AI-fuelled Adaptive Handovers and Energy-aware Mechanisms in 5G Cellular Networks

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***Abstract*—5G networks introduce complex challenges in mobility management and energy consumption, including more frequent handovers as users move between cells, network congestion, service disruptions, increased power consumption due to higher path loss, and the need for beamforming. This work performs an experimental validation on optimal mobility management and energy consumption efficiency in 5G networks fuelled by Artificial Intelligence (AI) models. To achieve this, we conducted two real-world experiments in a 5G testbed, assessing the: (i) dynamics of handovers (HOs) between gNodeBs (gNBs) within a single operator network; and (ii) energy consumption characteristics of 5G base stations under various traffic conditions. To advance location-aware and energy-saving intelligence in 5G networks, we leverage adaptive AI-fuelled policy-enforcement mechanisms by harvesting traffic data from the 5G testbed and learning patterns for optimal energy consumption and mild handover events. The results of this work demonstrate significant insights for network operators which aim to reconcile performance network demands with energy consumption limitations, and develop sophisticated predictive models for large scale 5G network deployments.**

***Index Terms*—energy efficiency, location-aware policy-enforcement mechanisms, AI-fuelled predictive 5G network mobility patterns**

I. Introduction

In recent years, fifth-generation (5G) networks have fundamentally transformed user communication experiences. The progression of 5G technology promises enhanced Mobile Broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC), thereby providing dependable connectivity for diverse applications and emerging use cases [1].

Nonetheless, these advancements pose diverse challenges in mobile communications, such as ensuring seamless user connectivity and managing the increased energy consumption necessitated by high-demand applications. The first challenge pertains to mobile handover (HO), the process by which an active connection is transferred from one base station (i.e., gNB, in the context of 5G networks) to another. This capability is an essential aspect of such communication networks, given the inherent mobility of users and the movement of devices through different cellular coverage areas during use. HO is critical for maintaining uninterrupted service to end users [2]. The second challenge involves the energy requirements of base stations servicing 5G devices. The rising number of devices demanding high bandwidth while preserving Quality of Service (QoS) in densely used mobile environments leads to power consumption issues that impact both environmental preservation and the sustainability of extending 5G infrastructure. Although traditional network optimization techniques offer partial solutions, the complexity inherent in modern 5G networks necessitates more sophisticated approaches. Mobile HO, a pivotal process for seamless connectivity, may encounter inefficiencies such as delays, increased latency, and lapses in Service Level Agreements (SLA) adherence, especially in high-mobility scenarios. Similarly, the growing demand for high-bandwidth applications, such as video streaming, exacerbates power consumption. Recent advancements in AI and Machine Learning (ML) present new opportunities to analyse real-time network data and dynamically optimize performance. AI-driven models can predict optimal handover conditions, minimize energy waste, and enhance network performance and efficiency. However, the efficacy of these AI-driven solutions should be rigorously validated through real-world experimental evaluations to ensure their reliability in 5G settings [3].

Crucially, the theoretical promise of AI-driven solutions should be rigorously validated through real-world experimental assessments. This is the motivation of the proposed work, which conducts extensive experiments on mobile handover performance and power consumption, followed by AI-fuelled analyses to explore optimizations under competitive conditions and enforce policy-driven network actions employing rules. The main contributions of this work encompass an experimental data analysis over a real 5G testbed highlighting enhanced mobile handover performance and energy efficiency. They are, as follows:

- We introduce an insightful evaluation of energy consumption trade-offs during high-bandwidth streaming scenarios by analysing 5G network data in diverse cases, which is crucial for maximizing operational efficiency.
- We showcase the application of AI-driven models to derive policies for enforcement on the 5G network through rules, significantly advancing network reliability and energy efficiency.
- We employ these AI-fuelled network mechanisms to allow for proactive HO and fine-grained control over competitive metrics resulting in significantly improved energy efficiency.

The rest of the paper is organized, as follows: Section II provides the current literature review around 5G networks efficient mobility management, and power consumption in such networks while using AI and ML models. Section III presents and describes the conducted experiments. Section IV presents the deployed AI pipeline, Section V discusses the experimental results, and Section VI concludes the paper.

II. Literature Review

The advent of 5G networks has brought forth unprecedented demands on efficient mobility management, particularly in handover procedures and energy consumption optimisation. The need for seamless connectivity, low latency, and high reliability has driven extensive research into optimizing 5G handover and energy efficiency processes.

Several studies emphasize the importance of context awareness for efficient handovers. Chabira et al. [4] focus on how recent advances in AI, ML and Deep Learning (DL) are being applied to improve predictive handover decisions and enable real-time, adaptive load distribution. Similarly, Khan et al. [5] present a thorough survey on existing solutions regarding vehicularility management. Last, Song et al. [6] proposed a context-aware handover decision algorithm that considers network load, user preferences, and service requirements to select the optimal target cell. All these works highlight the shift from reactive to proactive handover strategies, leveraging contextual data to improve handover efficiency. This work differentiates by integrating a crucial, yet underexplored, dimension: energy efficiency as a primary optimization objective alongside seamless 5G connectivity.

The application of AI serves as a promising avenue for optimizing 5G handovers and energy efficiency. Jahandar et al. [7] explored AI / ML for distributed handover management, enabling collaborative learning across multiple base stations. Silva et al. [8] examined mmWave handover optimization for vehicular networks, demonstrating the need for beam management and fast context transfer. Last, Papaioannou et al. [9] introduced an adaptive and intelligent resource allocation method driven by AI to increase network capacity. These efforts underscore the potential of AI/ML to adapt to the dynamic nature of 5G networks and optimize their performance. The proposed work carves a distinct niche by explicitly addressing the critical interplay between adaptive handovers and energy efficiency through AI-driven resource allocation.

Existing works are surveying the literature [10] and are limited either on the context reliability leading to incorrect handover decisions [11], or on efficiently balancing trade-offs as optimizing 5G handovers involves balancing competing objectives, such as energy efficiency, latency, throughput, and reliability [12].

Understanding the limitations of non-AI schemes in 5G implies that 5G handover relies on fixed thresholds (e.g., Received Signal Strength Indicator (RSSI), etc.), reactive mechanisms, and frequent "ping-pong" handovers leading to suboptimal cellular network management. Compared to the above-mentioned works and non-AI schemes, the contribution of this work is the proposition of a novel approach that combines event-driven context reliability assessment for mild handovers with a predictive energy efficiency method. The merits of this work allow for proactive mitigation of context incompleteness or uncertainties and a fine-grained control over the trade-offs resulting in significantly improved handover efficiency coupled with energy-efficient optimization.

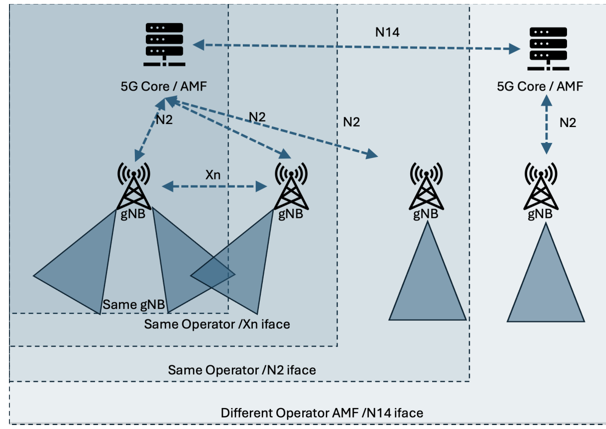

Fig. 1. 5G Handover scenarios

III. Conducted Experiments

Our experiments have been performed at the University of Patras 5G facility [13], an academic non-public 5G infrastructure. This facility offers end-to-end support to various application verticals using the lab-based 5G infrastructure for experimentation. We detail below the scenarios for mild mobility HO and power consumption.

A. Mobility

The mobility scenarios are following and can be illustrated in Figure 1:

- Mobility between cells served by the same gNB.
- Mobility between different gNBs that are served by the same Access And Mobility Management Function (AMF) of the 5G Core, which means that both are managed by the same operator. Depending on the connectivity of the gNBs, this HO can be performed either through the N2 interface (connecting the gNB with the AMF) or the Xn interface (connecting gNBs directly).
- Mobility between gNBs connected to different AMFs. This is the case when during a HO the device moves to a gNB of a different operator. This HO is performed over the N14 interface. In such cases agreements between the operators allow such usage without the user having to be subscriber to both operators.
- Mobility between different Radio Access Technology (RAT), where the HO needs to be done from 5G networks to 4G/LTE networks and vice versa, performed over the N26 interface. This is not shown in Fig.1 since the conducted tests were under 5G netowrks only.

More information about the basic architecture of 5G and the various interfaces can be found at [14]. In a 5G system, there are various reasons for a HO to occur, and this HO can be either initiated by User Equipment (UE) or triggered by the network itself. Some of the factors that can trigger a HO include:

- Signal Strength: If a neighbour cell's signal is stronger, then the signal from the serving cell becomes weak, and thus a handover may be performed.
- Mobility Management: In high-mobility and/or dense scenarios, such as with vehicles, high-speed trains, or urban environments, the system predicts where the device will move and prepares the handover in advance to avoid interruptions.
- Load Balancing: If one base station is overloaded, a handover may be triggered to a neighbouring cell with less load, ensuring optimal resource utilization.
- QoS: In cases where the device experiences poor QoS below the required SLA threshold, such as high latency or low throughput, a handover can be used to connect to a different base station offering better performance and satisfying the SLA threshold.

The mobility experiments we conducted have focused on HO between different gNBs that belong to the same operator. Each gNB was serving a cell. The topology of the cells allowed for a common coverage area between the two cells. The tests consisted of a person moving around the coverage area holding a mobile phone that was simulating traffic streaming. The traffic pattern was to move starting from one gNB in the direction of the other gNB, return to the first, and repeat. This was repeated many times with various paths and random stops between the two gNBs.

In Figure 2, the connected UEs per gNB are illustrated. In this snapshot of the experiment, 8 handovers were performed between the two gNBs, with the single UE alternating connection between the two base stations.

To evaluate the various conditions that may affect the handover decision, a number of metrics have been gathered to be further analysed later. These metrics have been gathered from the UE perspective and include, among others, the Modulation Coding Scheme (MCS), which defines the number of bits carried by every symbol during transmission and is a signal quality indicator. In general, high MCS means high quality and higher bitrates. Signal to Noise Ratio (SNR) for the uplink direction is also considered. SNR is the ratio of signal power to noise power. It is usually expressed in dB and compares the actual useful signal to the background noise. The Channel Quality Indicator (CQI) is a metric reported by the UE to the gNB indicating the quality of the connection between them from the UE perspective. The higher the value, the better the quality. This value is used to calculate the MCS used for transmission. All the metrics gathered for this experiment are presented in Table I.

B. Power Consumption

The second set of experiments has been conducted measuring the power consumption of a 5G base station under various conditions. The gathered metrics are presented in Table II. Besides the 5G-related metrics (i.e., bitrate, connected UEs, etc.), power metrics have also been collected. These power metrics were gathered for both the Radio Unit (RU) and the gNB. In general, the RU handles the radio communication of the network and is responsible for transmitting and receiving radio signals to and from UEs by performing Radio Frequency (RF) processing, such as modulation, demodulation, filtering, and amplification. The gNB handles all the other aspects of the 5G communication, from mobility management and encryption to forwarding the traffic to the data path.

The experiments conducted aimed to collect these metrics under different network usage scenarios. The scenarios followed these steps: (i) connecting multiple devices, (ii) initiating traffic (i.e., uplink, downlink, or both), (iii) modifying the connected UEs by dynamically adding or removing devices, and (iv) modifying traffic (either increasing or decreasing it).

The results are presented in Figure 3. This figure shows that the experiment-induced traffic variations directly impact the power consumption of the gNB, while the RU power remains largely unchanged. As uplink and downlink traffic increases, the gNB power consumption follows a stepped pattern, rising in discrete increments. This suggests that the gNB actively scales its power consumption based on network demand rather than maintaining a constant energy usage and that the gNB increases its power only when traffic increases. Conversely, when traffic decreases, the gNB power consumption also reduces, reflecting a dynamic adaptation to network load.

In contrast, the RU power consumption remains relatively stable throughout the experiment, showing little to no variation in response to traffic changes. This implies a correlation between bitrate fluctuations and gNB power consumption that is directly influenced by the traffic load.

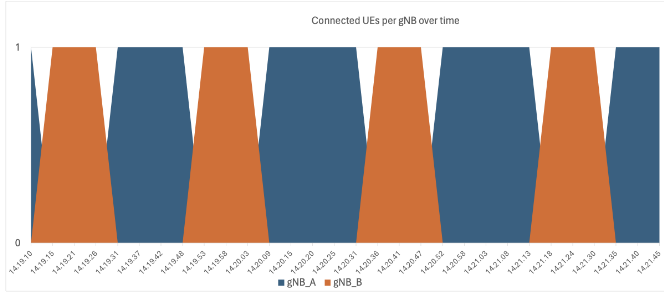

Fig. 2. Connected UEs per gNB

Name	Unit	Description
dl_bitrate	bps	Downlink bitrate.
ul_bitrate	bps	Uplink bitrate.
dl_tx	Integer	No. of DL transport blocks.
ul_tx	Integer	Number of received uplink transport blocks.
dl_err	Integer	Number of downlink non-transmitted blocks.
cqi	Number	Last reported CQI.
ri	Number	Last reported rank indicator.
dl_mcs	Number	Average downlink MCS.
ul_mcs	Number	Average uplink MCS.
pusch_snr	Number	Last received PUSCH SNR.
ul_path_loss	dB	Last UL path loss.
p_ue	Number	UE transmission power in dB.

TABLE I
METRICS GATHERED FOR HO EXPERIMENTS

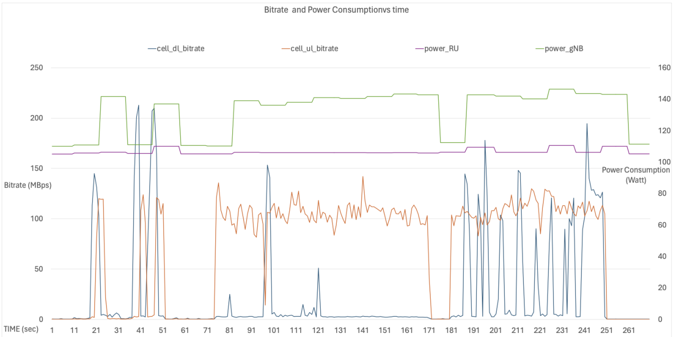

Fig. 3. 5G Power vs. Throughput

Name	Unit	Description
cell_dl_bitrate	bps	Cell DL bitrate.
cell_ul_bitrate	bps	Cell UL bitrate.
curA	A	The measured current.
pwrA	W	The measured power.
ue_count	Integer	Number of connected UEs.

TABLE II
METRICS GATHERED FOR POWER CONSUMPTION EXPERIMENTS

IV. Data Analytics Pipeline

A critical component in the analysis of collected data is the Data Analytics Pipeline. The analytics pipeline fulfills two essential functions: (i) it aggregates telemetry data to forecast handover occurrences, assess energy utilization, and facilitate slicing and service orchestration; and (ii) it provides Application Programming Interfaces (APIs) to reinforce the AI as a Service (AIaaS) paradigm. The exposure of the learnt patterns through AIaaS APIs facilitates the adaptation of the 5G testbed configuration, thereby optimizing its operational efficacy. We harvest 5G data from the conducted experiments, and we further feed the data analytics pipeline to learn patterns about the HO events and power consumption. Last, the trained AI models are being exposed via dedicated AIaaS APIs to support a set of predictive tasks.

A. Data Aggregation, Cleaning and Normalisation

We aggregate the experimental data into a single data structure, and add a new column specifying the handover event for the first experiment. This new column is then used as the target value (i.e., label) for the analysis in Section V. The same procedure is followed for the power (energy) experiments, but in these experiments, we use the exact value of power as the target value to support a regression task. We then replace all NaN values with zero (0), since all of them are numeric values that vary over time. Last, we normalize the data by using the standard scaling method (i.e., subtract by the mean value and divide by the standard deviation), and in some specific cases (e.g., in the Deep Neural Network (DNN) model) we normalize by the Min-Max normalisation method.

B. Feature Extraction, Correlation and Selection

The features presented in Table I were extracted for both gNBs in our experimental network setup and were labeled : node_a and node_b nodes. Each feature was recorded separately for the two nodes using distinct names.

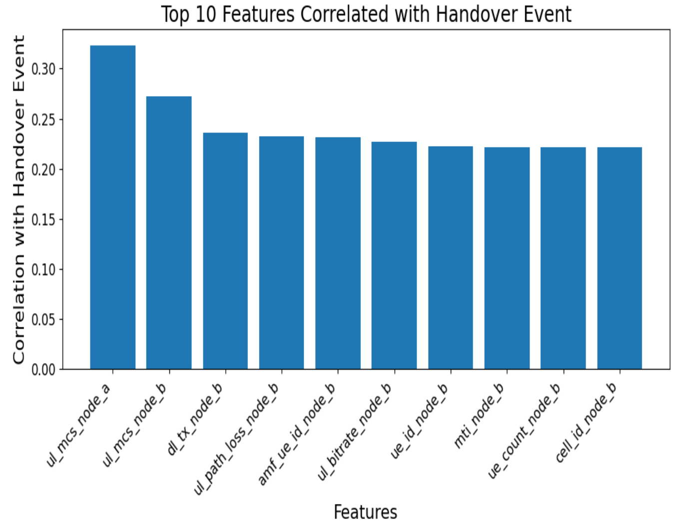

Fig. 4. Top 10 Features correlated with Handover Event

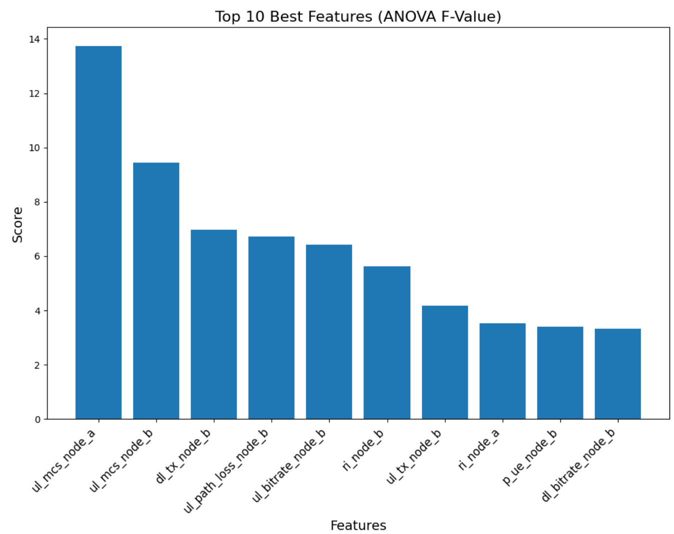

Fig. 5. Top 10 Features selected by ANOVA F-value for Handover Event

Before proceeding to the modeling phase, we perform feature selection using correlation and other methods. Only features related to the cell uplink/downlink bitrates, UE devices, and details about the gNB service state are kept. Feature correlation is then used as a statistical measure to understand the relationship between the 5G network features. This measure expresses how much two features change together. Feature correlation is used to ease feature selection and extract the most important features for the next step, which is data modeling. Figure 4 and Figure 6 illustrate the correlation for handover events and power consumption.

C. Data Analytics and Predictive Tasks

The curated data are used to train various AI models and expose the AIaaS predictive tasks as APIs. We also benchmark

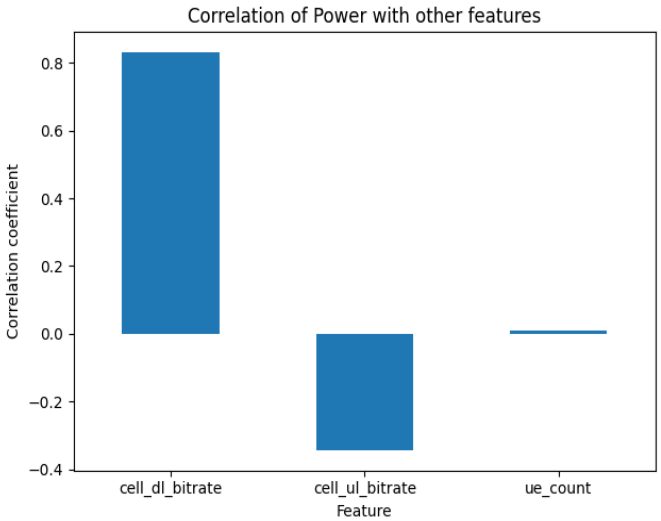

Fig. 6. Features correlated with Power (Energy)

over different DL and ML methods to measure their performance through accuracy, precision, recall, and MSE based on the learning task.

We chose classical methods (i.e., Logistic Regression, Random Forest, GradientBoost) and deep neural network models (i.e., DNN, DNN–LSTM) to keep a balance between simplicity, speed, and predictive power. The DNN consists of feed-forward fully-connected layers with ReLU activations, whereas the DNN-LSTM augments that same stack with an LSTM layer inserted after the second hidden layer to better capture temporal dependencies in the input. This combination lets us compare trade-offs in efficiency, and accuracy for both "now" estimates and next-step forecasts.

We deployed three predictive tasks to leverage our 5G telemetry data:

a) Model I: Time-Series Handover Classifier: A binary classifier that ingests a sequence of network feature windows $X_{t-T+1:t}$ (with $T = 30$ s) and predicts whether a handover occurs in the next interval:

$$\hat{y}_t = \text{Classifier}\big(X_{t-T+1:t}\big), \quad y_t \in \{0,1\}.$$

b) Model II: Static Network-Feature Regression (Power Now): A standard regression mapping from current network measurements X_t to current power consumption E_t:

$$\hat{E}_t = f\big(X_t\big),$$

where f is learned via Random Forest, Logistic Regression, GradientBoost, or deep models. This isolates the instantaneous impact of network state on energy usage.

c) Model III: Dynamic Time-Series Regression (Power Next): A forecasting model that combines the same network features X_t with one or more lagged power readings $\{E_t, E_{t-1}, \dots\}$ to predict the*next energy value:

$$\hat{E}_{t+1} = g\big(X_t,\, E_t,\, E_{t-1}, \dots\big).$$

This captures both network-driven effects and temporal effects in consumption.

We split the data into training (80%) and test sets (20%) to assess models' accuracy. We trained both traditional ML models (e.g., Random Forest, Logistic Regression, GradientBoost) and DL models (DNN, Long Short-Term Memory (LSTM) + DNN). All models use a 1D feature vector, except LSTM, which takes a 2D input representing time-windowed features.

V. Experimental Results

This section presents the experimental results on the telemetry data collected by the 5G testbed. We evaluate the performance of the AI models using accuracy, precision, recall, Mean Squared Error (MSE) and R-Squared according to the learning task.

A. Preparatory Steps on 5G Datasets

We ingest 5G testbed telemetry into our Data Analysis Pipeline to train AI models—benchmarking Random Forest, Logistic Regression, Gradient Boost, DNN and a DNN model with LSTM layers—and expose the resulting AIaaS predictive tasks via APIs. We evaluate each method on accuracy, precision, recall, and MSE across three time-series challenges: forecasting future handover events with high precision; deriving a regression model to predict critical power-reservation needs from network features; and performing advanced time-series regression that fuses historical network data with past power consumption metrics to forecast future power usage.

B. Analytic Tasks and Results

Table III presents the evaluation metrics for the classification models. Deep Neural Network (DNN) achieved the best performance with 0.9684 accuracy, 0.8500 precision, 0.9500 recall, and an F1-score of 0.8833, effectively balancing false positives and negatives. K-Nearest Neighbors (KNN) followed with 0.9263 accuracy but lower precision (0.5500) and recall (0.4833). Random Forest had 0.8947 accuracy and high precision (0.8000) but a low recall of 0.3000, missing many true positives. Gradient Boosting (0.8421 accuracy, 0.6083 precision, 0.4167 recall) and Logistic Regression (0.7895 accuracy, 0.3250 precision, 0.5167 recall) performed worse. These results highlight DNN as the most effective model for handover event prediction.

Classification (Handover Event)				
Algorithms	Accuracy	Precision	Recall	F1
Logistic Regression	0.7895	0.3250	0.5167	0.3834
Gradient Boosting	0.8421	0.6083	0.4167	0.4034
Random Forest	0.8947	0.8000	0.3000	0.4200
K-Nearest Neighbors	0.9263	0.5500	0.4833	0.5100
DNN	0.9684	0.8500	0.9500	0.8833

TABLE III
Handover Event - Results in [0-1] Range

In Table IV: Power (Energy) Regression, Random Forest achieved the lowest MSE (0.005) and highest RSS (0.90), making it the most accurate model. Gradient Boosting followed closely with an MSE of 0.007 and RSS of 0.86. Linear Regression struggled with an MSE of 0.014 and RSS of 0.74, indicating difficulty in capturing non-linear patterns. The DNN model performed better than the Linear Regression (MSE: 0.0135, RSS: 0.78) but was slightly inferior to tree-based models.

In Table V: Power (Energy) Time-Series Regression, LSTM+DNN outperformed all models with the lowest MSE (0.0008) and highest RSS (0.95), making it the most effective for time-series forecasting. Random Forest and Gradient Boosting had an MSE of 0.0145 and RSS of 0.67, showing strong but slightly inferior performance. Linear Regression had the highest MSE (0.016) and lowest RSS (0.64), making it the least effective. The standalone DNN model had a higher MSE (0.019) and RSS (0.95), performing worse than LSTM+DNN but remaining competitive.

Random Forest and Gradient Boosting emerged as top performers for non-time-series regression, consistently capturing complex feature relationships, while LSTM-based DNNs excelled at time-series forecasting by effectively modeling sequential dependencies; in contrast, Linear Regression lagged behind. For handover-event classification, the DNN achieved the highest accuracy and balance in detecting cell transitions, ensuring seamless connectivity. In power-reservation prediction, tree-based models reliably anticipated critical needs, whereas the LSTM+DNN architecture delivered superior forecasts of future consumption by fusing historical network and power data. These results underscore the importance of a hybrid AIaaS strategy—leveraging traditional ML for structured patterns and DL for temporal dependencies—to optimize both mobility management and energy efficiency in 5G networks.

Power (Energy) Regression (Experiment 1)		
Algorithm	MSE	RSS
Random Forest	0.005	0.90
Linear Regression	0.014	0.74
Gradient Boosting	0.007	0.86
DNN	0.013	0.78

TABLE IV
ENERGY REGRESSION - RESULTS

Power (Energy) Time-Series Regression (Experiment 2)		
Algorithm	MSE	RSS
Random Forest	0.0145	0.67
Linear Regression	0.016	0.64
Gradient Boosting	0.0145	0.67
DNN	0.019	0.95
LSTM+DNN	0.0008	0.95

TABLE V
TIME SERIES REGRESSION - RESULTS

VI. CONCLUSION

This study has employed ML and DL methods to address the need for adaptive decisions for handover events and power efficiency in 5G networks through a comprehensive experimental approach. By conducting a thorough data analysis on top of a real-world 5G testbed, we derived valuable insights into the trade-offs between energy efficiency and handover performance, particularly in high-bandwidth streaming scenarios. This empirical approach allowed us to demonstrate the efficacy of AI-driven models in generating actionable network policies, enforced through rules, to significantly enhance network reliability and energy efficiency.

Furthermore, the implementation of AI-fuelled network mechanisms enables proactive handover management and fine-grained control over competing performance metrics, resulting in substantial improvements in energy efficiency. This work provides a practical pathway for optimizing 5G network operations, demonstrating the potential of integrating AI with real-world testbed data to drive policy-driven network actions.

Our future research will focus on extending these findings to larger-scale deployments and exploring the adaptability of our AI-driven models in dynamically changing network environments, contributing to the development of more sustainable and efficient 5G networks.

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