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

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Table of contents

01

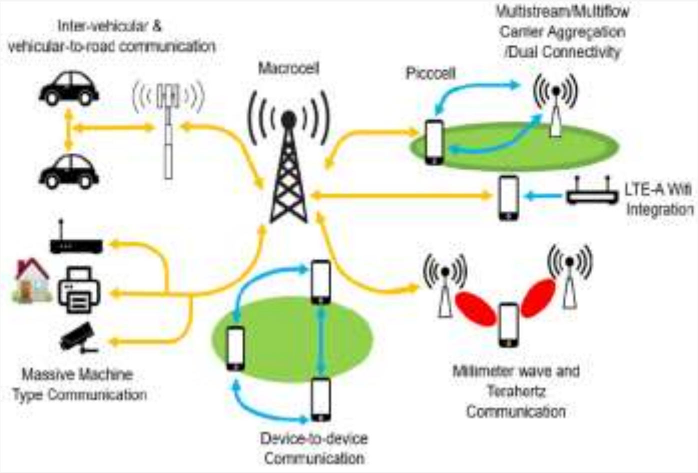
Introduction

Introduction

5G is complex—dense networks, low latency, high energy demands.

Challenges[1]

- Complex scenarios that are hard to model
- Gathering even simple data is difficult
- Legacy networks not designed for AI, need to rethink/rebuild



[1]

R. Agrawal, ‘Machine Learning for 5G RAN’, 2018.

Problem Statement

Despite the potential of Artificial Intelligence, its application to critical 5G operational components—specifically, predictive link adaptation (MCS selection) under realistic conditions and granular energy consumption forecasting—remains underdeveloped. This research addresses this gap by developing and evaluating AI models for each of these distinct tasks, aiming to demonstrate their individual efficacy and pave the way for more intelligent network management.

Research Objectives

Data Extraction & Modelling

RO1: **Identify and extract relevant KPIs** from 5G-LENA simulations, including SNR, CQI, transmission power, and buffer size, to support AI-based MCS prediction.

RO2: Develop and evaluate an **AI model to predict MCS values** based on historical network states, targeting improved robustness in the absence of frequent CSI updates.

RO3: Design a separate **AI model to estimate energy consumption** under varying transmission parameters using an external dataset.

Analysis & Validation

Practical Relevance

Research Objectives

Data Extraction & Modelling

Analysis & Validation

RO4: Analyze and **compare energy efficiency patterns** derived from the energy model, highlighting trade-offs with performance.

RO5: Integrate findings to formulate **practical recommendations** for optimizing 5G link adaptation strategies with sustainability considerations.

Practical Relevance

Research Objectives

Data Extraction & Modelling

Analysis & Validation

Practical Relevance

RO6: **Investigate the practical utility** of AI-driven optimization techniques for 5G systems, demonstrated within the 5G-LENA simulation framework, and identify path ways for their integration or enhancement in alignment with the objectives of industry partner Effnet.

SDG


9
INDUSTRY, INNOVATION
AND INFRASTRUCTURE


11
SUSTAINABLE CITIES
AND COMMUNITIES


13
CLIMATE
ACTION

02

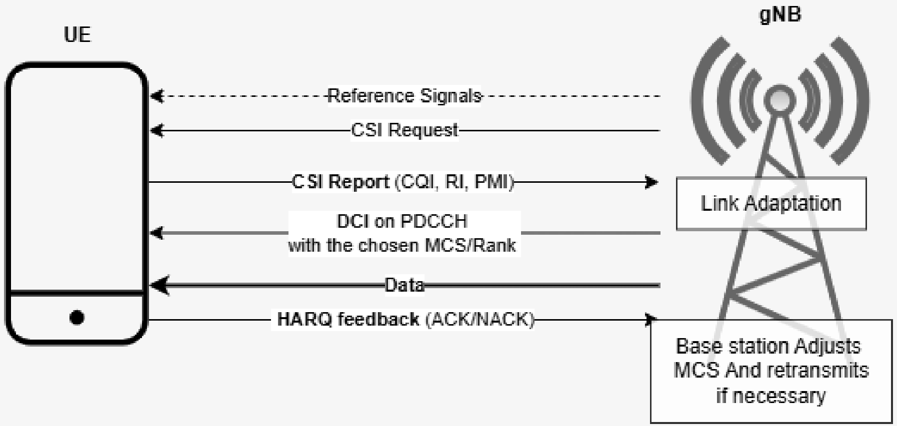
Link Adaptation

Link Adaptation

Adjusts modulation and coding scheme (MCS) based on channel quality

Aims to maximize throughput while keeping error rate acceptable

Decision made at the gNB, based on UE feedback (SINR, CQI, HARQ)



Traditional Approaches

AMC (Adaptive Modulation and Coding)

Inner Loop Link Adaptation (ILLA)

Uses instantaneous SINR or CQI feedback from the receiver to select the best Modulation and Coding Scheme (MCS) based on a predefined lookup table

Outer Loop Link Adaptation (OLLA)

Adjusts an SINR offset dynamically using ACK/NACK feedback to ensure the target Block Error Rate (BLER) is met. Works on top of ILLA.

Hybrid Automatic Repeat Request (HARQ) with AMC

Retransmits failed packets with additional coding redundancy (incremental redundancy or chase combining) while also adapting MCS dynamically to improve reliability.

Link Adaptation– Traditional

Excessive Feedback Dependency

Reactive Adjustment

Lack of Predictive Insight

AI Optimisation for Link Adaptation

Direct vs Indirect MCS Prediction[1]

- Direct: Models predict MCS from features like SINR, CQI [1][2]
- Indirect: First predict channel metrics (e.g., SNR), then map to MCS

Temporal Models Perform Better[3]

- Recurrent models (e.g., LSTM, GRU) outperform CNNs and MLPs in dynamic channels
- These models capture short-term channel memory better, especially in mobile scenarios

[1] M. Elwekeil, S. Jiang, T. Wang and S. Zhang, "Deep Convolutional Neural Networks for Link Adaptations in MIMO-OFDM Wireless Systems," in IEEE Wireless Communications Letters, vol. 8, no. 3, pp. 665-668, June 2019, doi: 10.1109/LWC.2018.2881978.
[2] J.-E. Oh, A.-M. Jo, and E.-R. Jeong, 'MCS Selection Based on Convolutional Neural Network in Mobile Communication Environments', in *2023 Fourteenth International Conference on Ubiquitous and Future Networks (ICUFN)*, Jul. 2023, pp. 684–686. doi: 10.1109/ICUFN57995.2023.10201063.
[3]O. Stenhammar, G. Fodor, and C. Fischione, 'A Comparison of Neural Networks for Wireless Channel Prediction', *IEEE Wireless Communications*, vol. 31, no. 3, pp. 235–241, Jun. 2024, doi: 10.1109/MWC.006.2300140.

AI Optimisation for Link Adaptation

Simulation Data Dominates[1]

- Due to lack of real-world datasets, most research uses simulators (NYUSIM, MATLAB, custom tools)
- Realism varies widely: many simplify SINR traces or skip HARQ logic

Single-Direction Traffic

- Most studies target downlink, since MCS is gNB-controlled
- Uplink-focused works are rarer; datasets are harder to obtain

[1] M. Elwekeil, S. Jiang, T. Wang and S. Zhang, "Deep Convolutional Neural Networks for Link Adaptations in MIMO-OFDM Wireless Systems," in IEEE Wireless Communications Letters, vol. 8, no. 3, pp. 665-668, June 2019, doi: 10.1109/LWC.2018.2881978.
[2] J.-E. Oh, A.-M. Jo, and E.-R. Jeong, 'MCS Selection Based on Convolutional Neural Network in Mobile Communication Environments', in *2023 Fourteenth International Conference on Ubiquitous and Future Networks (ICUFN)*, Jul. 2023, pp. 684–686. doi: 10.1109/ICUFN57995.2023.10201063.
[3]O. Stenhammar, G. Fodor, and C. Fischione, 'A Comparison of Neural Networks for Wireless Channel Prediction', *IEEE Wireless Communications*, vol. 31, no. 3, pp. 235–241, Jun. 2024, doi: 10.1109/MWC.006.2300140.

Simulation

1 gNB, 4 Ues
3GPP UMa Channel Model (NLOS)

Frequency: 30.5 GHz
Bandwidth: 100 MHz
Random Walk mobility
Gaming traffic over UDP
Logged: SINR, CQI, MCS, HARQ
10 seeds × 3 runs → ~21,000 samples

Fig. 1. Usage scenarios of IMT for 2020 and beyond [3].

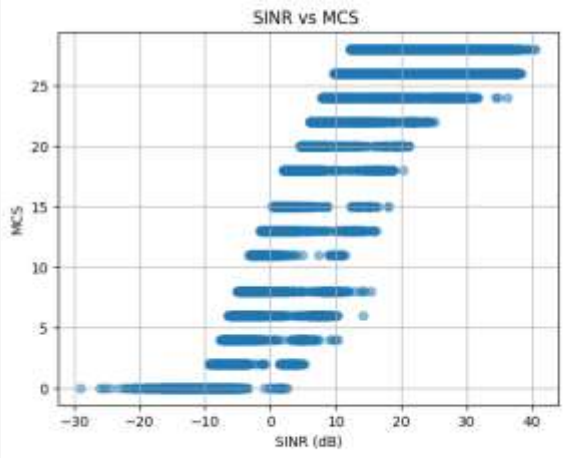
Data Preprocessing

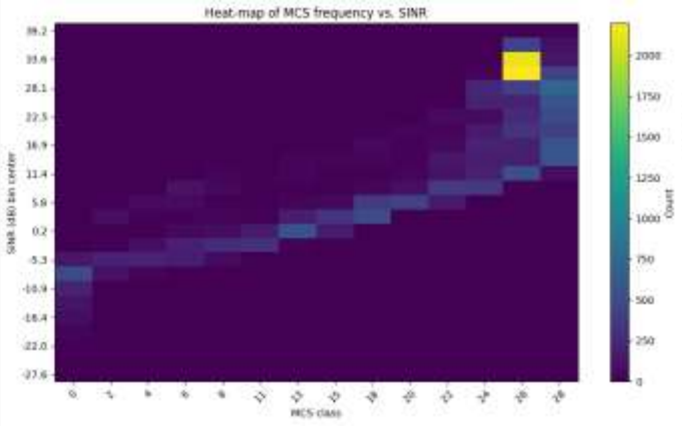
Simulation Output

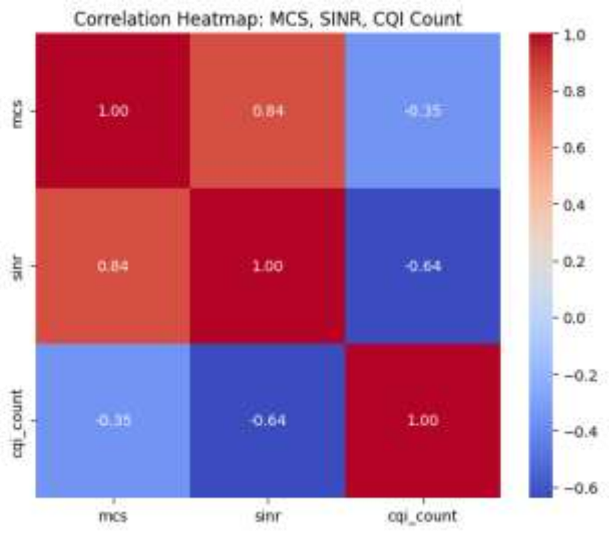
```
NrDlMacStats.txt (MCS assignments)
DlDataSinr.txt (downlink SINR events)
RxedGnbMacCtrlMsgsTrace.txt (CQI reports)
```

	time	mcs	sinr	RNTI	run	cqi_count
0	0.0765	26	33.4369	seed100_run1_rnti_2	seed100_run1	1.0
1	0.1585	26	32.6890	seed100_run1_rnti_2	seed100_run1	1.0
2	0.2145	26	33.4499	seed100_run1_rnti_2	seed100_run1	1.0
3	0.2745	26	33.1776	seed100_run1_rnti_2	seed100_run1	1.0
4	0.3265	26	34.2603	seed100_run1_rnti_2	seed100_run1	1.0

70% Training
30% Validation


SINR vs MCS
MCS
SINR (dB)


Heat-map of MCS frequency vs. SINR
SINR (dB) bin center
MCS class
Count


Correlation Heatmap: MCS, SINR, CQI Count
mcs
sinr
cqi_count
1.00
0.84
-0.35
0.84
1.00
-0.64
-0.35
-0.64
1.00

AI Modelling

Input

Sequences of SINR (and CQI, in some versions), with T = 10

Output

Next MCS

Models

CNN (baseline – sliding window of SINR)
CNN + CQI (adds feedback)
CNN + CQI + Masking (simulates missing feedback)
LSTM (captures longer temporal dependencies)

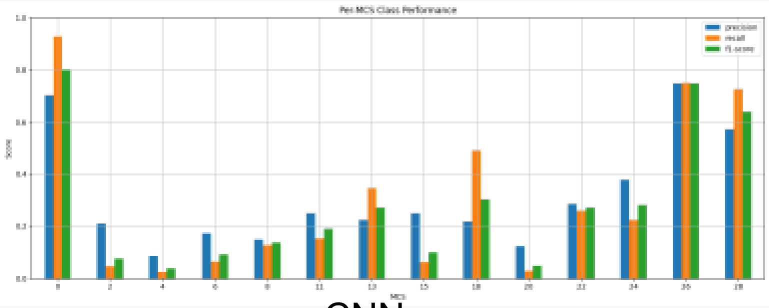
Training Details

Optimizer: Adagrad
Loss: Cross-Entropy
Epochs: 50.
Handled Class Imbalance: Weighted Random Sampler.

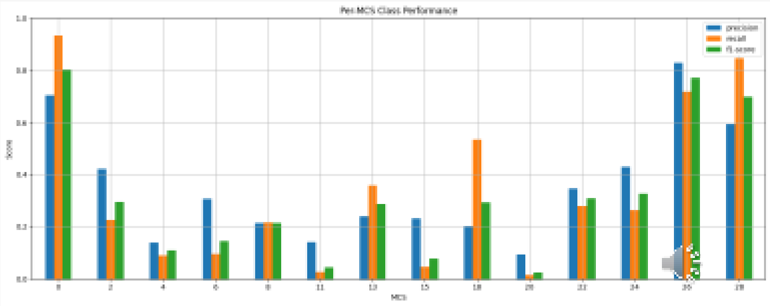
Hyperparameter Tuning: Basic sweep performed (12 configs for CNN, identified best params like 128 filters, 8D RNTI embedding, LR 0.005 leading to ~53.5% Acc).

Result

Model	Input Features	Architecture	Accuracy
CNN	SINR only	Conv1D + Dense	52.3%
CNN + CQI	SINR + CQI	Conv1D + Dense	53.7%
CNN + Masking	SINR + CQI + mask	Conv1D + Dropout	54.1%
LSTM	SINR + CQI	LSTM layers	55.1%



CNN



LSTM

03

Energy Prediction

Literature Review

Energy Optimization are Often Reactive & Rule -Based

AI Models Are Rare – And Often Use Synthetic or Simplified Data

Underuse of Temporal and Contextual Features

Dataset

Source: dataset that was provided by the international telecommunication union (ITU) in 2023 as part of a global challenge[1]

Size: 92,629 entries from 1,019 base stations

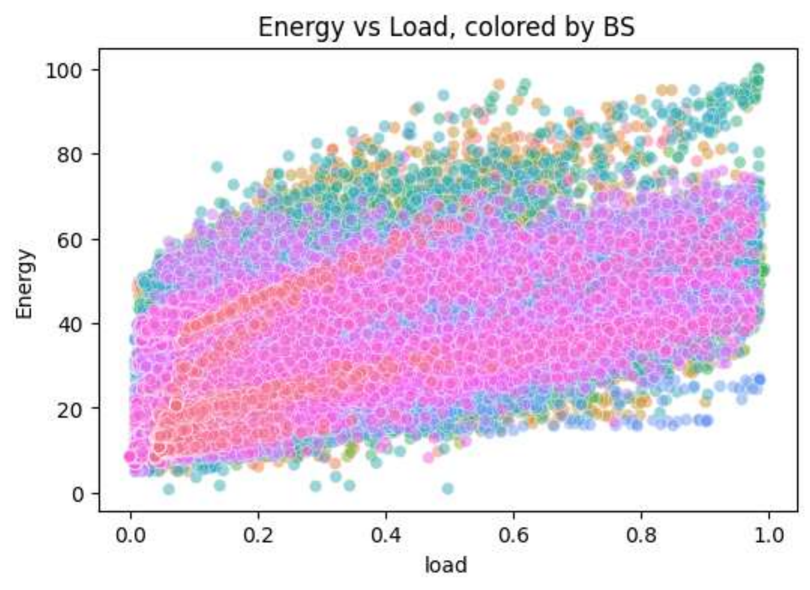
Granularity: Hourly logs

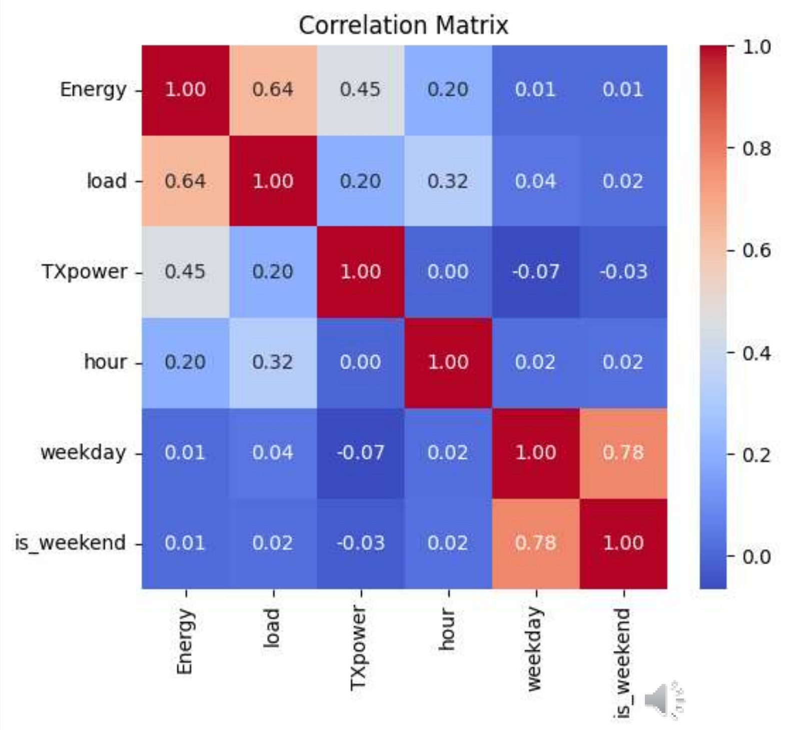
Key Features

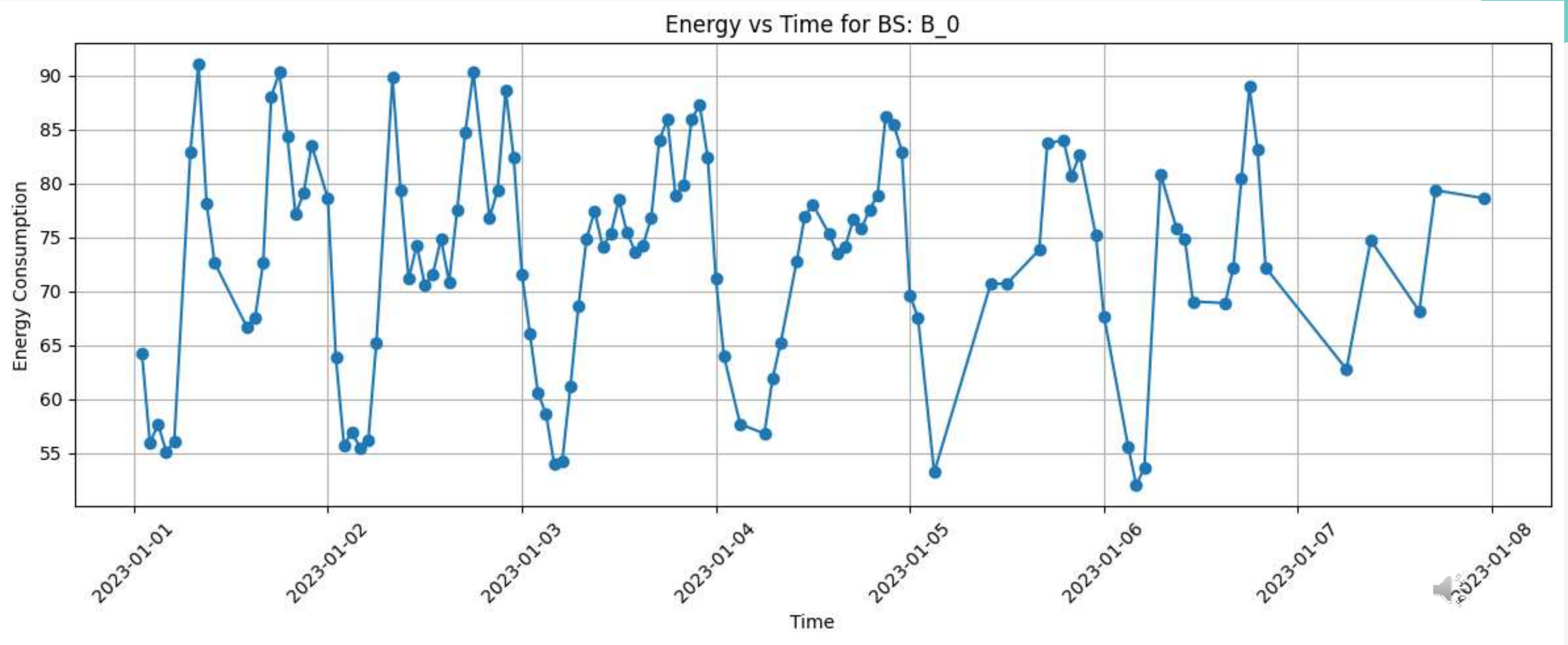
- Energy (Watt-hours)
- Load (traffic load)
- TXpower (transmission power)
- ESMODE (energy-saving mode)
- BSID
- Timestamp

	Time	BS	Energy	load	ESMODE	TXpower
0	20230101 010000	B_0	64.275037	0.487936	0.0	7.101719
1	20230101 020000	B_0	55.904335	0.344468	0.0	7.101719
2	20230101 030000	B_0	57.698057	0.193766	0.0	7.101719
3	20230101 040000	B_0	55.156951	0.222383	0.0	7.101719
4	20230101 050000	B_0	56.053812	0.175436	0.0	7.101719

[1]'5G-Energy consumption Dataset'. Accessed: May 20, 2025. [Online]. Available: https://www.kaggle.com/datasets/nadiatriki/5g-energy-consumption-dataset


Energy vs Load, colored by BS
Energy
load
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0

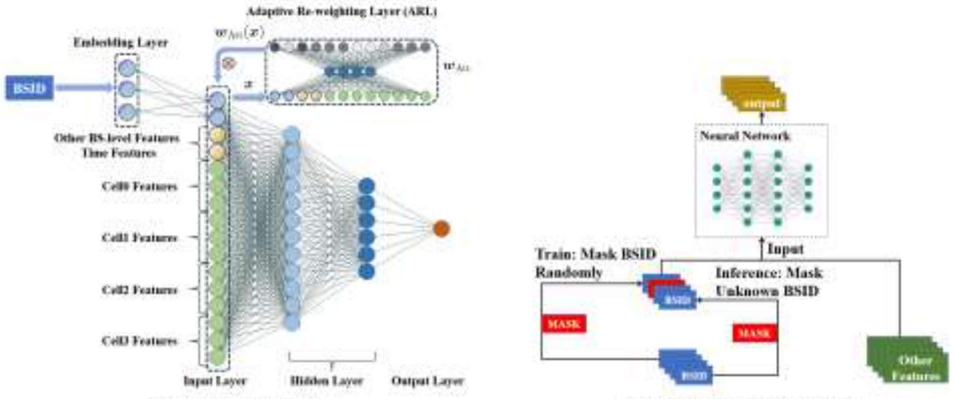

Correlation Matrix
Energy
load
TXpower
hour
weekday
is_weekend
1.00 0.64 0.45 0.20 0.01 0.01
0.64 1.00 0.20 0.32 0.04 0.02
0.45 0.20 1.00 0.00 -0.07 -0.03
0.20 0.32 0.00 1.00 0.02 0.02
0.01 0.04 -0.07 0.02 1.00 0.78
0.01 0.02 -0.03 0.02 0.78 1.00
1.0
0.8
0.6
0.4
0.2
0.0


Energy vs Time for BS: B_0
Energy Consumption
90
85
80
75
70
65
60
55
2023-01-01
2023-01-02
2023-01-03
2023-01-04
2023-01-05
2023-01-06
2023-01-07
2023-01-08
Time

AI Modelling

Input	Load, TXpower, ESMODE Time-based features (hour, weekday/weekend) Encoded Base Station IDs (one-hot or learned embeddings)
Target	Hourly energy consumption of base stations
Loss Function	Mean Absolute Percentage Error (MAPE) $\mathrm{MAPE} = \frac{\sum_{i=1}^{n} \lvert y_i - \widehat{y}_i \rvert}{\sum_{i=1}^{n} \lvert y_i \rvert},$

AI Modelling



(a) Deep learning model (b) Training and inference phase

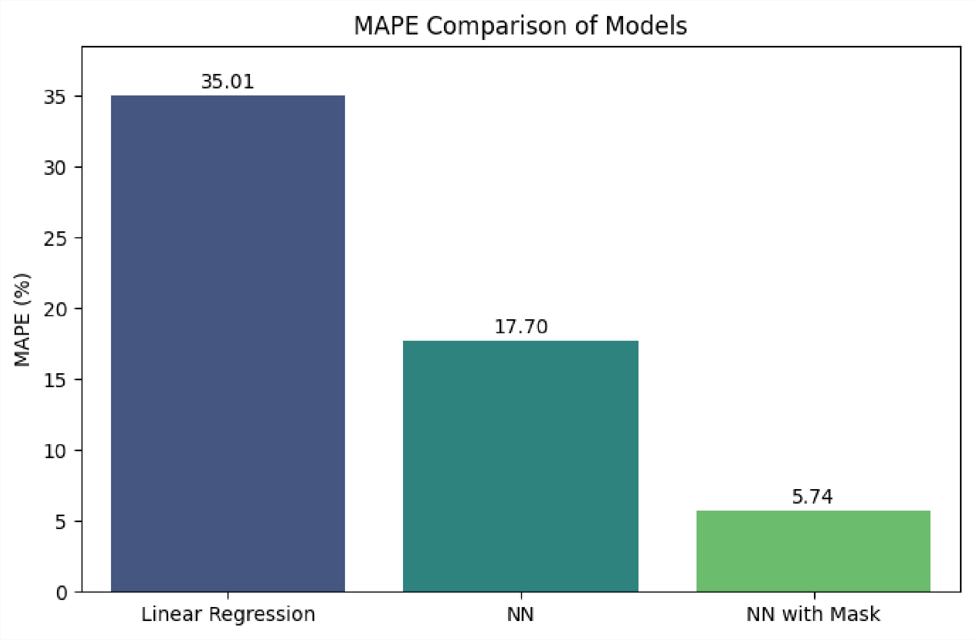
Fig. 2. Model Architecture: Our model is a two-layer Feed Forward Network. In the training phase, random masking is applied to randomly reassign BSIDs to 'Unknown BS'.

Models

- Linear Regression
- 3-layer Neural Network
- Masked Neural Network

Chen, Tingwei, et al. "Modelling the 5G Energy Consumption using Real-world Data: Energy Fingerprint is All You Need." *arXiv preprint arXiv:2406.16929* (2024).

Result



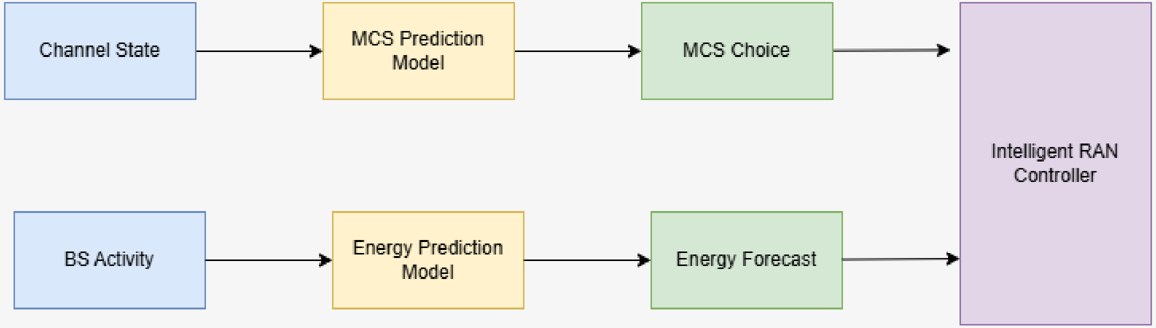
MAPE Comparison of Models
35.01
17.70
5.74
MAPE (%)
0
5
10
15
20
25
30
35
Linear Regression
NN
NN with Mask

04

Analysis

Analysis

- **Link Adaptation:** AI (LSTMs/tuned CNNs) show promise (~55% acc.) in learning temporal channel dynamics for MCS prediction, outperforming simpler methods.
- **Energy Prediction:** Advanced AI (Masked NN) achieved high accuracy (5.5% MAPE) in forecasting real-world BS energy use.
- Though not yet integrated, these findings lay a **foundation for dual-objective (Performance & Sustainability) optimization.**



Discussion & Key Insights

- **Data Challenge:** Acquiring realistic, comprehensive 5G datasets remains a hurdle.
- **Link Adaptation** :
  - Temporal models are crucial
  - Data imbalance is a real-world challenge.
- **Energy Modelling**:
  - Granular Energy Prediction in feasible and can provide remarkable insight even with limited Dataset
- AI models can learn from **structure in data**, but results depend heavily on data realism and balance.

05

FutureWork

Future Work

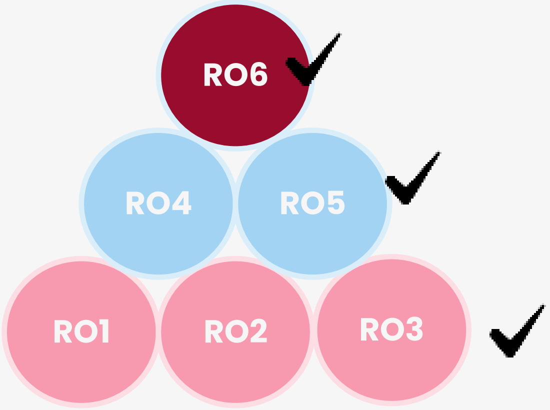
- **Explore temporal architectures** like GRU, MiniROCKET, and Hyperdimensional Computing (HDC) to improve MCS prediction under volatile channel conditions
- **Simulate denser, more diverse network scenarios** to address MCS class imbalance and improve generalizability
- Use richer energy datasets with detailed BS configurations (e.g., antenna count, RU type, deployment mode)
- **Integrate** link adaptation with energy modelling, enabling joint optimization of throughput and consumption

06

Conclusion

To Conclude

- Have successfully developed and evaluated AI models for both **MCS prediction** (simulation-based) and **energy estimation** (real-world data)
- Addressed key challenges in preprocessing, temporal modeling, and dataset realism
- All research objectives were successfully met
- This thesis demonstrates the potential of AI to support **smarter, greener 5G networks,** even when working with real-world complexity



Thanks ☺

Questions???

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Appendix A1

Table A.1. Comparison of Datasets in Recent MCS/Channel Prediction Studies

Study	Data Method	Scenario	Realism	Tool / Company
Varshney et al. (2023)	NYUSIM-based mmWave sim	28 GHz Urban Macro	High	NYUSIM / NYU
Zhang et al. (2018)	MIMO-OFDM, SNR sweep	Synthetic system-level	Medium-Low	–
Herath et al. (2019)	Real RSS from 5 networks	LTE, WiFi, Zigbee, etc.	Real-world	CRAWDAD / G5
Li et al. (2024)	RSSI via spectrum analyzer	2.4 GHz RSSI trace	Real-world	Spectrum Analyzer
Seeram (2022)	MATLAB 5G testbed	SU-MIMO, mobility, HARQ	Medium-High	Huawei
Oh et al. (2023)	Rayleigh/Rician in MATLAB	5G NR-like setup	Medium	MATLAB/TensorFlow
Elgabroun (2019)	mmWave sim (UL)	28 GHz, walking UE	High	Ericsson tool
Stenhammar et al. (2024)	3GPP TDL-A model	2 GHz NLOS, mobile UE	Medium-High	3GPP / –
Tsipi et al. (2024)	Ray-tracing + LTE overlay	Urban 2.1 GHz NSA	High	Altair FEKO
Yun et al. (2024)	5G NR sim, Rayleigh/Rician	UAV, 3.6 GHz, 100 MHz	Medium	MATLAB/TensorFlow

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

Appendix B1