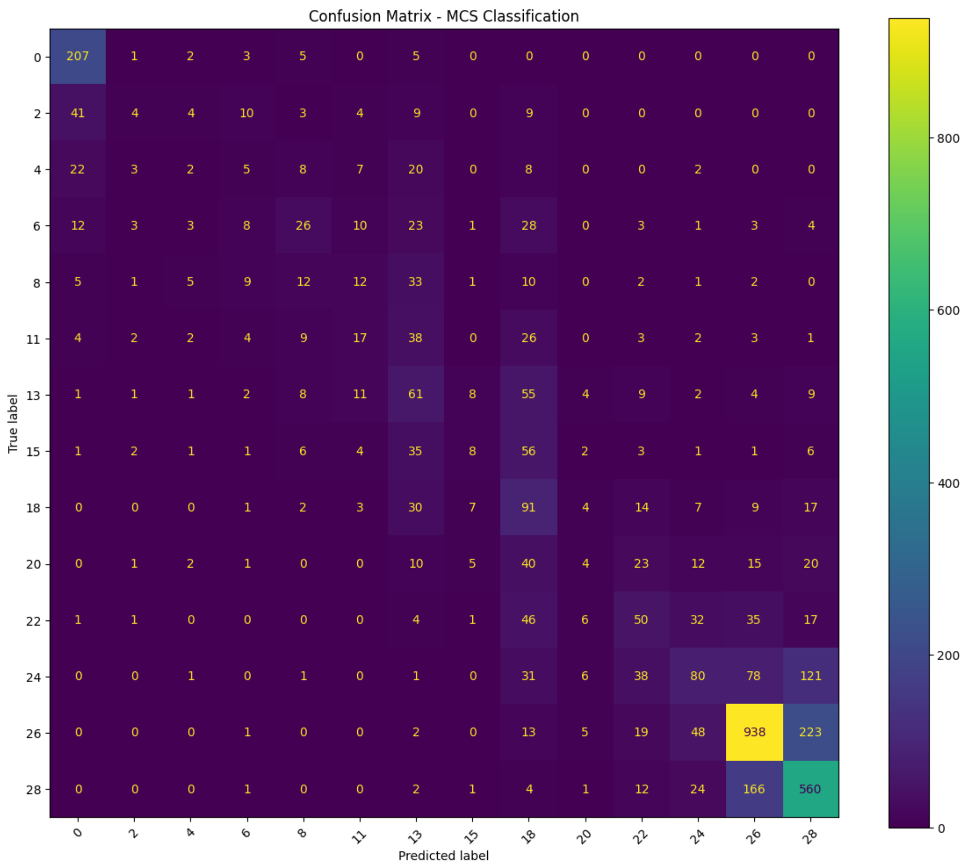

Figure B3: Confusion Matrix for the CNN with Mask Model on the Validation Set. The vertical axis represents the true MCS labels, and the horizontal axis represents the predicted labels. The strong diagonal and clustering of errors indicate successful learning of the MCS scale's ordinal nature.

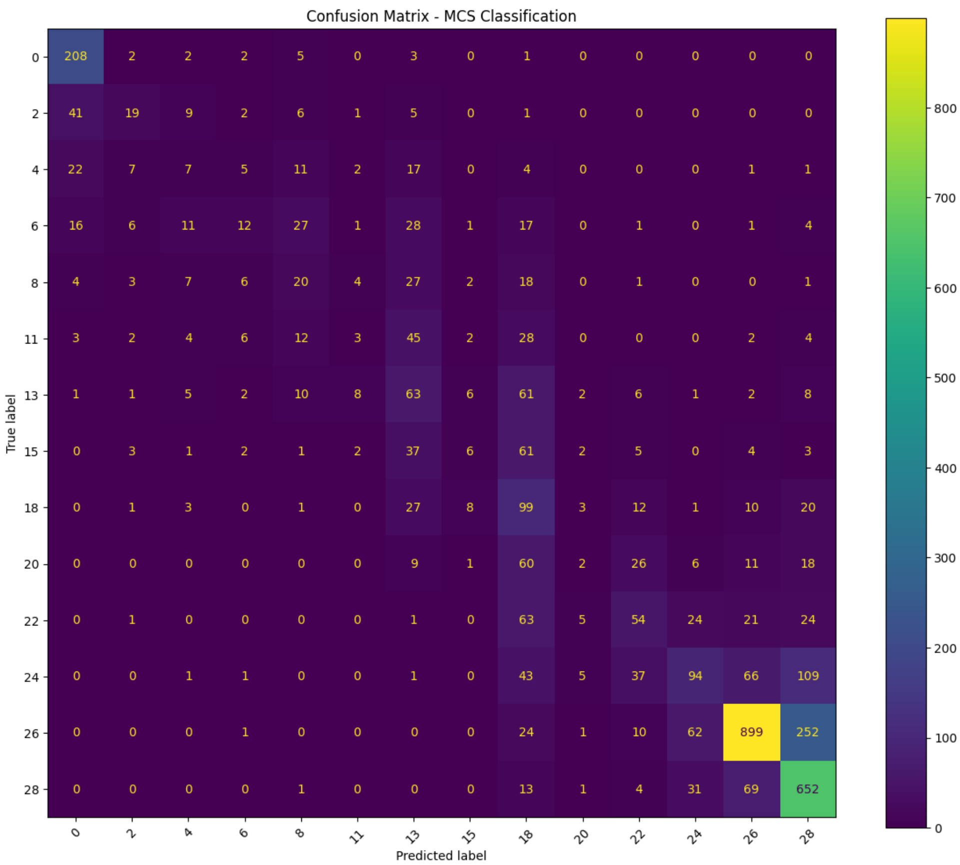

Figure B4: Confusion Matrix for the LSTM Model on the Validation Set. The vertical axis represents the true MCS labels, and the horizontal axis represents the predicted labels. The strong diagonal and clustering of errors indicate successful learning of the MCS scale's ordinal nature.