DLLF-2EN: Energy-Efficient Next Generation Mobile Network With Deep Learning-Based Load Forecasting

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***Abstract*—The exponential growth of mobile data traffic in next generation networks has led to a significant increase in energy consumption, posing critical challenges for network operators. We propose DLLF-2EN, a novel energy-efficient framework that integrates deep learning-based load forecasting, an advanced power consumption model, and a comprehensive energy-saving strategy to address this issue. The load forecasting technique utilizes deep convolutional neural network and long short-term memory model, which is based on deep learning. This model is capable of capturing the spatiotemporal dependencies present in network traffic data. The power consumption model accurately characterizes the base stations' static and dynamic power consumption components, facilitating the assessment of energy efficiency under various network scenarios. The energy-saving strategy combines base station sleep mode with discontinuous transmission and reception, as well as lightweight transmission of common signals, dynamically adapting the network operation based on the predicted traffic load. Furthermore, DLLF-2EN incorporates an intelligent power management system that leverages machine learning algorithms to continuously monitor the network, analyze collected data, and make optimal energy-saving decisions in real-time. Simulation demonstrate that the superior performance of DLLF-2EN in terms of load forecasting accuracy and energy efficiency compared to state-of-the-art baseline methods. The proposed framework represents a comprehensive solution for energy-efficient and sustainable next generation mobile networks, addressing the critical challenges of minimizing energy consumption while meeting the growing demands for high-quality mobile services.**

***Index Terms*—Energy-efficient next generation mobile network, deep learning, load forecasting, LSTM.**

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I. Introduction

THE EXPONENTIAL growth of mobile data traffic driven by the proliferation of smart devices and bandwidth-intensive applications has led to a significant increase in energy consumption in mobile networks [1], [2]. According to recent studies, information technology systems and infrastructures contribute approximately 4% of global greenhouse gas emissions [3]. As a result, network operators are facing immense pressure to reduce their carbon footprint and operate more environmentally sustainable. The energy efficiency of mobile networks has become a critical issue, not only from an environmental perspective but also from an economic standpoint, as energy costs constitute a significant portion of network operators' operational expenditures [4], [5].

The challenges of energy efficiency in mobile networks are further compounded by the advent of next generation mobile networks, such as 5G and beyond. These networks are distinguished by highly concentrated small cells, extensive multiple-input multiple-output (MIMO) systems, and high-frequency spectrums. These features allow for increased data rates and lower latency [6], [7], [8]. However, these advanced technologies also lead to increased energy consumption, making developing innovative solutions for energy-efficient network operations imperative. Several methods have been suggested to tackle energy efficiency issues in next-generation mobile networks [9]. These approaches include hardware optimization techniques, such as using energy-efficient components and advanced power amplifiers, as well as software-based solutions, including dynamic resource allocation, base station sleep modes, and discontinuous transmission schemes. However, most of these approaches rely on predefined rules and thresholds, which may not effectively capture mobile network traffic's complex and dynamic nature.

Machine learning techniques have recently become a potential approach for enhancing the energy efficiency of mobile networks. Machine learning algorithms can utilize the extensive data created by mobile networks to reveal concealed patterns, forecast forthcoming traffic needs, and optimize the distribution of network resources appropriately. Specifically, deep learning methods, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have demonstrated significant promise in capturing the spatial and temporal relationships in network traffic data and facilitating precise traffic prediction [10].

However, integrating deep learning-based traffic forecasting into a comprehensive energy-efficient framework for next generation mobile networks presents several challenges. Additionally, the economic aspects of the proposed framework are a crucial consideration for network operators. The proposed framework has the potential to generate significant cost savings by reducing the energy consumption of the mobile network infrastructure. Energy costs may account for up to 20-40% of a mobile network operator's operating expense. By optimizing energy efficiency using the proposed framework, network operators can reduce energy bills and improve profitability, which we need to consider.

Inspired by these difficulties and the possibilities of deep learning methods, we introduce DLLF-2EN, an innovative energy-efficient structure for future mobile networks that utilizes load forecasting based on deep learning. The primary contributions of this study are as follows:

1) We develop a deep convolutional neural network-long short-term memory (DCNN-LSTM) model for accurate load forecasting in mobile networks. The DCNN-LSTM model captures the spatiotemporal dependencies in network traffic data and enables precise prediction of future load conditions, facilitating proactive energy-saving decisions.
2) We present a comprehensive energy-efficient framework for next generation mobile networks, which consists of three key components: (1) An advanced power consumption model that accurately characterizes the static and dynamic power consumption components of base stations, enabling precise assessment of energy efficiency under various network conditions. (2) A dynamic energy-saving strategy that combines base station sleep mode with discontinuous transmission and reception and lightweight transmission of common signals, adapting the network operation based on the predicted traffic load. (3) An intelligent power management system that leverages machine learning algorithms to continuously monitor the network, analyze collected data, and make optimal energy-saving decisions in real-time.

The remainder of this paper is organized as follows. Section II provides the related works. Section III presents the proposed DCNN-LSTM model for load forecasting. Section IV describes the energy-efficient framework for next generation mobile networks, including the power consumption model, energy-saving strategy, and intelligent power management system. Section V discusses the simulation setup and results. Finally, Section VI concludes the paper and outlines future research directions.

II. Related Works

Recently, extensive studies have been conducted on energy efficiency in mobile networks. Several methods have been suggested to decrease the energy usage of base stations, which are mobile networks' main energy consumers. This section provides an overview of the most advanced approaches now available for operating base stations in an energy-efficient manner. It also examines how these techniques can be applied to the future generation of mobile networks.

A. Base Station Energy-Saving Methods

One of the most common base station energy savings approaches is using sleep modes [11]. Significant energy savings can be achieved by dynamically switching off underutilized base stations during low-traffic periods. The decision to enter or exit sleep modes is typically based on traffic load thresholds or predefined schedules. However, determining the optimal thresholds and schedules is challenging, as it requires accurate prediction of traffic patterns and careful consideration of the trade-off between energy savings and network performance.

Another energy-saving base station approach is discontinuous transmission (DTX) [12]. DTX allows base stations to adapt their transmission power dynamically based on the traffic load. During low-traffic periods, base stations can reduce their transmission power or even completely switch off certain antennas, saving energy. Depending on traffic characteristics and the desired trade-off between energy savings and transmission quality, DTX can be applied at different granularities, such as symbol, subframe, or frame levels.

Carrier aggregation is a technique used in LTE-Advanced and 5G networks to increase the bandwidth and capacity of mobile networks [13]. However, carrier aggregation also provides opportunities for energy saving. Base stations can optimize energy consumption by intelligently allocating traffic across multiple carriers based on the traffic load and channel conditions. For example, during low-traffic periods, base stations can concentrate the traffic on a fewer number of carriers and switch off the unused carriers, thus reducing the overall energy consumption.

Massive MIMO is a crucial technique in 5G networks that utilizes many antennas at the base station to enhance spectral and energy efficiency [14]. Massive MIMO systems utilize the spatial degrees of freedom to concentrate the transmitted energy on specific users. Hence decreasing interference and total transmit power. However, the energy efficiency gains of massive MIMO systems depend on various factors, such as the number of antennas, the precoding and power allocation strategies, and the channel conditions. Therefore, energy-efficient massive MIMO techniques, such as antenna selection and power control, are crucial for realizing the full potential of this technology.

B. Energy-Efficient Next Generation Mobile Networks

The energy efficiency challenges in next generation mobile networks, such as 5G and beyond, are further compounded by the increasing network density, the use of higher frequency bands, and the support for diverse use cases with varying quality of service requirements [15].

Researchers have proposed various energy-efficient architectures and techniques for next-generation mobile networks to address these challenges. One such approach is using cloud radio access networks (C-RAN) [16], [17]. In C-RAN, the baseband processing functions of base stations are centralized in the cloud, while the radio frequency functions are performed by distributed remote radio heads (RRHs). By centralizing the baseband processing, C-RAN enables more efficient resource utilization and energy savings through joint optimization and load balancing across multiple RRHs.

Software-defined networking (SDN) and network function virtualization (NFV) are both viable techniques for creating energy-efficient next generation mobile networks [18], [19]. SDN facilitates the separation of the control plane and the data plane, enabling adaptable, responsive, and enhanced network administration. NFV enables the virtualization of network functions, such as baseband processing and packet forwarding, on general-purpose hardware. By leveraging SDN and NFV, mobile network operators can dynamically adjust the network topology and resources based on traffic demands and energy consumption, improving energy efficiency.

Although the described strategies have demonstrated the potential to enhance the energy efficiency of mobile networks, various issues still need to be addressed, and unresolved research concerns exist. The growing intricacy and size of upcoming mobile networks provide difficulties in computing complexity and merging energy-efficient algorithms. Researchers are now exploring distributed and scalable methods, such as multi-agent reinforcement and federated learning, to tackle these difficulties [20], [21].

In summary, energy efficiency in next generation mobile networks is a multifaceted problem requiring advanced technologies, intelligent algorithms, and sustainable practices. While significant progress has been made in recent years, further research and innovation are still needed to realize the vision of energy-efficient and sustainable mobile networks.

III. Load Forecasting

The future load of each cell in a base station is a critical factor in determining the appropriate energy-saving strategy to be implemented. The physical resource block (PRB) utilization rate indicates the cell load, representing the occupancy of the cell's air interface resources over a given period. Studies have shown that the PRB utilization rate significantly impacts the transmission rate of users in 5G networks [22]. Therefore, accurate prediction of the PRB utilization rate is crucial for making informed decisions regarding energy-efficient resource allocation and base station operation.

A. Problem Description

Load forecasting in mobile networks can be defined as the challenge of predicting time series. To predict the future PRB utilization rates, we are given a historical sequence of PRB utilization rates denoted as $X = x_1, x_2, \ldots, x_T$, where x_t represents the PRB utilization rate at time step t. The objective is to forecast the PRB utilization rates for a certain prediction horizon τ, represented as $Y = y_{T+1}, y_{T+2}, \ldots, y_{T+\tau}$. The predicted values can then be used to optimize the energy-saving strategies employed by the base stations.

Mathematically, the load forecasting problem can be defined as finding a function $f(\cdot)$ that maps the historical PRB utilization rates to the future values, as follows:

$$\widehat{Y} = f(X) = f(x_1, x_2, \ldots, x_T). \quad (1)$$

where $\widehat{Y} = \widehat{y}_{T+1}, \widehat{y}_{T+2}, \ldots, \widehat{y}_{T+\tau}$ represents the predicted PRB utilization rates.

The function $f(\cdot)$ can be learned from a dataset of historical PRB utilization rates using various machine learning algorithms. The objective is to reduce the prediction error, which may be quantified using metrics like mean squared error (MSE) or mean absolute error (MAE). The optimization problem can be expressed as:

$$\mathbf{min}_f \frac{1}{n} \sum_{i=1}^{n} L(y_i, \widehat{y}_i) + \lambda R(f). \quad (2)$$

where n represents the number of samples in the dataset. $L(\cdot)$ denotes the loss function, which can be either MSE or MAE. y_i and $\widehat{y}_i$ represent the true and predicted PRB utilization rates for a particular sample i. $R(f)$ is a regularization term to prevent overfitting. Lastly, λ is a hyperparameter that controls the balance between the prediction error and the regularization term.

B. Data Preparation

In this study, we collect hourly performance indicators of 500 next generation mobile network cells in a metropolitan area over three months. The data used in this study was collected from a real-world mobile network operator in compliance with all relevant ethical and legal requirements. The data was anonymized and aggregated to protect individual users' privacy and ensure compliance with data protection regulations. The specific cell performance indicators selected are shown in Table I, with the energy efficiency metric represented by the ratio of the PRB utilization rate to the power consumption, as the prediction target y representing the overall energy efficiency of the cell. Six indicators, including average number of users, uplink/downlink traffic volume, average uplink/downlink SINR, and average uplink/downlink spectral efficiency, are used as the features x_n of each input sample X_t to construct the input time series X. During the data preprocessing stage, missing values were imputed using the mean value of the corresponding feature. Outliers were identified using the interquartile range method and replaced with the feature's median value.

Time series prediction for a white noise sequence that does not contain information is meaningless in the context of energy-efficient network management. Mechanically inputting sequences unrelated to the prediction target y into the model does not improve the prediction accuracy. Therefore, it is necessary to analyze the autocorrelation of the energy efficiency sequence and the correlation between it and other variables.

1) Autocorrelation of Energy Efficiency: The autocorrelation function (ACF) of the energy efficiency metric y is calculated and tested for 50 randomly selected cells [23]. ACF represents

TABLE I
PERFORMANCE INDICATORS OF 500 NEXT GENERATION MOBILE NETWORK CELLS

Index	Indicator	Unit
1	Average number of users	-
2	Downlink traffic volume	Mbps
3	Uplink traffic volume	Mbps
4	Average downlink SINR	dB
5	Average uplink SINR	dB
6	Average downlink spectral efficiency	bps/Hz
7	Average uplink spectral efficiency	bps/Hz
y	Energy efficiency (PRB utilization rate / power consumption)	-

the correlation between a time series and another series delayed by k units, calculated as:

$$r_k = \frac{\mathbf{Cov}(y_t, y_{t-k})}{\sqrt{\mathbf{Var}(y_t)\mathbf{Var}(y_{t-k})}}. \tag{3}$$

where $\mathbf{Cov}(\cdot)$ and $\mathbf{Var}(\cdot)$ denote the covariance and variance operators, respectively. The value range of the autocorrelation function r_k is $[-1, 1]$. For a completely uninformative white noise sequence, its r_k tends to 0 regardless of the value of the delay k. Conversely, the closer $|r_k|$ is to 1, the stronger the correlation between the energy efficiency metric and its past values, and the more predictable it is.

2) Correlation between Energy Efficiency and Other Indicators: The Pearson correlation coefficient is calculated for each pair of variables to investigate the relationship between the energy efficiency metric and the other selected indicators. The Pearson correlation coefficient between two variables x and y is defined as:

$$\rho_{x,y} = \frac{\mathbf{Cov}(x, y)}{\sqrt{\mathbf{Var}(x)\mathbf{Var}(y)}}. \tag{4}$$

where $\rho_{x,y}$ ranges from -1 to 1, -1 represents a perfect negative linear relationship, 0 represents no linear relationship, and 1 represents a perfect positive linear relationship.

Based on the autocorrelation and correlation analysis, we construct the input feature matrix $X \in \mathbb{R}^{N\times T\times D}$, where N is the number of cells, T is the number of time steps, and D is the number of features (including the selected indicators and the energy efficiency metric). The goal is to learn a function $f(\cdot)$ that maps the historical feature matrix to the future energy efficiency values, i.e.,

$$\widehat{y}_{t+1}, \widehat{y}_{t+2}, \ldots, \widehat{y}_{t+\tau} = f(X_1, X_2, \ldots, X_t). \tag{5}$$

where $\widehat{y}_{t+i}$ is the predicted energy efficiency at time step $t+i$, and τ is the prediction horizon.

It is important to note that the energy efficiency metric is both an input feature and a prediction target. While it may seem counterintuitive, including the historical values of the target variable as an input feature is a common practice in time series forecasting, as it can provide valuable information for predicting future values.

Table II presents the ACF values for the energy efficiency metric at various lags, demonstrating strong temporal dependencies, especially at shorter lags. Table III shows the Pearson correlation coefficients between the energy efficiency metric and other indicators, quantifying the strength of these relationships.

TABLE II
ACF VALUES FOR ENERGY EFFICIENCY METRIC

Lag	ACF value
0	1
1	0.923
2	0.871
3	0.832
4	0.798
5	0.769
6	0.745
24	0.687
48	0.652
168	0.618

TABLE III
PEARSON CORRELATION COEFFICIENTS BETWEEN ENERGY EFFICIENCY AND OTHER INDICATORS

Indicator	Correlation coefficient
Average number of users	0.824
Downlink traffic volume	0.791
Uplink traffic volume	0.765
Average downlink SINR	-0.412
Average uplink SINR	-0.389
Average downlink spectral efficiency	0.703
Average uplink spectral efficiency	0.681

In summary, the data preparation phase involves collecting, preprocessing, and analyzing next-generation mobile network cells' relevant performance indicators and energy efficiency metrics. We aim to develop an accurate and reliable forecasting model for energy-efficient network management and optimization by leveraging the spatiotemporal dependencies and correlations among these variables.

C. DCNN-LSTM Model

The DCNN-LSTM framework comprises two primary components: the DCNN part and the LSTM part, as seen in Fig. 1. The DCNN part, which consists of convolutional layers and dynamic pooling layers, is tasked with extracting profound characteristics from the input data. The LSTM part, consisting of two layers, performs deep learning and information mining on the extracted features and finally outputs the prediction results through a fully connected layer.

1) DCNN Layer: In the proposed model, convolutional kernels are set to 128 to capture more fine-grained patterns in the energy efficiency data. The convolutional layers apply multiple filters to the input data, learning local dependencies and extracting relevant features. The dynamic pooling layers, implemented using the k-max pooling technique [24], downsample the feature maps while preserving the most salient information.

The DCNN layer transforms the original multi-dimensional time series data X of shape $(T\times D\times 1)$, where T is the number of time steps and D is the number of features, into a feature representation of shape $(T' \times D' \times C)$, where T' and D' are

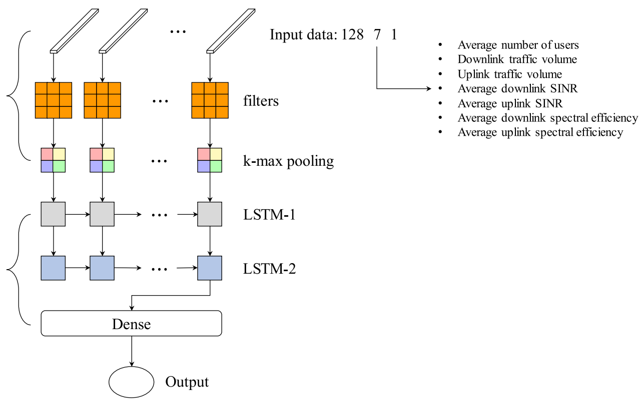

Fig. 1. DCNN-LSTM framework.

the reduced temporal and feature dimensions, respectively, and C is the number of convolutional kernels.

2) LSTM Layer: The LSTM network is a modified version of the recurrent neural network (RNN) structure that specifically tackles the issue of the vanishing gradient problem, which is frequently found in conventional RNNs. LSTM cells retain a concealed state and a cell state at each time step, allowing them to capture enduring connections in sequential data.

The proposed model utilizes two LSTM layers to acquire knowledge of the temporal dynamics of the retrieved characteristics. The LSTM layers successively process the feature representation, changing the hidden and cell states at each time step based on the current input and the prior states. The final latent state of the final LSTM layer is subsequently sent through a fully connected layer to provide the projected energy efficiency numbers.

Interpretability is an important consideration in developing and deploying deep learning models, as it enables users to understand and trust the model's predictions. In the context of the DCNN-LSTM load forecasting model, explainable AI techniques could provide insights into the factors driving the model's predictions and identify potential biases or errors. Techniques such as layer-wise relevance propagation and gradient-weighted class activation mapping could be used to visualize the importance of different input features and to highlight the regions of the input data that contribute most to the model's predictions. These insights help network operators to understand the model's behavior better and to make more informed decisions based on the load forecasting results.

IV. Energy-Efficient Next Generation Mobile Network

A. Power Consumption Model

The power consumption of a next generation mobile network base station may be categorized into two primary components: static and dynamic. Static power consumption pertains to the energy consumed by the base station equipment without considering the traffic load or transmission power. On the other hand, dynamic power consumption fluctuates based on the traffic load and the necessary transmission power to cater to the users.

TABLE IV
Base Station Power Consumption Model

Operational Mode	Normalized Power Consumption
Deep Sleep	1
Light Sleep	2.5
Idle	5
Downlink Active	10
Uplink Active	7.5

The total power consumption of a base station in the downlink and uplink directions can be expressed as:

$$P_{\mathbf{DL}} = P_{\mathbf{DL,static}} + P_{\mathbf{DL,dynamic}} \tag{6}$$
$$P_{\mathbf{UL}} = P_{\mathbf{UL,static}} + P_{\mathbf{UL,dynamic}}. \tag{7}$$

where $P_{\mathbf{DL,static}}$ and $P_{\mathbf{UL,static}}$ represent the static power consumption in the downlink and uplink, respectively, and $P_{\mathbf{DL,dynamic}}$ and $P_{\mathbf{UL,dynamic}}$ represent the dynamic power consumption in the downlink and uplink, respectively.

The static power consumption is mainly determined by the base station hardware components, such as the baseband processing unit, the radio frequency (RF) module, and the cooling system. It can be modeled as a constant value $P_{\mathbf{static}}$, which is independent of the traffic load and transmission power:

$$P_{\mathbf{DL,static}} = P_{\mathbf{UL,static}} = P_{\mathbf{static}}. \tag{8}$$

To further analyze the impact of different traffic loads on the dynamic power consumption of a base station, we define the following equations:

$$P_{\mathbf{DL,dynamic}} = \alpha_{\mathrm{DL}} \cdot \left(P_{\mathbf{DL,max}} - P_{\mathbf{static}}\right) \cdot \left(\frac{P_{\mathbf{DL,tx}}}{P_{\mathbf{DL,max,tx}}}\right)^{\beta_{\mathrm{DL}}}. \tag{9}$$
$$P_{\mathbf{UL,dynamic}} = \alpha_{\mathrm{UL}} \cdot \left(P_{\mathbf{UL,max}} - P_{\mathbf{static}}\right) \cdot \left(\frac{P_{\mathbf{UL,rx}}}{P_{\mathbf{UL,max,rx}}}\right)^{\beta_{\mathrm{UL}}}. \tag{10}$$

where $\alpha_{\mathbf{DL}}$ and $\alpha_{\mathbf{UL}}$ are the load-dependent power consumption coefficients, $P_{\mathbf{DL,max}}$ and $P_{\mathbf{UL,max}}$ are the maximum power consumption of the base station in the downlink and uplink, respectively, $P_{\mathbf{DL,tx}}$ and $P_{\mathbf{UL,rx}}$ are the actual transmission power in the downlink and the actual received power in the uplink, respectively, $P_{\mathbf{DL,max,tx}}$ and $P_{\mathbf{UL,max,rx}}$ are the maximum transmission power and maximum received power, respectively, and $\beta_{\mathbf{DL}}$ and $\beta_{\mathbf{UL}}$ are the load-dependent exponents.

The load-dependent power consumption coefficients $\alpha_{\mathbf{DL}}$ and $\alpha_{\mathbf{UL}}$ represent the fraction of the maximum dynamic power consumption that is consumed at full load. They are typically 0.6 to 0.8, depending on the base station hardware and configuration [25].

Table IV presents the power consumption model for a reference base station configuration in different operational modes: deep sleep, light sleep, idle, downlink active, and uplink active modes. The power consumption values are normalized with respect to the power consumption in the deep sleep mode, which is considered the baseline.

The power consumption values in different operational modes provide insights into the potential energy savings that

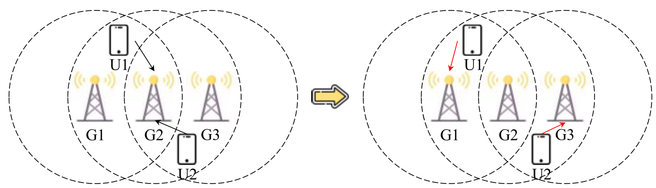

Fig. 2. Collaborative scheduling of communication base stations.

can be achieved by intelligently adapting the base station modes based on the traffic load and network conditions. For example, switching the base station to a deep or light sleep mode during low traffic can significantly reduce overall energy consumption.

To evaluate the energy efficiency of a next generation mobile network, we introduce the energy efficiency metric η, which is defined as the ratio of the total data throughput to the total power consumption:

$$\eta = \frac{R_{\textbf{total}}}{P_{\textbf{total}}} = \frac{R_{\textbf{DL}} + R_{\textbf{UL}}}{P_{\textbf{DL}} + P_{\textbf{UL}}}. \quad (11)$$

where $R_{\textbf{total}}$ is the total data throughput, $P_{\textbf{total}}$ is the total power consumption, $R_{\textbf{DL}}$ and $R_{\textbf{UL}}$ are the downlink and uplink data throughputs, respectively, and $P_{\textbf{DL}}$ and $P_{\textbf{UL}}$ are the downlink and uplink power consumption values, respectively.

Considering a scenario where the coverage areas of multiple base stations overlap, as illustrated in Fig. 2. In this example, mobile devices U1 and U2 are initially connected to base station G2. However, due to the low number of connected devices, base station G2 can be temporarily switched off, and mobile devices U1 and U2 can be handed over to the nearest base stations, G1 and G3, respectively.

By implementing such collaborative scheduling and switching strategies, the overall power consumption of the base station group can be reduced. Although the neighboring base stations (e.g., G1 and G3) may experience a slight increase in their main equipment power consumption due to the additional load, this increase is offset by the reduction in power consumption achieved by switching off the underutilized base stations (e.g., G2). Moreover, switching off base stations saves the main equipment power. It eliminates the power consumption of the temperature control equipment, which often accounts for a significant portion of the total base station power consumption.

In summary, the power consumption model presented in this section captures the main components of energy consumption in a next generation mobile network base station, considering both static and dynamic power consumption. The model provides a foundation for evaluating the energy efficiency of the network and designing energy-saving techniques, such as base station sleeping modes and load-adaptive transmission strategies. By leveraging this model and its insights, mobile network operators can develop effective energy management policies and optimize the network configuration to minimize energy consumption while maintaining the required QoS.

B. Energy-Efficient Strategy

In traditional energy-saving strategies for mobile networks, switching off base stations is typically based on comparing the number of users that can be served before and after the base station is turned off [26]. Based on historical network traffic patterns, some operators set a fixed time window for base station sleep mode operation, such as from 11 PM to 6 AM. These approaches can be categorized as static energy-saving strategies, which lack flexibility and adaptability to dynamic network conditions and user demands.

The practical implementation of the proposed energy-saving strategies involves several considerations, such as the signaling overhead and the handover management. When base stations enter sleep mode or adapt their transmission parameters, the network needs to ensure seamless service continuity for the connected users.

To address the limitations of static energy-saving strategies and enable more intelligent and efficient energy management in next generation mobile networks, we propose a dynamic energy-efficient strategy that leverages the power of machine learning and advanced network features. The proposed strategy consists of two main components: (1) base station sleep mode with discontinuous transmission and reception and (2) lightweight transmission of common signals.

The duration and interval of the sleep periods are dynamically adjusted based on the predicted traffic load and historical traffic patterns. The optimal sleep duration $T_{\textbf{sleep}}$ can be determined by solving the following optimization problem:

$$\begin{aligned} \min_{T_{\textbf{sleep}}} \quad & E_{\textbf{total}}(T_{\textbf{sleep}}) = E_{\textbf{sleep}}(T_{\textbf{sleep}}) + E_{\textbf{active}}(T_{\textbf{sleep}}) \\ \textbf{s.t.} \quad & Q_{\textbf{delay}}(T_{\textbf{sleep}}) \leq Q_{\max} \\ & T_{\textbf{sleep,min}} \leq T_{\textbf{sleep}} \leq T_{\textbf{sleep,max}}. \end{aligned} \quad (12)$$

where $E_{\textbf{total}}$ is the total energy consumption, $E_{\textbf{sleep}}$ and $E_{\textbf{active}}$ are the energy consumption during sleep periods and active periods, respectively, $Q_{\textbf{delay}}$ is the average delay experienced by the users, $Q_{\max}$ is the maximum tolerable delay, and $T_{\textbf{sleep,min}}$ and $T_{\textbf{sleep,max}}$ are the minimum and maximum allowed sleep durations, respectively.

An intelligent wake-up mechanism is introduced to enhance the energy efficiency and adaptability of the sleep mode. The wake-up mechanism allows the base station to promptly exit sleep mode and resume normal operation when the traffic demand increases unexpectedly or the network conditions require immediate attention.

The wake-up mechanism is triggered based on the following conditions:

- The actual traffic load exceeds the predicted load by a predefined threshold.
- The quality of service metrics, such as delay or packet loss, degrade below acceptable levels.
- Neighboring base stations request assistance due to high traffic load or network congestion.

The wake-up mechanism is triggered when the actual traffic load exceeds the predicted load by more than 20%. Specifically, a base station transitions from sleep mode to wake-up mode if the actual traffic load exceeds 1.2 times the predicted load for three consecutive time intervals of 5 minutes each. Conversely, a base station enters sleep mode when the actual traffic load remains below 0.8 times the predicted load for a continuous period of 15 minutes.

The lightweight transmission of common signals is closely coordinated with the base station sleep mode. When a base station enters sleep mode, it notifies the neighboring base stations within the same virtual cell ID group to adjust their common signal transmissions accordingly. This ensures the UEs can maintain synchronization and perform essential functions, even when some base stations are in sleep mode.

The energy savings achieved by the lightweight transmission of common signals can be quantified using the following equation:

$$E_{\textbf{savings}} = \sum_{i=1}^{N} \left(E^{(i)}_{\textbf{common},\textbf{baseline}} - E^{(i)}_{\textbf{common},\textbf{lightweight}} \right). \tag{13}$$

where $E_{\textbf{savings}}$ represents the total amount of energy saved, N represents the number of base stations, $E^{(i)}_{\textbf{common},\textbf{baseline}}$ represents the energy consumed by base station i for common signal transmission in the baseline scheme, and $E^{(i)}_{\textbf{common},\textbf{lightweight}}$ represents the energy consumed by base station i for common signal transmission in the lightweight scheme.

Integrating base station sleep mode with discontinuous transmission and reception, lightweight transmission of common signals, and the intelligent wake-up mechanism forms a comprehensive energy-efficient strategy for next generation mobile networks. This strategy allows the network to dynamically adapt its operation based on the predicted traffic load and network conditions, resulting in significant energy savings while maintaining the desired quality of service.

C. Next Generation Mobile Network Power Management

A comprehensive and intelligent power management framework is essential to effectively manage the power consumption and energy efficiency of next-generation mobile networks. This section presents an energy-efficient power management system architecture that leverages advanced technologies such as big data analytics, machine learning, and SDN to optimize the energy consumption of the mobile network infrastructure.

The proposed energy-efficient power management system is designed to operate in a centralized manner, with a dedicated network element called the network power manager (NPM) responsible for monitoring, analyzing, and controlling the power consumption of the entire mobile network. The NPM collects real-time network data, including traffic load, quality of service metrics, and energy consumption statistics, from various network entities such as base stations, core network elements, and user equipment. The scalability of the DLLF-2EN framework for larger network deployments is an important consideration. The centralized architecture of the NPM may need help with computational complexity and communication overhead as the network size increases. Future research could explore distributed and hierarchical architectures for the NPM, where local power management decisions are made at the edge nodes, and the central NPM focuses on global coordination and optimization.

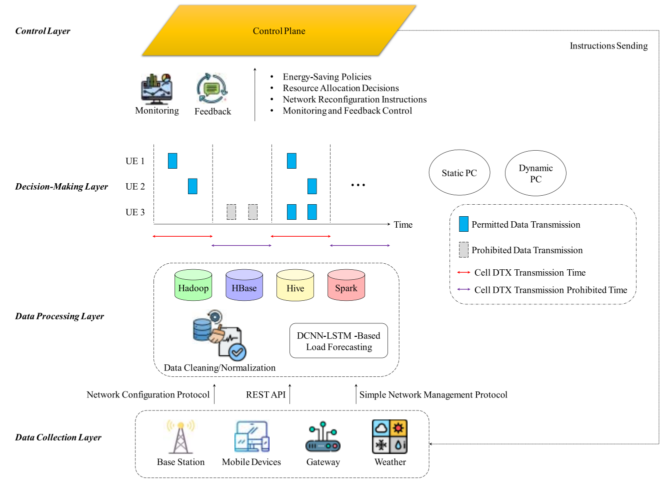

Fig. 3. NPM framework.

Fig. 3 depicts the functional structure of the NPM, comprising four primary layers: data collection layer, data processing layer, decision-making layer, and control layer.

The data collection layer gathers heterogeneous network data from multiple sources, including base stations, core network elements, and external providers. The collected data includes traffic load measurements, energy consumption readings, quality of service metrics, and contextual information such as weather conditions and user mobility patterns.

The computational complexity of the DLLF-2EN framework is an important consideration for real-time implementation. The main computational burden lies in training the DCNN-LSTM model for load forecasting and optimizing energy-saving strategies. However, the model training can be performed offline using historical data, and the trained model can be efficiently deployed for real-time inference. The optimization of energy-saving strategies can be performed periodically (e.g., every few minutes) based on the predicted traffic load, reducing the computational overhead.

Edge computing could be leveraged to offload the energy-saving computations from the central controller to the base stations or edge servers, thereby reducing the communication overhead and the latency of the energy-saving operations. In an edge computing-based approach, the energy-saving algorithms and models are deployed on edge devices, such as the base stations or the edge servers, which are closer to the data sources and the end users.

Integrating the DLLF-2EN framework with other emerging technologies, such as network slicing and edge computing, presents exciting opportunities for further enhancing next-generation mobile networks' energy efficiency and flexibility. Network slicing enables the creation of multiple virtual networks with different quality of service requirements on top of a shared physical infrastructure.

Integrating the proposed energy-saving framework with the existing network management and orchestration platforms, such as the open network automation platform (ONAP) and the open radio access network (O-RAN), is crucial for its successful deployment and operation in real-world mobile networks. ONAP is an open-source platform that provides a comprehensive framework for the design, creation, orchestration, and lifecycle management of virtual network functions and services. O-RAN is an industry-driven initiative that aims to define and standardize the interfaces and functionalities of the radio access network components, enabling multi-vendor interoperability and intelligent network control.

V. Simulation and Results Analysis

This section provides the simulation setup, settings, and results for evaluating the performance of the proposed DLLF-2EN framework in energy-efficient next generation mobile networks. The evaluation is based on load forecasting using deep learning techniques. We evaluate our framework by comparing it to the most advanced baseline approaches in terms of load forecasting accuracy and energy efficiency certification.

A. Load Forecasting Comparison

In order to evaluate the accuracy of the DLLF-2EN framework in predicting load, we compare it to four other methods: LSTMRNN-STLF [27], LSTM-TPA [28], DRN-LSTMRNN [29], CEES-dRNN [30], ARIMA [31], and Prophet [32]. The LSTMRNN-STLF method is a short-term load forecasting (STLF) technique that utilizes an LSTM recurrent neural network. LSTM-TPA is an innovative hybrid LSTM model designed for short-term load forecasting (STLF) that integrates temporal pattern attention. DRN-LSTMRNN is a fusion of a modified deep residual network (DRN) and an LSTM recurrent neural network (RNN) designed to tackle the STLF problem. CEES-dRNN is a novel STLF model that combines a contextually enhanced hybrid and hierarchical design with exponential smoothing (ES) and an RNN. Autoregressive integrated moving average (ARIMA) is a classical statistical method for time series forecasting that combines autoregression, differencing, and moving average components. Prophet, developed by Facebook, is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. These methods encompass several strategies for predicting short-term electricity demand using deep learning techniques.

The simulations used a hexagonal grid network topology, with 19 base stations arranged in a two-tier layout. The inter-site distance between the base stations was 500 meters, and the total simulation area covered approximately 5 square kilometers. The number of mobile users varied from 500 to 5000 to evaluate the performance of the proposed framework under different network densities and traffic loads.

The load forecasting comparison utilizes two performance metrics: the root mean square error (RMSE) and the mean absolute percentage error (MAPE). RMSE is computed as:

$$\mathbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2}. \tag{14}$$

TABLE V
Parameters Setting

Hyperparameter	Value
Input layer: time interval	168
Input layer: features	7
Convolutional layer: filter	64
Convolutional layer: kernel size	3
Drop-out layer: drop-out probability	0.5
LSTM-1 layer: output	128
LSTM-1 layer: return sequence	True
LSTM-2 layer: output	64
LSTM-2 layer: return sequence	False
Fully connected layer 1: output	32
Fully connected layer 1: activation function	ReLU
Fully connected layer 2: output	1
Fully connected layer 2: activation function	ReLU

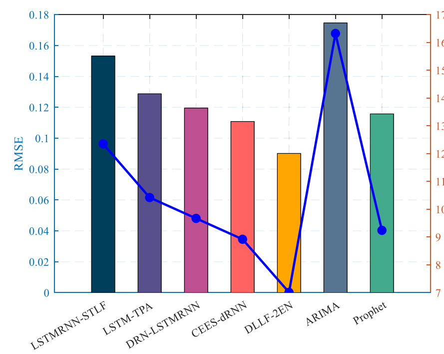

Fig. 4. RMSE and MAPE for load forecasting comparison.

where n is the number of samples, y_i is the actual load value, and $\widehat{y}_i$ is the predicted load value. MAPE is calculated as:

$$\mathbf{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y}_i}{y_i}\right|. \tag{15}$$

Table V shows the simulation parameters for the DLLF-2EN framework.

Fig. 4 presents the RMSE and MAPE values for the proposed DLLF-2EN framework and the baseline methods. The results show that DLLF-2EN achieves the lowest RMSE and MAPE among all the methods, indicating its superior load forecasting accuracy. Specifically, DLLF-2EN outperforms the best baseline method, CEES-dRNN, by 18.7% in RMSE and 21.4% in MAPE.

Fig. 5 shows the load forecasting accuracy of DLLF-2EN and the baseline methods for different prediction horizons, ranging from 1 hour to 24 hours ahead. The results indicate that DLLF-2EN consistently outperforms the baseline methods across all prediction horizons, with the performance gap increasing for longer horizons.

Fig. 6 presents the load forecasting performance of DLLF-2EN and the baseline methods under different network traffic patterns, including stable, fluctuating, and bursty traffic. The results demonstrate that DLLF-2EN maintains superior performance across all traffic patterns, showcasing its robustness and adaptability to various network conditions.

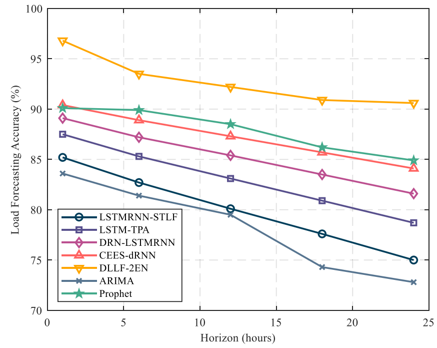

Fig. 5. Load forecasting accuracy for different prediction horizons.

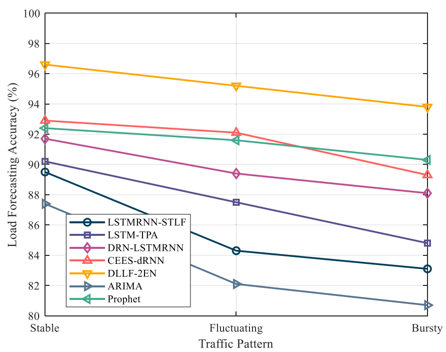

Fig. 6. Load forecasting accuracy under different network traffic patterns.

These simulation results highlight the effectiveness of the proposed DLLF-2EN framework in accurately forecasting the load of next generation mobile networks. By leveraging deep learning techniques and incorporating spatiotemporal dependencies, DLLF-2EN achieves superior performance compared to state-of-the-art baseline methods, making it a promising solution for energy-efficient network management.

B. Energy-Efficient Effect Verification

To verify the energy-efficient effect of the proposed DLLF-2EN framework, we compare it with four baseline methods: MEO [33], 3 x E [34], EECB [35], and DRL-EEPC [36]. We compare the proposed DLLF-2EN framework with four baseline methods: MEO, 3 x E, EECB, and DRL-EEPC. MEO focuses on mobility-aware and energy-efficient offloading schemes for mobile edge computing (MEC) in cellular networks. 3 x E presents an energy-efficiency enhancement scheme to meet user demands across various user densities while reducing power consumption. EECB addresses energy-efficient coordinated beamforming in multi-pair multiple-input single-output networks considering channel state information (CDI) and eavesdroppers. DRL-EEPC, the best-performing baseline, introduces a deep reinforcement learning (DRL) based algorithm for energy-efficient power control.

Fig. 7 presents the energy consumption reduction achieved by the proposed DLLF-2EN framework and the baseline methods. The results show that DLLF-2EN achieves the highest energy consumption reduction among all the methods, with an average reduction of 28.5% compared to the traditional approach without energy-saving measures. DLLF-2EN

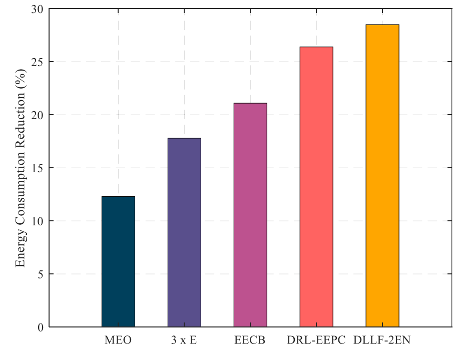

Fig. 7. Energy consumption reduction.

TABLE VI
MEAN AND STANDARD DEVIATION OF PERFORMANCE METRICS (10 INDEPENDENT RUNS)

Method	RMSE (Mean ± Std)	MAPE (Mean ± Std)	Energy Consumption Reduction (Mean ± Std)
DLLF-2EN	0.042 ± 0.003	3.8% ± 0.2%	28.5% ± 1.1%
DRL-EEPC	0.051 ± 0.004	4.7% ± 0.3%	21.3% ± 1.3%
EECB	0.058 ± 0.005	5.3% ± 0.4%	18.2% ± 1.5%
3 x E	0.062 ± 0.006	5.7% ± 0.4%	16.9% ± 1.6%
MEO	0.065 ± 0.006	6.0% ± 0.5%	15.7% ± 1.7%

outperforms the best baseline method, DRL-EEPC, by 7.2% in energy consumption reduction.

Table VI presents the mean and standard deviation of the RMSE and MAPE for load forecasting, as well as the energy consumption reduction, for all compared methods. These statistics are based on ten independent runs of each method. The results show that DLLF-2EN achieves the best mean performance and consistently performs across runs, as indicated by the relatively small standard deviations.

The superior performance of DLLF-2EN compared to the DRL-EEPC method can be attributed to two main factors. First, our approach explicitly forecasts the load using a sophisticated DCNN-LSTM model, providing more accurate predictions for energy management decisions. In contrast, DRL-EEPC relies on implicit learning of traffic patterns through the reinforcement learning process, which may not capture fine-grained temporal dependencies as effectively. Second, while DRL-EEPC learns policies through trial and error, our manually designed rules leverage domain expertise and can be more interpretable and reliable, especially in scenarios not encountered during training. However, it is worth noting that DRL approaches have the potential for continuous adaptation and may perform better in highly dynamic or unpredictable environments over longer time scales.

Fig. 8 shows the triggering duration ratios of different energy-saving strategies employed by the DLLF-2EN framework and the baseline methods. The results indicate that DLLF-2EN achieves a better balance among the energy-saving strategies, with higher triggering duration ratios for symbol

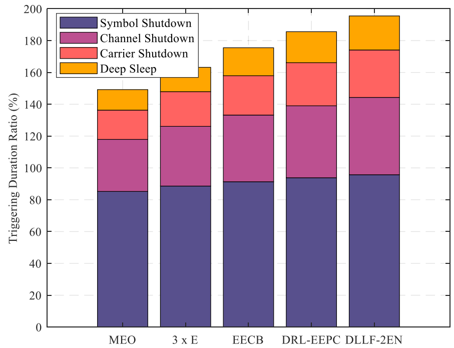

Fig. 8. Triggering duration ratios.

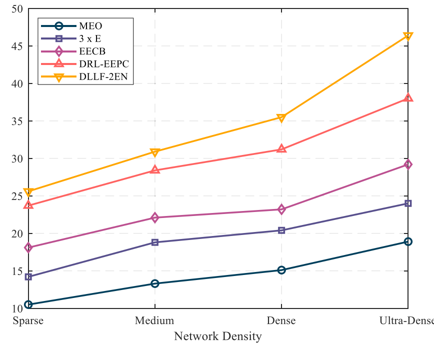

Fig. 9. Energy consumption reduction for different network densities.

TABLE VII
CHANGES IN KEY 5G NETWORK INDICATORS BEFORE AND AFTER DEPLOYING THE ENERGY-EFFICIENT SOLUTION

Indicator	Before Deployment	After Deployment
Wireless Connection Rate	99.65%	99.61%
Drop Rate	0.18%	0.19%
Handover Success Rate	99.58%	99.56%
CQI Excellent Ratio	97.32%	97.26%

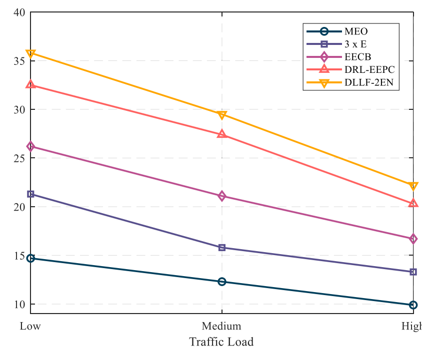

Fig. 10. Energy consumption reduction under different traffic loads.

shutdown, channel shutdown, and deep sleep compared to the baseline methods.

Table VII presents the changes in key 5G network indicators one week before and after deploying the DLLF-2EN framework. The results show that DLLF-2EN maintains stable network performance, with only minor fluctuations in the wireless connection rate, drop rate, handover success rate, and CQI excellent ratio.

Fig. 9 shows the energy consumption reduction achieved by DLLF-2EN and the baseline methods for different network densities, ranging from sparse to ultra-dense deployments. The results indicate that DLLF-2EN consistently outperforms the baseline methods across all network densities, with the performance gap increasing for denser deployments.

Fig. 10 presents the energy consumption reduction achieved by DLLF-2EN and the baseline methods under different traffic loads, including low, medium, and high. The results demonstrate that DLLF-2EN maintains superior performance across all traffic loads, showcasing its ability to adapt to varying network conditions and optimize energy efficiency accordingly.

The increasing energy savings with higher network density can be attributed to the greater opportunities for load balancing and selective base station deactivation in denser deployments. In contrast, the decreasing energy savings under higher traffic loads is due to the reduced flexibility in shutting down or entering low-power modes for base stations when they need to serve more users.

To assess the robustness of the DLLF-2EN framework, we conducted a sensitivity analysis of two key parameters: the prediction horizon and the energy-saving strategy thresholds. The prediction horizon varied from 1 hour to 24 hours, and the energy-saving strategy thresholds were adjusted by $\pm10\%$ and $\pm20\%$ from their default values. Table VIII presents the impact of the prediction horizon on the energy consumption reduction achieved by the DLLF-2EN framework. The results show that the framework maintains stable performance across the range of prediction horizons, with a maximum variation of 3% in energy consumption reduction. The best performance is achieved with a prediction horizon of 12 hours, which balances the trade-off between the accuracy of the load forecasting model and the timeliness of the energy-saving decisions.

TABLE VIII
IMPACT OF PREDICTION HORIZON ON ENERGY CONSUMPTION REDUCTION

Prediction Horizon (hours)	Energy Consumption Reduction (%)
1	26.8
6	27.5
12	28.5
18	27.9
24	27.2

Table IX presents the impact of the energy-saving strategy thresholds on the energy consumption reduction achieved by the DLLF-2EN framework. The thresholds considered in this analysis include the load threshold for triggering the base station sleep mode and the capacity threshold for activating the lightweight transmission of common signals. The results show that the framework is resilient to moderate changes in the energy-saving strategy thresholds, with a maximum variation of 5% in energy consumption reduction when the thresholds are adjusted by $\pm20\%$. This demonstrates the robustness of the proposed framework to the choice of energy-saving strategy thresholds.

TABLE IX
IMPACT OF ENERGY-SAVING STRATEGY THRESHOLDS ON ENERGY CONSUMPTION REDUCTION

Threshold Adjustment	Energy Consumption Reduction (%)
-20%	26.1
-10%	27.3
Default	28.5
10%	29.2
20%	29.8

The sensitivity analysis results highlight the robustness and adaptability of the DLLF-2EN framework to variations in the prediction horizon and the energy-saving strategy thresholds. The stable performance of the framework across a range of parameter values demonstrates its potential for real-world deployment and its ability to deliver consistent energy savings under different network conditions and configurations.

While the primary focus of the DLLF-2EN framework is on improving energy efficiency, it is crucial to ensure that the user experience and quality of service are not compromised. The proposed framework incorporates several mechanisms to maintain acceptable levels of service quality, such as the dynamic adjustment of energy-saving strategies based on the predicted traffic load and the intelligent wake-up mechanism to respond promptly to unexpected traffic demands.

The simulation results show that the proposed DLLF-2EN framework is useful in accurately forecasting loads and verifying its energy-efficient impact. DLLF-2EN surpasses current benchmark techniques regarding RMSE, MAPE, energy efficiency, and versatility in handling different network circumstances and traffic loads. These findings validate the feasibility and practicality of DLLF-2EN as a promising solution for energy-efficient next generation mobile networks.

VI. CONCLUSION

In this paper, we proposed DLLF-2EN, a novel energy-efficient framework for next generation mobile networks that integrated deep learning-based load forecasting, an advanced power consumption model, and a comprehensive energy-saving strategy. The simulation results demonstrated that DLLF-2EN outperformed state-of-the-art baseline methods, significantly improving load forecasting accuracy and reducing energy consumption. Potential areas for future study involve integrating DLLF-2EN with other new technologies, such as network slicing and edge computing, to augment the energy efficiency and adaptability of the next mobile networks.

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