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A CONCEPTUAL FRAMEWORK OF ENODEB PEAK PATTERNS PREDICTION BASED DYNAMIC PRICING SCHEME FOR ENHANCED QUALITY OF LTE NETWORK SERVICES

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Abstract: The telecommunication industry in sub–Saharan Africa is experiencing a notable seismic change. With exponential technological growth, evolving teledensity and customer base, telecommunications are at a crossroads. However, the consequence of this growth has been a continuous degradation in the quality of service (QoS) provided by Long Term Evolution (LTE) service providers, which has resulted in unsatisfactory experiences for subscribers and customers. In light of the extant literature and research on pricing and artificial intelligence in the context of network management, this study proposes the application of Long Short–Term Memory (LSTM) model of deep learning to predict the eNodeB peak patterns and, develop a dynamic pricing scheme in LTE network. Each of the interconnected components that make up our proposed architectural framework is essential to the dynamic pricing and design process. This ensures seamless integration of predictive modelling, decision–making algorithms, and communication with users. In addition to the comprehensive analysis, the model is apply to real–world 4G LTE traffic dataset to evaluate and examine the proposed framework. Finally, result of this study will demonstrate the utility of the scheme to enhance the quality of LTE network services in sub–Saharan Africa.
Keywords: Long short–term memory, eNodeB, Long term evolution (LTE), Dynamic pricing

1. INTRODUCTION

Cellular network is a significant mobile communication that has transformed modern society by providing reliable, high–bandwidth, and low–latency communication through diverse technologies, from Wireless Fidelity (WiFi) networks to 4G and beyond (Wu et al., 2023). The ongoing progress and recognition of these technologies have resulted in a substantial surge of mobile users, high–data–demanding applications across sectors such as education, media, banking, transportation, and manufacturing and their usage. According to Ericsson (2022) and Huawei (2020), the total global mobile data traffic shall reach 90EB/month by 2022 and increase to approximately 115EB/month by the end of 2028. This represents a significant challenge for telecommunications operators in managing the large network flow while maintaining and enhancing quality service. Moreover, the number of mobile data users is, expected to rise significantly, with 7.3 billion wireless data devices in 2022, and an anticipated increase to over 9.2 billion devices by 2028. Thus, the flag was raised to address the challenges associated with maintaining quality in LTE network services. Installing additional base stations to expand the capacity of cellular network and achieve load balancing is the most straightforward approach but it comes at a significant cost to telecommunications operators. Numerous solutions proposed including using dynamic pricing scheme based on network conditions such as quality of service (QoS) (Masli et al., 2022). This scheme can help to incentivize end users to reduce their demand for network resources during periods of high congestion, thereby enhancing user experience rate and good network planning. Dynamic pricing scheme may also give telecommunication service providers the opportunity to increase its revenues.

Under the abovementioned context, the authors aim to develop a dynamic pricing scheme based on predicted eNodeB peak patterns using deep learning–based models to enhance the quality of LTE service. To achieve this objective, the study seek to answer the following research questions: What methodology is employ to identify and predict eNodeB peak patterns in LTE networks? What methodology is employ to develop a dynamic pricing scheme based on predicted eNodeB peak

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patterns? The paper is organize as follows: Section 2 outlined the related review in the area and introduced the knowledge gaps of state–of–the art. Section 3 displayed conceptual framework and Section 4 summarized methodological study design. Under Section 5, proposal validation are stated. Finally, conclusion and future direction of the research provided in section 6.

2. RELATED REVIEW

Long Term Evolution (LTE)

The Third Generation Partnership Project (3GPP) developed the Long Term Evolution (LTE) and the technology standard aligned with the underlying cellular network architecture. This involves the division of a large geographical area into smaller cells, with each separate cell served by a base station called the evolved NodeB (eNodeB) respectively. These eNodeBs facilitate communication with each other and with the core network thereby providing data transfer and voice communication services to the end–users (Nisar & Baseer, 2021; Salih et al., 2020). An LTE network consists of three main components that work together to deliver enhanced performance and quality of service. The core network (CN), the access network and the end user equipment (Jaffry, 2020). The user equipment (UE) is an essential component of LTE networks. They are equi pped with LTE–compatible modems and antennas to establish wireless communication with the evolved NodeB over the access network. The core network, known as evolved packet core (EPC) is the central component of an LTE network. It consists of logical multiple elements, including the mobility management entity (MME), serving gateway (SGW), and packet data network gateway (PGW). The deployment of LTE offers a number of advantages to end–users, including higher data transfer rates, lower latency, and improved spectral efficiency. These benefits assist the streaming of high–definition videos, playing of online games, and the utilization of other data–intensive applications with minimal difficulty. As a result, LTE has become a popular choice for mobile network operators, with LTE networks deployed globally. Over the years, the LTE network has undergone several upgrades, with the introduction of LTE–Advanced and LTE–Advanced Pro introduced to further, improve the performance and capabilities of LTE networks.

Artificial Intelligence (AI)

Artificial Intelligence (AI) has emerged as a prominent area of interest within the domain of LTE network management, offering promising avenues for enhancing service quality and; maximize resource utilization. The ability of artificial intelligence models to evaluate large volumes of data and derive meaningful insights enables network operators to make well– informed decisions and predictions (Susanto et al., 2023). Numerous studies have shown the effectiveness of statistical, machine learning, and deep learning–based models in various aspects of LTE network management. In their study, Alsaade and Al–Adhaileh (2021) applied statistical time series model like single exponential smoothing (SES) with autoregressive integrated moving average (ARIMA), to model and predict the traffic volume of LTE network , this achieved superior performance for predicting the network traffic. Gijon et al. (2021) presented a study comparing different supervised learning models and statistical time series analysis approaches to predict monthly peak–hour data traffic on a cell basis in a Long Term Evolution (LTE) network, the models considered include random forest (RF), artificial neural networks, support vector regression (SVR), seasonal–ARIMA and Additive Holt–Winters. The results demonstrated that supervised learning–based models performed better than the time series approaches in predicting peak hour traffic, while simultaneously reducing data storage and capacity requirements. Jiang (2022) and Alekseeva et al. (2021) conducted an extensive analysis of existing studies in the field of LTE network management with artificial intelligence mechanisms.

Dynamic pricing and Cellular networks

Dynamic pricing schemes have been widely studied and applied in various industries, such as transportation, hospitality, and e–commerce (Guo et al., 2022). In the telecommunications industry, the use of dynamic pricing is relatively new but holds great potential for optimizing network efficiency, increase revenues, and enhance the whole user experience. In a recent study, Balakumar et al. (2024) used a dynamic pricing technique based on machine learning to control variations in electricity in a smart grid network. The authors calculated the dynamic pricing based on the feeder anticipated power usage by using Internet of Things (IoTs) devices to get a real–time dataset from the Distribution Smart Substation (DSS) and several individual feeder lines. Avoided were individual feeders' overload, because of dynamic pricing, the grid's robustness and dependability increased. Additionally, the method reduces the likehood of breakdowns and disruptions while making better use of the current infrastructure. Using their pricing strategies of mobile data bundles, Inegbedion et al. (2023) used the Nash Equilibrium (NE), to stimulate and test the competitive behaviours of GSM operators in Nigeria. According to the study's findings, game theory is an appropriate and proven technique for stimulating and forecasting subscribers' behaviours in a competitive setting in order to improve revenues.

Bajracharya el al. (2022) explored incentivizing users to offload their traffic to unlicensed frequency bands in cellular networks. It proposed an economical approach, utilizing unlicensed bands to enhance capacity. The article models the operator–user interaction as a stackelberg game, considering fairness with legacy WiFi users. Multi–armed bandit algorithms adapt to user behaviors. Simulation results validate the approach, but limitations include scalability and dynamic network conditions. Overall, the study presents cost–effective approach to encourage traffic offloading, utilizing game theory and adaptive algorithms, with room for further research.

Puspita et al. (2022) analyzed the sensitivity of an internet pricing scheme model using a modified C–RAN model. The research explores different pricing schemes, incorporates fair network traffic management, and utilizes the CES utility function. Based on analysis using secondary data, the study suggests the potential profitability of the improved model for Internet Service Providers (ISPs). The sensitivity analysis reveals that the model's behaviors vary based on specific variable values. Overall, the study provides insights into the sensitivity of the pricing scheme model and its potential implications for ISPs. In the context of priority pricing for usage –based mobile internet access charging, the author (Cho–S, 2021) introduced a heuristic algorithm priority dynamic pricing with multiple service levels for optimal price selection. The pricing scheme hereby produces a pricing plan that can efficiently and effectively control radio resource usage and manage user needs on networks.

Chounos et al. (2020) in their study introduced a novel framework for dynamic policy and charging rules in 5G multi–tenancy environments The study concentrates on adaptive pricing scheme to allocate network resources when existing resources are inadequate. The framework stimulate the negotiation between mobile network operators and infrastructure providers (InPs) as service level agreements (SLAs) and provides an analytical structure, collaboration methods, and testbed trials to validate the framework's ability to handle further traffic demands. Overall, it offers a way out to price and allocate resources in a more effective way in dynamic network environments.

Zhou et al. (2020) examined the application of time–dependent pricing for resource allocation in software–defined cellular networks (SDN) given both mobile users' complete and incomplete information and price disparity. The authors design the joint pricing and bandwidth demand as a two–stage Stackelberg leader–follower game to increase the surpluses of network service provider (NSP) and minimize the peak–to–average traffic ratio (PATR). On the other hand, NSPs might incentive users to shift their demand for a higher revenue and lower PATR. Qian et al. (2020) discussed the challenges of dynamically sharing the multi–mode spectrum in 5G–VANET to optimize network throughput. It proposes a dynamic stackelberg pricing game approach, including an access price strategy and distributed mode selection for vehicle users (VUEs). The algorithm evaluate using traffic scenarios, demonstrating a significant improvement in VANET's transmission

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rate. Overall, the paper presents a solution for optimizing network performance in 5G–VANET through spectrum sharing. Xiong et al. (2020) introduced a modified sequential pricing policy among mobile users, where the authors offer each user a certain price in multiple periods, sequentially and repeatedly, in order to ensure social fairness. This dynamic pricing scheme helps the mobile network operator gain greater revenue and mobile users achieve higher total utilities compared to a baseline static pricing scheme. Besides, none of the studies appears to be dependent on the predictive techniques of both user behavioural and eNodeB peak patterns to enhance the performance of the network system and ensure an unbiased distribution of network radio resources among users.

3. CONCEPTUAL FRAMEWORK

This section presents the overarching architectural framework (Figure 1) that underlies our dynamic pricing scheme for postpaid users. The architecture serves as a conceptual framework that orchestrates the dynamic adjustment of pricing tiers in response to the predicted user behaviour and eNodeB peak patterns.

Each of the many interrelated parts that make up the architectural framework is essential to the dynamic pricing process. The architecture is design to ensure seamless integration of predictive modelling, decision–making algorithms, and user communication.

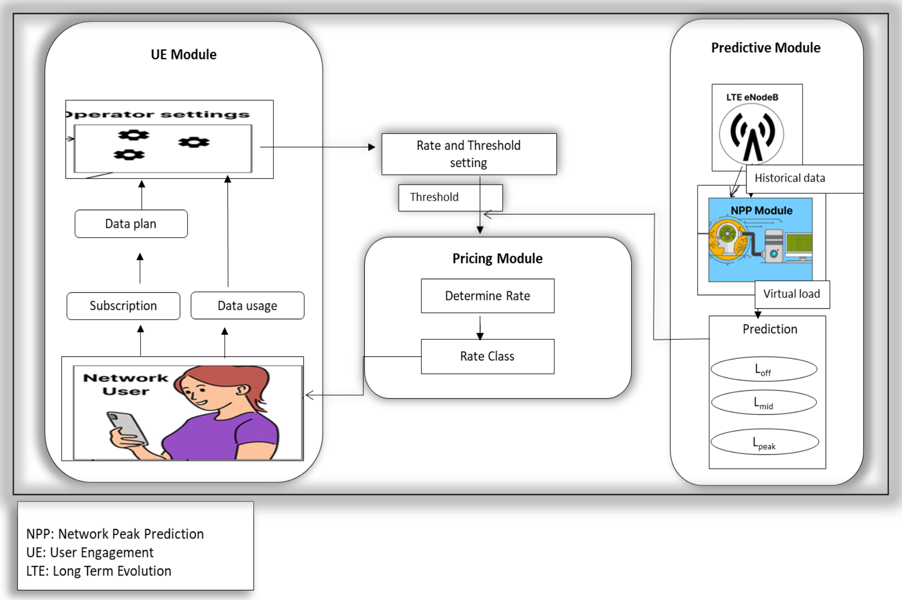

Figure 1. The proposed architectural framework for dynamic pricing scheme

This study applied research focusing on a scheme to address a problem of enhancing the quality of LTE network services. It is theoretical–descriptive research, analyzing and investigating specific aspects of reality and establishing a description and specific context. Both quantitative and qualitative data collection methods are employ for the study.

4. DYNAMIC PRICING SCHEME

At its core (Figure 1), the architectural framework comprises three main modules: predictive models, pricing engine, and user interface. These modules collaborate harmoniously to achieve the dynamic pricing goals, ensuring equitable resource distribution and enhanced QoS provisioning.

Predictive Module

The module is capable of generating accurate prediction of peak traffic patterns for eNodeB. The predictive module employs deep learning–based models and historical dataset to forecast traffic volumes and congestion trends in the network. The eNodeB peak pattern is design as a time series–forecasting tool that employs deep learning models to predict fluctuations in LTE network traffic. The model incorporates historical dataset, including user traffic, signal quality, and timestamps to forecast future states of network congestion. The analysis of trends and patterns in data usage over

time enables the effective learning of these sequence dependencies, which are crucial for accurate prediction. The model output is useful in identifying specific times that are likely to experience peak or off–peak traffic, thereby enabling telecommunication operators to prepare or adjust resources accordingly. This predictive capability is fundamental to ensuring efficient network management and optimal allocation of bandwidth and other resources, with the help of these features. The prediction problem reformulated (Ferreira et al. (2023) below:
Given an eNodeB $\mathbf{b}$ network traffic load at previous time step $\mathbf{t}$

$$X_t^b = [x_1, \dots \dots \dots, x_t]$$

where: $b = 1, \cdots, n_a$
then

$$y = f(X_t^n; \theta) + \varepsilon_n \tag{1}$$

where: y signify the predicted eNodeB peak traffic at the next time step t_{a+1} , X_t^n is the function that maps input features to the target variable y parameterized by(θ), ε_n is the prediction errors (residual) that could influence the prediction quality and $\mathbf{n}$ is the total number of inputs.

Machine learning models

The Long Short–Term Memory (LSTM) model is a variant of the recurrent neutral networks (RNNs) that are adept at handling data sequences and capturing temporal dependencies. RNN incorporate a memory element that enables them to store and utilize information from previous inputs to generate subsequent outputs in the sequence (Orievto et al., 2023). However, RNNs are not able to handle long–term dependencies in the data. They suffer from the vanishing gradient and exploding gradient problems. Figure 2 depicts the basic RNNs single cell architecture. It consists of an input at a time step x_t, a hidden state (memory) at a time step h_{t-1} and an output at a time step O_t . At a specific time step t, these parameters, are connected and expressed as

$$x_t \in \mathbb{R}^{n_x}; \quad h_t = \tanh(W_x . x_t + W_h . h_{t-1} + b_h) \tag{2}$$

$$O_t = (W_o . h_t + b_o) \tag{3}$$

where: W_x, W_h, W_o are the weight parameters, $\tanh$ is the non–linear activation function, and b_h , b_o are the bias parameters

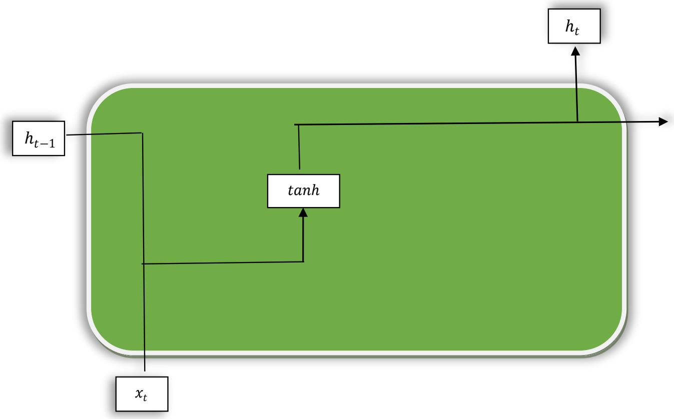

Figure 2. A basic RNN architecture

LSTM was introduced by Hochreiter and Schmidhuber in 1997 (Siami-Naminiet al., 2018) to improve on the deficiencies of RNNs and this capability makes them highly suitable for time series data, such as network traffic usage and its associated statistics, which are inherently sequential, and where the order of data points are of critical importance. They are capable of retaining significant information over extended periods, which is essential for accurate prediction where past usage patterns influence future behaviour. LSTM ability to learn from the long–term dependencies in data usage patterns endow them with the ability to forecast future network traffic effectively, thereby making them an optimal choice for predictive task.
As in Figure 3, LSTM process sequences of data, with each unit in the layer having the capability to remember information for an extended period. The LSTM modifies its cell state by a combination

of three gates: input, forget, and output as shown in equations (4–8) to control the information flow, the cell state C_{t-1} acts as a memory that carries information across the entire cell.

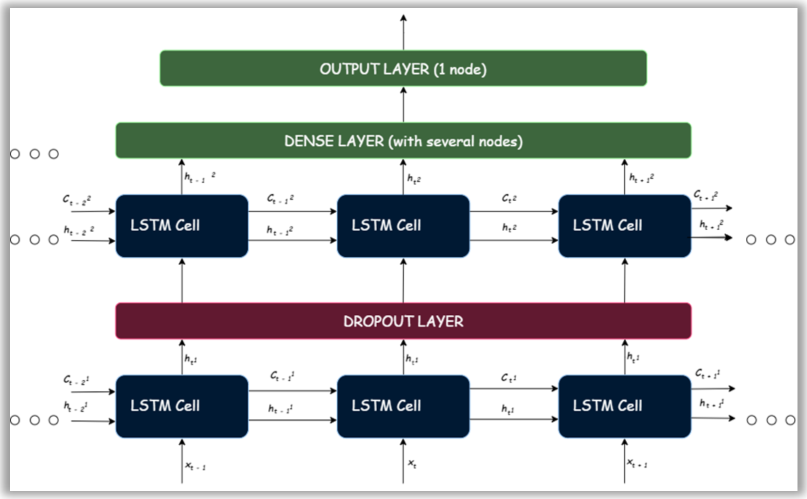

Figure 3. Two–layered architecture of the LSTM

The forget gate f_t decides what information to be discarded or retained where x_t is the input feature at the current time step $t+1$, h_{t-1} is the previous hidden state of the LSTM cell. , σ is the sigmoid function, W_f, weight parameters and b_f is the bias parameter. Based on the forget gate, the input gate i_t determines what new information to be stored or updated in the cell state. The new cell state C_t is updated with new information. An activation function $\tanh$ creates a vector of new information $C_t\hat{}$, and, add it to the state. Depending on the new cell state, the output gate O_t decides what the next hidden cell state should be with respective W weight parameters to be learned during training and Hadamard product (·). For this study, the internal state of the network is process by iterating the following equations below (Santos Escriche et al., 2023):

— Forget Gate: Decides what information to discard from the cell state

$$f_t = \sigma(W_f \,.\, [h_{t-1}, x_t] + b_f) \tag{4}$$

— Input Gate: Decides what new information to store in the cell state

$$i_t = \sigma(W_i \,.\, [h_{t-1}, x_t] + b_i) \tag{5}$$

$$C_t\hat{} = \tanh(W_c \,.\, [h_{t-1}, x_t] + b_c) \tag{6}$$

— Output Gate: Decides what to output based on cell state

$$O_t = \sigma(W_o \,.\, [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = O_t \,.\, \tanh(C_t) \tag{8}$$

Machine learning workflow

This paper employs the CRISP–DM methodology for the machine learning process to achieve the desired goal (Schröer et al., 2021). The methodology consists of the steps shown in Figure 4. The CRISP–DM technique has been most widely used standard for data mining and machine learning projects. This continue to serve as the established norm, and an industry–independent process model for the execution of machine learning projects.

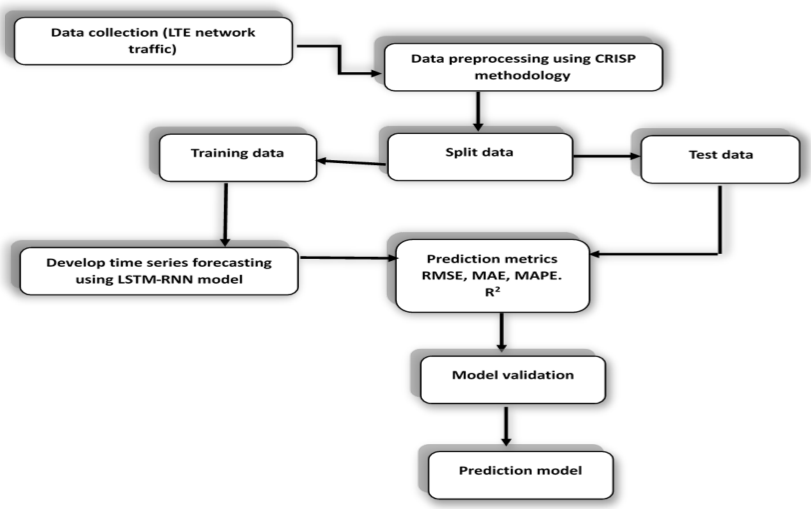

Figure 4: The machine learning workflow

Assessment metrics

Four forecast assessment metrics were manipulated to evaluate the accuracy of the predictions. The assessment metrics used are the root mean square error (RMSE), this measures the mean deviations of the predictions from the true values. It is the square root of the mean square error. A lower RMSE value indicate a better performance of the model, and smaller deviations from the predicted to the true values (Terven et al., 2023). It therefore penalizes large errors. RMSE is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \hat{y}_t)^2} \tag{9}$$

The mean absolute error (MAE) measures the mean of the absolute difference between the predicted values and the true values. The smaller the value, the closer the forecasts are to actual values and the better the model. MAE is calculated as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} | x_t - \hat{y}_t| \tag{10}$$

The mean absolute percentage error (MAPE) is a measure of the mean percentage error of the model's predictions associated to the true values. MAPE is easy to interpret, as it is expressed in percentage terms. It is also scale–independent, a property that facilitates the comparison of models across diverse scales of the target variable. It is calculated as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n} | \frac{|x_t - \hat{y}_t|}{x_t} \mathrm{X}\ 100 \tag{11}$$

The coefficient of determination (R^2) does measure how well the model can explain the deviation in the predicted variable. It measures the percentage of the variance in the predicted variable that the deep learning–based algorithms explain on a scale of between 0 and 1. The higher the value of R^2, the better the model would be in predicting the traffic peak hours of the cellular network accurately. It is calculated as follows:

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(x_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(x_t - \ddot{x}_t)^2} \tag{12}$$

where: x_t be the true value, $\hat{y}_t$ be the predicted value, $\ddot{x}_t$ be the mean of the true values and n be the total number of the testing dataset.

Proposed Implementation

The study will implement the proposed dynamic pricing scheme in a simulated network using Objective Modular Network Testbed (OMNeT++ 5.0), a component–based simulator with an extensive library of predefined components for modelling common typical network elements. The validation will be carry out using real–work 4G LTE traffic dataset from a sub–Saharan African LTE service provider. The results will assess in terms of network throughput, latency, price paid per user and operator revenue. Python programming language and its related libraries used for all experimental procedures and numerical calculations.

Throughput: It measures the rate at which data is successfully, transferred through the LTE network.

Latency: The actual period for data packet to move from its source to destination. It assesses the delay in data delivery.

5. CONCLUSION AND FUTURE WORK

The authors look at the potential of utilizing prediction of data traffic patterns and dynamic pricing scheme to optimize the quality of LTE network services. A conceptual framework for a dynamic pricing scheme based on predicted eNodeB peak pattern is introduce to achieve this, which utilizes deep learning–based techniques for traffic modelling and prediction. The long short–term memory (LSTM) is a variant of recurrent neural networks (RNNs) that is particularly adept at processing sequences of data and capturing long–term temporal dependencies. The LSTM–RNNs is capable of retaining significant information over extended periods, which is vital for precise forecasting in situations where historical usage patterns shape future behaviour. Their capacity to discern long–

term dependencies in data usage patterns endows them with the ability to forecast future network loads with remarkable efficacy, rendering them an optimal choice for this predictive task.

Perform further work and investigations on the other modules to ascertain their functionality in relation to the proposed scheme.

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