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Enhancing LTE Handover Decision using Optimised Extreme Gradient Boosting and Rule-Based Decision-Support

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ABSTRACT

Long-Term Evolution (LTE) provides low-latency, high-data-rate services, which are essential for delay-sensitive applications such as video streaming and online gaming. Despite this, user mobility among cells can degrade network performance, so efficient handover management is crucial to maintain Quality of Service (QoS). Traditional handover mechanisms use static control parameters, such as hysteresis margin and time-to-trigger, that are not flexible for working with users' dynamic mobility or a range of user trajectories. In this paper, we present a learning-based optimised data-driven approach for LTE handover decision support. An XGBoost model trained with Hyperopt to learn the relationship between user movement angle and handover performance parameters. Interpretable if–then rules are developed to modify the handover control parameters adaptively. Experimental results further show that the performance of the fixed-parameter solutions depends on the maximum handover delay and the mean time to handover, including the minimum handover rate, indicating that a single configuration is unlikely to provide the best performance across all mobility scenarios. The solution offers an efficient, scalable, and interpretable decision-support system to improve LTE handover efficiency in dynamic wireless networks.

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1. INTRODUCTION

To meet the demands of content-rich applications and offer higher data rates with high user mobility, the Long-Term Evolution Network (LTE) has been deployed. Nonetheless, LTE services deteriorate as the mobile user moves from one location to another and the signal weakens. Thus, handovers are necessary to maintain the mobile user's network connection. A handover occurs when the serving base station transfers control to the destination base station. It is used to keep the user's connection. To start the handover procedures, the user equipment (UE) sends the measurement results to the base station. This allows the network operator to collect significant data from both the network and its users [1]. Furthermore, this amount of data can offer opportunities for value creation and knowledge discovery [2].

The handover process is controlled by two critical parameters known as handover control parameters (HCPs): the hysteresis margin (HM) and the time-to-trigger (TTT). The algorithm relies on a series of trigger events identified as A1, A2, A3, A4, and A5 [3]. The hysteresis margin acts as a buffer for the difference in signal strength between the serving base station and the new target base station. Its purpose is to ensure that the target station has a significantly higher Reference Signal Received Power (RSRP) than the serving station before initiating a handover. The hysteresis margin can be set to a value between 0 dB

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and 15 dB, with increments of 0.5 dB. The time-to-trigger (TTT) is the duration during which the hysteresis margin must remain satisfied before the handover can initiate. A handover can only occur once this time interval has passed. The possible values for TTT include 0, 40, 64, 80, 100, 128, 160, 256, 320, 480, 512, 640, 1024, 1280, 2560, and 5120 milliseconds. [4].

For mobile network operators, maintaining reliable and stable communications during the movement of mobile users is a significant problem, as the incorrect setting of handover control parameters can lead to a loss of performance [5]. Thus, determining or predicting the appropriate setting of handover control parameters (HCPs) has been an important area of research in recent years [6]. Fuzzy logic, self-organising networks (SON), machine learning, artificial intelligence, and a one-time approach that is manually updated as needed are among the methods used by previous researchers to determine appropriate handover control settings. Nonetheless, all the methods proposed by the above researchers have a standard limitation: they do not utilise the rich data generated from handover activities and prediction results in improvement activities. Thus, this study proposes a novel rule-based prescriptive analytics technique that prescribes the optimal handover control parameter setting using rich data from the network and the user.

2. RELATED WORKS

Several predefined triggering conditions must be met for an LTE handover to occur. Nonetheless, these conditions are not always sufficient to make an accurate and timely handover decision in all scenarios. Thus, researchers have proposed several approaches to improve the accuracy and effectiveness of the handover. This section, therefore, provides an overview of the triggering event and a summary of previous research.

2.1 Handover Triggering

As mentioned earlier, the algorithm triggers events that meet the conditions for executing the handover. Table 1 describes the various trigger conditions [3]. These event-triggering conditions aim to determine when the handover should occur. The events starting with A are used for intra-LTE systems, while those starting with B are used for IRAT conditions.

2.2 Data Taxonomy

In a network environment, the data generated during handover activities can be divided into two main categories, which are the structured and unstructured [7], [8]. As shown in Figure 1, the structured data in LTE handover is divided into network-related and subscriber-related data.

Table 1: *LTE event triggering conditions.*

Events	Conditions
A1	The serving cell becomes better than a threshold.
A2	The serving cell becomes worse than a threshold.
A3	A neighbouring cell becomes better than the serving cell by an offset. Event-A3 is triggered only when this condition is satisfied for the entire TTT duration.
A4	A neighbouring cell meets the threshold.
A5	The serving cell becomes worse than threshold-1, while a neighbouring cell becomes better than threshold-2.
A6	The measurement from the neighbouring eNB becomes offset better than the neighbouring eNB
B1	When the measurements from neighbouring eNB deploying a distinct RAT from that of the serving eNB (known as inter-RAT neighbours) become better than the specified threshold
B2	When the measurements from the serving cell become worse than threshold1, and the measurements from the inter-RAT neighbours become better than threshold2

Network-related data are generated in a network owned by the network operators. They mainly result from interactions between mobile terminals and base stations, including throughput, delay, link availability, uplink and downlink data transmission, handover, and transmission of system information.[9]. At the same time, the subscriber-related data is customer data such as user ID, location, device type, timestamp, type of service, location mobility patterns [9]. Conversely, unstructured data refers to data that cannot be easily processed in a predefined format. Examples include text messages, personal assistance data, social media data, and call centre transcripts [10].

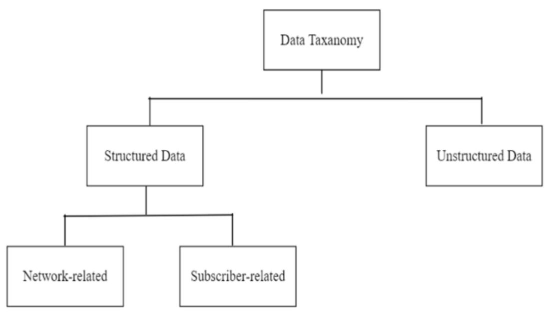

Fig.1: *Data taxonomy from the handover activities.*

2.3 Related Works of the Handover Control Parameters (HCPs)

Due to increasing concerns about LTE handover performance, a growing number of studies have engaged researchers in examining handover control parameters. As shown in Figure 2, numerous methods have been developed to determine control parameter values to improve handover performance.

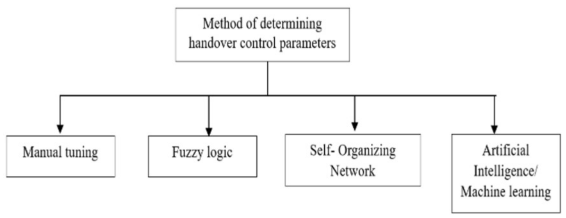

Fig.2: *Methods of determining handover control parameters.*

Traditionally, some researchers have used manual tuning to optimise the handover control parameters. For example, Priyadharshini and Bhuvaneswari [11] Investigate the appropriate combination of HM, A3offset, and TTT in a macro-to-macro scenario. The experiments show that as the distance between base stations increases, handover rates decrease. The TTT values, which varied depending on the combination of HM and A3offset, also became smaller as the distance between the macro base stations increased.

Following a similar line of enquiry, Harja and Hendrawan [12] manually fine-tuned the control parameters of the RSRP and RSRQ algorithms to improve LTE handover performance. This manual tuning increased TTT values from 256ms to 640ms, while the overall HM values ranged from 1 to 15dB.

Mina and Rezaiee [13] investigate four handover parameters- HM, TTT, Serving Cell Threshold, and Serving Cell Offset- that affect the A3RSRP and A2A4RSRQ handover algorithms at different user speeds. The performance of both algorithms was compared under specific optimal settings. To conclude, the experiment demonstrates that various factors can affect LTE performance.

Pinem *et al.*, [14] investigated this further by adjusting the hysteresis and threshold settings. Their study found that a threshold margin of -115 dBm and a hysteresis margin of 24 dB resulted in the highest active value. This indicates that as the active value increases, the probability of a handover error decreases.

From the review above, all of these approaches are not only time-consuming but also costly for mobile operators, making it an inefficient strategy [15], [16]. Furthermore, human analysts can only estimate parameter values based on a limited number of data points, which may not be sufficient to represent the actual state of a cell accurately [17].

Instead of traditional manual tuning, fuzzy logic began to attract researchers' attention. Several studies have investigated how fuzzy logic can be used to improve handover decisions [18]–[20]. For example, Alraih et al. [19] proposed a robust handover optimisation technique with fuzzy logic controller (RHOT-FLC. Throughout the experiment, the handover margin (HOM) and time-to-trigger (TTT) will be automatically adjusted using the reference signal received power (RSRP), user equipment (UE) speed, and reference signal received quality (RSRQ). The result shows comparable performance to both traditional fuzzy logic controllers (FLC) and signal level-based vertical handover (SLV).

Similarly, Hwang *et al.* [20] developed an FLC method to optimise TTT and HOM, specifically for highly congested SBS networks. They used SINR and UE speed to measure improvements in throughput, handover latency, and decision accuracy compared with previous handover algorithms.

More recently, Tashan *et al.* [18] proposed a fuzzy logic controller with a weighting function (WF) and improved it to a velocity-aware fuzzy logic controller with weighting function (VAW-FLC-WF) and noted that the combined approach led to a significant positive change in handover outcomes through the Reduction of Radio Link Failures (RLF), increase of Reference Signal Received Power (RSRP), and Reduction of HOPP associated with previously implemented algorithms.

Moreover, the Self-Organising Network has been developed. Within Self-Organising Networks (SON), Mobility Robustness Optimisation (MRO) is essential for addressing handover issues. Recent studies by Achhab, Abboud, and Assalem [21] tackled this by developing adaptive methods that automatically tune handover control parameters. Instead of sticking to a fixed ratio for ping-pong handovers or radio link failures, their approach considers the relationship between the hysteresis margin and time-to-trigger. That way, the network can find the best handover control settings.

Recently, Alhammadi *et al.* [22] took a fresh approach to handover management. They adjusted the handover margin and time-to-trigger based on the strength of the user's signal and their speed. Their innovative algorithm significantly reduced issues like ping-pong handovers and dropped connections compared to older techniques. It turns out that previous methods, including manual tuning and fuzzy logic, struggled to handle the vast amounts of data available, leading to missed opportunities for crucial insights.

In recent times, researchers have turned to AI and machine learning to refine the handover process, particularly in selecting optimal hysteresis margins and time-to-trigger settings. For example, Lema introduced particle swarm optimisation (PSO) [5] to fine-tune parameters such as time-to-trigger, handover offset, and handover margin. They didn't stop there; by enhancing PSO and integrating it with Self-Organising Networks, they achieved marked improvements, including fewer ping-pong instances and fewer failed handovers. However, managing the numerous hyperparameters required by PSO can be challenging.

In another interesting twist, Farrokh *et al.* [23] experimented by merging Extreme Learning Machine (ELM) with Least-Squares Support Vector Machine (LS-SVM) to model hysteresis. They managed to simplify hysteresis into a single-valued mapping that LS-SVM could learn from, making parameter identification much more straightforward. Meanwhile, Abbas and Alenazi [24] took a different route by integrating Software-Defined Networking (SDN) with a machine learning classifier to keep mobile nodes seamlessly connected. Their SSHS system utilises a decision tree to forecast handover events, thereby enhancing throughput and minimising packet delays.

Lastly, Mannem, Rao, and Chandra Shekhar [25] applied the Chaotic Whale Optimisation Algorithm (CWOA) to improve handover processes across various network technologies, including 5G, Wi-Fi, and LTE. The CWOA delivered impressive results by improving key performance metrics, including signal strength, delay, and throughput, particularly in 5G networks.

According to the literature mentioned above, artificial intelligence or machine learning can be considered a feasible system, as it offers new perspectives for improving handover performance. Machine learning has already been used, but it is insufficient, as the approach cannot utilise prediction results to take actions that lead to improvement; it can only make predictions and not advocate for actions or judgments. To provide the most practical parameters for handover control in LTE handovers, it is desirable to utilise machine learning methods that incorporate analytics, such as prescriptive analysis.

3. METHODOLOGY

3.1 NS-3 Simulation setup

The NS-3 simulation framework used in this study is based on the work presented by Ali *et al.* [26], including three macro base stations (eNBs), three mobile nodes (UEs), and a coverage gap around eNB2. While the network topology, number of users, and traffic patterns follow the original work, which implemented the A2 event-triggered deterministic handover algorithm. However, the handover algorithm in the current study has been replaced with the A3-RSRP algorithm, and the handover triggering parameters, including hysteresis margin and time-to-trigger, were adjusted empirically to evaluate their effect on handover performance.

Based on Figure 3, the simulation scenario includes three macro base stations (eNBs), three mobile nodes (UEs), and a coverage gap within the coverage area of eNB2. Initially, each UE is connected to a single eNB and downloads a TCP file from a remote host. In this setup, UE1 is connected to eNB1 and moves at random angles from 0° to -60° toward eNB2 and eNB3,

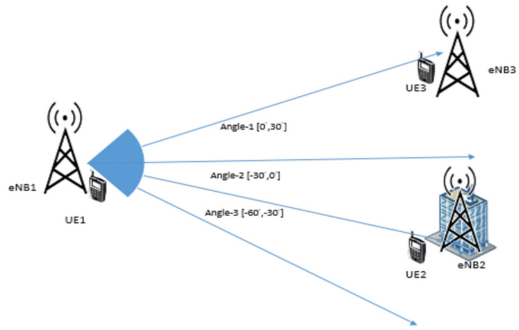

Fig.3: *Experiment scenario adapted from Ali et al. [26].*

while the remaining two UEs remain stationary. Each UE downloads a 15 MB TCP file, aiming to complete the download within 100 seconds. After the downloads are finished, no further data exchange occurs between the UEs and the eNBs. Meanwhile, Tables 2 and 3 present the simulation parameters and handover control parameters (HCP) used in the A3RSP handover algorithm. All raw simulation data were subsequently processed into a series of .csv datasets, yielding approximately 2,500 data samples for analysis.

Table 2: *Simulation parameters adapted from Ali et al. [26], with modifications to the handover algorithm.*

Parameters	Values
Handover algorithm	A3 RSRP
System bandwidth	5 MHz
Inter-site distance	500m
Adaptive modulation and coding scheme	MiErrorModel
Simulation area	2000×2000 m^2
Number of Maco enbs	3
enbs Tx Power	46 dBm
Carrier Frequency	2GHz
Number of UEs in system	3
Velociy of UE1	16.6667 m/s
Mobility model	RandomWalk
Path Loss Model	OkumuraHata
eNB Antenna Height	30m
Obstacle Height	35m
File Size	15MB
Simulation time	100s

3.2 Predictive model

The IF-THEN rules use the outcome of a predictive model to recommend a specific course of action. Accordingly, Extreme-Gradient Boosting was first implemented as a regression-based predictive machine learning model. Figure 4 illustrates the process by which a predictive model leads to prescriptive analytics.

Table 3: *The Handover Control Parameter (HCP) For the A3RSRP Algorithm.*

Hysteresis Margin (HM)(dB)	Time to Trigger (TTT)(ms)
3	64
6	64
9	64
12	64
15	64
3	160
6	160
9	160
12	160
15	160
3	480
6	480
9	480
12	480
15	480
3	1024
6	1024
9	1024
12	1024
15	1024
3	5120
6	5120
9	5120
12	5120
15	5120

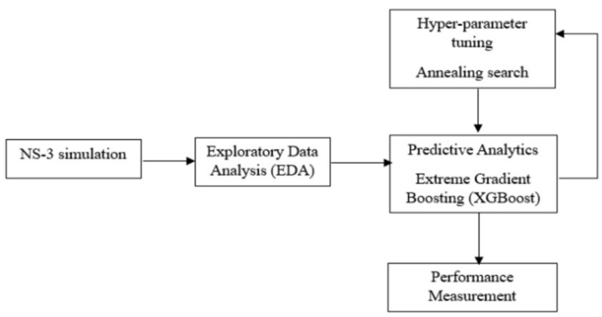

Fig.4: *Predictive model.*

- Exploratory Data Analysis

Subsequently, in this study, exploratory data analysis was conducted to identify and address missing values, outliers, and other data quality issues before proceeding with further analysis. Subsequently, instead of the hysteresis margin, the following features were identified as new features using feature engineering: time to trigger, angle of movement, serving cell, RSRP, target cell RSRP, and handover start. The new features are distance, X coordinates, and Y coordinates.

- Feature selection

Featurewiz [27] was used as a feature selection tool in this experiment. The features selected were hysteresis margin, time-to-trigger, angle of movement, target cell RSRP, handover starts, and X-coordinates.

- Feature scaling

Feature scaling is performed to ensure that the features have similar magnitudes. A standard scaler was used to scale features to a more digestible form for selected machine learning algorithms.

- Dataset Split

The dataset was later divided into training, validation, and test sets using a holdout method. At the same time, the dataset was split into training, validation, and test sets, with proportions of 70%, 15%, and 15%, respectively. The training partition is used to train or create the model. The validation set is used to refine the model. The test set, on the other hand, is used to test the model.

- Predictive Analytics and Hyper-parameter tuning

The Extreme Gradient Boosting regressor with annealing search was chosen to predict the KPI of the LTE handover, namely the throughput, average delay, and download time, under varying network conditions. For each sample i, the model predicts a value $\hat{x}_i$ corresponding to the KPI, while x_i represents the actual value obtained from the NS-3 simulation.

Later, the hyperparameter tuning process was performed using Hyperopt [28]. The Extreme Gradient Boosting Regressor was chosen for its efficient computation time and scalability across all scenarios, as it yields good results on various classification and regression tasks.

- Performance Measurement

The mean absolute error (MAE) represents the discrepancies between the actual and expected values represented by the mean absolute error (MAE). An MAE close to 0 indicates that the model can accurately predict this outcome. The following formula can be used to calculate the MAE [29]:

$$MAE = \frac{1}{n}\sum\nolimits_{i=1}^{n} |xi - \hat{x}i| \tag{1}$$

One way to measure the discrepancy between a model's predicted value and the actual or observed value is the Root Mean Squared Error (RMSE). The RMSE was calculated using the following equation.

$$RMSE = \sqrt{\sum\nolimits_{i=1}^{n} \frac{(xi - \hat{x}i)^2}{n}} \tag{2}$$

The coefficient of determination, also known as R-squared (R^2), can be interpreted as the proportion of the variance in the dependent variable that is predictable by the independent variables. The positive values of the coefficient of determination lie in the interval [0, 1], where 1 means a perfect prediction [30]. Nonetheless, this is not possible in the real world. The following equation was used to evaluate the R^2 [30].

$$R^2 = 1 - \frac{\Sigma(xi - \hat{x}i)^2}{\Sigma(xi - \bar{x}i)^2} \tag{3}$$

The mean absolute error (MAE), the root mean square error (RMSE), and the coefficient of determination (R^2) are used to evaluate the model's performance. Based on the findings, the model yields an MAE of 0.142, an RMSE of 0.802, and an R^2 of 0.963. The model outputs are subsequently used as inputs to the rule-based prescriptive analytics framework to guide the generation of IF-THEN rules for adjusting handover control parameters.

3.3 If-Then Rules Generation

Rules 1, 2, and 3 were generated using a data-driven approach based on the predictive machine learning model's outputs. The model features were categorised into three levels: LOW, MID, and HIGH. The IF-THEN rules were derived systematically from these categories. Each rule was then using the predictive model outputs to ensure that the IF conditions triggered the correct THEN actions under the intended scenarios. In this way, the rules are not purely manual nor purely automatic; they are fully data-driven, and their behaviour is verified through iterative testing using the simulation outputs. As shown in Figure 5, the model operates in three main phases: data-driven knowledge extraction, the derivation of data-driven rules for designing handover control parameters with an inference engine, and validation of the rules.

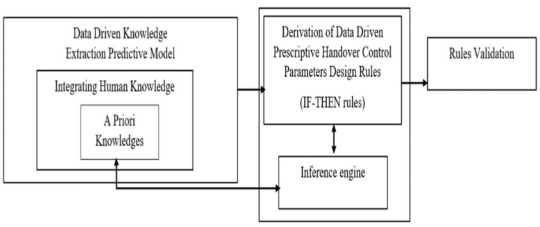

Fig.5: *A model for handover control parameters based on rule-based prescriptive analytics.*

- Data-Driven Knowledge Extraction Predictive Model

The predictive machine learning model serves as a knowledge base, providing insights from predictive analytics relevant to the experiments. To make the most of this information, human expertise is integrated to interpret and categorise the input and output features. Each feature is grouped into three levels, which are LOW, MID, and HIGH, to reflect its relative value or intensity.

- Derivation of Data-Driven Prescriptive Handover Control Parameters Design Rules with Inference Engine

The knowledge extracted from the predictive model is then organised into IF-THEN rules that guide adjustments to handover control parameters. These rules follow the template shown in Table 4.

Table 4: *Handover Control Parameters Rule Design Template.*

Data *(features = LOW, MEDIUM and HIGH)*
If (One or more test conditions = True) Then (Assign rule = actions)

The rule triggers during inference when the IF part of the rule is met. The inferencing engine searches for a match between the IF-THEN rules and the a priori information to determine whether to execute them. The forward chaining method is used to perform these matching actions. From Table 4, the IF conditions are based on the categorised feature values from the predictive model, whereas the THEN actions define the recommended adjustments to the handover parameters.

Rules 1, 2, and 3 were generated through the following process:

a) Identify the relevant input conditions for each category (LOW, MID, HIGH) from the predictive model outputs.
b) Propose potential actions for each condition based on domain knowledge and established handover management practices.
c) Validate each rule by running it through the inference engine in simulation to ensure that the correct handover parameter adjustments are triggered under the intended conditions.

In this way, the rules are data-driven but guided by expert knowledge. They are neither purely manual nor purely automatic, but a combination of predictive insights and human expertise.

- Inferences Engine

Each rule was applied to the predictive model's outputs. The IF conditions were evaluated against the categorised outputs (LOW, MID, HIGH), and the corresponding THEN actions were executed. This step ensures that the rules produce specific handover adjustments for each scenario.

- Rules Validation

Following the inference, the rules were tested to assess their effectiveness in obtaining a desired result. The decision model (Extreme Gradient Boosting) built in the previous experiment served as a baseline for comparing the rule-based system's outputs against expected results, ensuring that rules work properly across various contexts. Additionally, multiple methods, such as using a graph-based decision table or machine learning, can be applied to validate the rule-sets, too [31].

The knowledge obtained from the Phase 1 activity has been categorised into three levels: Low, Medium, and High. For the Hysteresis Margin (HM), the range of 0 dB to 5 dB has been classified as the LOW margin. The range of 6 dB to 10 dB falls within the MID, and the range of 11 dBm to 15 dB is classified as a high hysteresis margin.

In the meantime, for the Time-to-Trigger (TTT), the range of 0ms to 320ms was grouped under the LOW triggering time category. The 480ms to 640ms range falls under the MID category, and the 1024ms to 5120ms range falls under the HIGH category. Moreover, the Throughput of 0.04 Mbps to 0.05 Mbps was grouped as low throughput, 0.06 Mbps to 0.07 Mbps as mid-throughput, and 0.08 Mbps to 0.09 Mbps as high throughput.

For the time taken to complete the file download, 20s to 30s was considered low, 31s to 41s medium, and 42s to 52s long or high. And finally, for the average delay, a range of 0.017ms to 0.018ms was classified as a low average delay. The delays from 0.019ms to 0.020ms were grouped into a "MID" average delay, and those from 0.021ms to 0.022ms were considered a "HIGH" average delay.

- Derivation of Data-Driven Prescriptive Handover Control Parameters Design Rules with Inference Engine Result

Based on the predictive model's output, a set of actionable rules is created. The basic framework of rules is presented in Table 5 with the following explanation:

RULE 1: IF a mobile user is moving from a HIGH angle, AND he was located at a MID X coordinate from the target base station, AND obtaining a MID target cell RSRP, AND this will result in the MID handover start time. THEN assign a HIGH hysteresis margin with HIGH Time-to-trigger so that the throughput value will be HIGH to have a LOW average delay and LOW download time.

RULE 2: IF a mobile user is moving from a MID angle degree, AND he was located at a MID X coordinate from the target base station AND obtaining a MID target cell RSRP, AND this will result in the MID handover start time. THEN assign a HIGH hysteresis margin with HIGH time-to-trigger so that the throughput value will be HIGH to have a LOW delay and LOW download time.

RULE 3: IF a mobile user is moving from a LOW angle, AND he was located at a MID X coordinate from the target base station, AND obtaining a MID target cell RSRP, AND this will result in the MID handover start time. THEN assign a HIGH hysteresis margin with HIGH Time-to-trigger so that the throughput value will be HIGH to have a LOW delay and LOW download time.

Table 5: *Rules framework.*

Rules	Antecedents (Input)	Consequences (Output)
1	Angle = HIGH, X_coordinate = MID, Target Cell_RSRP = MID, Handover_Start(s)= MID	HM = HIGH, TTT = HIGH, predicted _Throughput = HIGH, Predicted _time = LOW, Predicted_Avg_Delay = LOW
2	Angle = MID, X_coordinate = MID, Target Cell_RSRP = MID, Handover_Start(s)= MID	HM = HIGH, TTT = HIGH, predicted _Throughput = HIGH, Predicted _time = LOW, Predicted_Avg_Delay = LOW
3	Angle = LOW, X_coordinate = MID, Target Cell_RSRP = MID, Handover_Start(s)= MID	HM = HIGH, TTT = HIGH, predicted _Throughput = HIGH, Predicted _time = LOW, Predicted_Avg_Delay = LOW

4. RESULT AND ANALYSIS

4.1 Rules Validation Result

Thus, to verify the correctness of the rules, we used the previous predictive model and inserted random values, as displayed in Figures 6-8 below. It evaluates the reliability of the system's decisions. As shown in Figure 6, Rule 1 can effectively predict network performance with a 15dB hysteresis margin and a TTT of 5120ms. Under these conditions, the specified values for hysteresis margin (15dB) and time to trigger (5120ms) indicate that the network has high throughput (0.09896 Mbps), low average delay (0.0178368ms), and low download time (22.654049s).

```
Xnew = np.array([[15,5120,51,567.8962269,16.0309,29.75]])
Xnew= sc_X.transform(Xnew)
ynew= XGBRegressor_opt.predict(Xnew)
#invert normalize
ynew = sc_y.inverse_transform(ynew)
Xnew = sc_X.inverse_transform(Xnew)
print("X=%s, Predicted=%s" % (Xnew[0], ynew[0]))

X=[  15.        5120.          51.         567.8962269   16.0309
   29.75     ], Predicted=[9.8958962e-02 2.2654049e+01 1.7836759e-02]
```

Fig.6: *Rule 1 validation.*

Next, as displayed in Figure 7, another random set of values for RSRP, X coordinates, handover start, and angle of movement was inserted into the model to verify Rule 2. Under these conditions, IF a mobile user is moving from a MID (-16.9195) angle degree, AND he was located at a MID (550.886m) of the X coordinate from the target base station AND obtaining a MID (51dBm) target cell RSRP, AND this will result in the MID (16.031s) handover start time. THEN assign a HIGH (14dB) hysteresis margin with HIGH (2560ms) time-to-trigger so that the throughput value will be HIGH (0.0984Mbps) to have a LOW (0.0179s) average delay and LOW (22.424s) download time.

```
Xnew = np.array([[14,2560,51,550.8865269,16.0310,-16.9195]])
Xnew= sc_X.transform(Xnew)
ynew= XGBRegressor_opt.predict(Xnew)
#invert normalize
ynew = sc_y.inverse_transform(ynew)
Xnew = sc_X.inverse_transform(Xnew)
print("X=%s, Predicted=%s" % (Xnew[0], ynew[0]))

X=[   14.         2560.           51.          550.8865269   16.031
  -16.9195    ], Predicted=[9.8373584e-02 2.2423716e+01 1.7860707e-02]
```

Fig.7: *Rule 2 validation.*

In Figure 8, the random values are inserted into the RSRP, X coordinates, handover start, and the angle of movement. According to the figure, IF a mobile user is moving from a LOW (-38.5297) angle, AND he is located at a MID (566.8962m) of the X coordinate from the target base station AND obtains a MID (51dBM) target cell RSRP, AND this will result in the MID (16.032s) handover start time. THEN assign a HIGH (15dB) hysteresis margin with HIGH (5120ms) time-to-trigger so that the throughput value will be HIGH (0.09888Mbps) to have a LOW (0.01783ms) average delay and LOW (24.2366s) of the download time.

```
Xnew = np.array([[15,5120,51,566.8962269,16.0320,-38.5297]])
Xnew= sc_X.transform(Xnew)
ynew= XGBRegressor_opt.predict(Xnew)
#invert normalize
ynew = sc_y.inverse_transform(ynew)
Xnew = sc_X.inverse_transform(Xnew)
print("X=%s, Predicted=%s" % (Xnew[0], ynew[0]))

X=[   15.         5120.           51.          566.8962269   16.032
  -38.5297    ], Predicted=[9.8888092e-02 2.4236614e+01 1.7831590e-02]
```

Fig.8: *Rule 3 validation.*

In addition to the above experiment, we conducted further experiments by entering random values within the ranges of the LOW, MID, and HIGH antecedents to validate each generated rule. The results of the predictions are further elaborated in terms of rule accuracy.

4.2 Rules Accuracy

Figure 9 illustrates the accuracy of three rules: Rule 1, Rule 2, and Rule 3. The accuracy measures how often the rule is correct.

As shown in Figure 9 above, all generated rules achieved a 100% accuracy. It means that all instances that met the conditions of each rule were classified correctly. These results show that the rules correctly identified the relevant instances in the dataset.

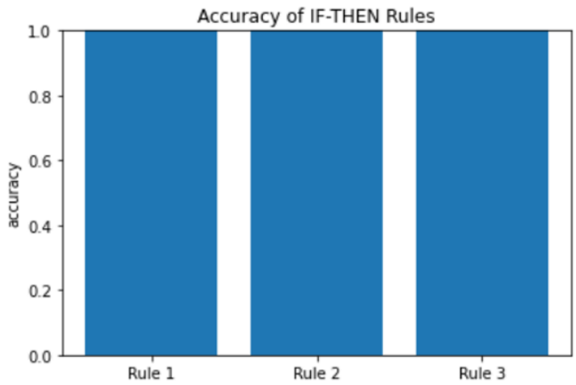

Fig.9: *Measuring rules accuracy.*

4.3 Comparison with a typical classic case of fixed setting for handover control parameters

The predictive XGBoost model not only forecasts network performance under different conditions but also guides the creation of data-driven IF-THEN rules to adjust handover control parameters. By describing a network state as LOW, MID, or HIGH, we can generate predictions with real implications for how the system functions. That helps us adjust to changes in where users are, how they're moving, and the strength of their signal. With this adaptive approach, we can achieve a smooth handoff as the user moves between networks, fewer call drops, and a more stable overall network than with fixed values alone.

In Table 6, the proposed method is compared withconventional fixed handover control parameters. We investigate this under three different paradigms ofuser motion. The handover controlparameters, hysteresis margin and time to trigger are held fixed at 6 dB and 480 ms [21]. In contrast, our approach utilised rule-based context-aware prescriptive analytics to determine the value of the hysteresis margin and time-to-trigger based on the direction of the user's movement.

In our proposed method, the user moving at angles 29.750^0 and -9.007190^0 was assigned the same hysteresis margin, 15dB, while the time-to-trigger was set to 5120ms and 1280ms, respectively. Conversely, the user's movement at an angle of -52.18450^0 was given a hysteresis margin of 13dB, while the time to trigger was set to 2560ms.

The results of the experiments show that the proposed method achieves comparable performance, producing higher throughput with lower average delay and a shorter time to complete file downloads. Under these conditions, the experiment showed that it is not possible to assign fixed parameters for handover control across all scenarios. This is because the fixed setting of control parameters cannot be adapted to the rapidly changing network conditions [32], [33]. Furthermore, there are no optimal fixed settings for handover control parameters that can achieve optimal handover performance for all handover key performance indicators [32].

Table 6: *Performance comparison between fixed settings of handover control parameters vs context-aware prescriptive analytics.*

	Classic Case of fixed HCP setting			Context-Aware Prescriptive Analytics		
Angle movement	29.75^0	-9.00719^0	-52.1845^0	29.75^0	-9.00719^0	-52.1845^0
Hysteres is margin (dB)	6	6	6	15	15	13
Time-to-trigger (ms)	480	480	480	5120	1280	2560
Through put (Mbps)	0.0706	0.0194	0.0725	0.09896	0.0980	0.0988
Avg_delay (ms)	0.0194	0.0494	0.0191	0.0179	0.0179	0.0178
Time for completing file downloading (s)	31.3901	45.0961	30.594	22.654	22.553	23.520

Furthermore, the increase in mobile users with different mobility patterns leads to a deterioration in performance if the fixed setting has been implemented. As mobile users move from one place to another, service deterioration can lead to unsatisfactory experiences. Thus, the gold standards based on a single fixed value for all scenarios cannot be accepted, as they may lead to poorer network performance [33], [34]. Nonetheless, in this dynamic environment, the proposed strategy based on contextual rule-based prescriptive analytics offers greater flexibility and adaptability than the fixed handover control parameters. This allows network service providers to make dynamic adjustments, ensuring optimal network performance through context-aware rule-based prescriptive analytics.

5. CONCLUSION

The current study used the results of a predictive model to develop a prescriptive framework with levels LOW, MID, and HIGH. Three specific rules resulting from these predictions were produced, validated, and tested using pre-set random variables. The outcome of this evaluation confirms that the original predictive model produces predictions that are consistent with the prescriptive framework established by the rules. Combining predictive analytics with rule-based prescriptive analytics will enable Mobile Network Operators (MNOs) to plan and allocate resources more effectively. The combined use of these features will allow MNOs to optimise operations and facilitate data-driven decision-making, thereby improving overall performance.

Future research will focus on assessing the two main areas of the framework developed in this study. The first area will examine the scalability of the XGBoost model by substantially increasing the dataset used (to more than 2500 instances) to enable a thorough evaluation in a larger, denser data environment. In addition, the current benchmarking method (the use of fixed-parameter baselines) will be enhanced by the addition of modern/adaptive baseline models, facilitating a more rigorous comparison with current methods of predictive and prescriptive analytics.

Finally, while this work is conducted in an LTE environment, the technology-agnostic nature of the introduced framework also makes it applicable to 5G networks. The framework will be evaluated in crowded 5G network scenarios, including 5G service categories such as eMBB (enhanced mobile broadband), URLLC (Ultra-Reliable Low-Latency Communications), and mMTC (massive Machine-to-Machine Communications). These will provide greater accuracy and granularity for predictive and prescriptive analysis and require only minor modifications to the framework.

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AUTHOR CONTRIBUTIONS

Conceptualization, NA and MNMMN; methodology, NA; software, NA and MNMMN; validation, NA, MNMMN and MNI; formal analysis, NA, MNMMN and MNI; investigation, NA; data curation, NA; writing original draft preparation, NA and MNMMN; writing review and editing, NA, MNMMN, MNI and MTI.; visualization, NA; supervision, MNMMN, MNI and MTI.; funding acquisition, NA and MNMMN. All authors have read and agreed to the published version of the manuscript.

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