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Original Article

Predictive Analysis Approach for Small Cell Base Station Sleeping Strategies

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Abstract *- With the rapid growth of the number of base stations (BS), reducing energy consumption and enhancing the stations' energy efficiency (EE) have become important research topics as BSs are the primary energy consumers in cellular networks. BS consumes 100% power even during low-traffic periods. One promising way to reduce power consumption during such periods is to deactivate lightly loaded small cell base stations or switch them to hibernation without compromising the quality of service (QoS) demanded by users. In This paper, the BS sleep mode algorithm proposes to switch the BSs to sleep mode during low traffic periods of a BS. The process starts with predicting the traffic load of BS and identifying the low traffic periods. This predicted traffic load is further used to identify the number of BSs to be kept in on mode and sleep mode for a particular time period. The appropriate BS mode (on, sleep, standby or off). After switching the BS to the desired mode, the power consumption of the BS is calculated. The prediction of traffic load helps BS to avoid frequent switching in case of consecutive low traffic periods, further enhancing energy efficiency. With the proposed BS switching technique 27% reduction in power consumption is achieved. This proposed algorithm can work with dynamic traffic load variations, which will help reduce the power consumption of a small cell BS.*

Keywords *- Energy Efficiency, BS sleeping, Predictive Analysis, Small Cell BS, etc.*

1. Introduction

The upcoming generation of communications, i.e. fifth generation (5G) network era and beyond, is challenged with large amounts of users. Hundreds of millions of devices will remain constantly connected to the base stations, and the user traffic of the cellular networks is exploded. Mobile communication networks need to realize sustainable development to promote spectrum efficiency, energy efficiency, and cost efficiency in 5G wireless technologies. In addition, future 5G networks are expected to have flexible deployment mechanisms along with efficient operation and maintenance mechanisms using 5G technology.

With the exponential increase in smartphones and mobile devices, the demand for traffic rate is also increased, which is, in turn, responsible for the deployment of base stations in cellular networks to cope with such user demands. The increased number of base stations will be the prime reason for increased energy consumption at a staggering rate [1]. No wonder these mobile operators are becoming the biggest energy-consuming sectors in today's era [2]. Nowadays, the biggest challenge the network operators faces is coping with the increased and diverse user demand and providing energy-efficient architecture as the energy efficiency (EE) issue plays a significant role in resource management, bringing great economic benefits.

Various unique approaches are proposed to reduce the energy consumption of mobile cellular networks. Various unique approaches are proposed to reduce the energy consumption of mobile cellular networks.

1) Enhancing the energy efficiency of hardware components;
2) Selectively turning off BS components;
3) Optimization of power consumption during the radio transmission process;
4) Efficient planning and deployment of heterogeneous cells;
5) Embracing the available renewable energy resources.

The base stations (BS) are the component that consumes the bulk of the energy in mobile networks, which account for around 65-80% of the network's total energy consumption [2]. Furthermore, a base station consumes 90% of its peak power without traffic. As the concept of an ultra-dense network is evolving in 5G, the network operators are deploying more base stations to cope with the ever-increasing traffic demand. Therefore, in order to minimize the total energy that is consumed by a network, first, the energy of the small cell must be reduced. The primary goal of a small cell is to provide sufficient cellular coverage to users anytime, anywhere. The small cell is a radio base station (BS) that offers low cost and power. In descending order of cell radius, the macro cells, pico cells, and femtocells are examples of such small cells. A heterogeneous cellular network is a combination of macro cells and small cells. In heterogeneous networks, the primary objective is to maintain seamless connectivity and mobility while achieving high data rates; heterogeneous networks are accomplished by potentially improving spatial reuse and coverage. Though cellular network operators embrace users with high data rates, they are gradually facing the energy efficiency problem. As a result of increased energy prices and an increasing focus on environmental factors, enhancing EE is gaining the attention of many researchers [3].

The BS consumes 90% of its peak power even without traffic. The power consumption of the BS can be reduced further if the traffic load of BS is forecasted for future time slots. If the future traffic load is known to network operators beforehand, they will be able to manage the BS resources properly during the low traffic periods by deactivating selected components of BS. The power consumption optimization problem of small cell BS is presented to solve the EE problem. In this study, the criteria for BS sleep mode selection is based on future traffic load forecasting, which further helps to reduce power consumption.

A long-short-term memory (LSTM) scheme is presented for the network traffic load forecasting to lever instantaneous traffic in a time series. LSTMs are recurrent neural networks (RNNs) consisting of dynamic feedback between the input layer of each step and the output layer of previous steps [9]. LSTM is suitable for learning and modeling dependencies encountered in a time series [10]. Further, the forecasted traffic load is considered a BS sleep mode selection criterion. Finally, we propose an optimization problem for the power consumption of BS, which considers the forecasted traffic load.

The structure of the remaining paper is as follows. In Section 2, we present the review of existing work carried out in the field of BS switching systems. In Section 3, the user traffic prediction model is presented, and the BS switching problem is formulated in section 4. we present the system model in section 5, and section 6 discusses the simulation results of the prediction model. Finally, Section 7 concludes this study.

2. Related Work

In this section, the existing work done on BS sleeping techniques has been studied. A base station sleeping technique based on marginal utility is proposed [1]. In the proposed study, authors considered user preference and base station load as reference parameters to decide the sleep mode of the base station. Chang Liu et al. [22] presented four different sleep modes of base stations considering the sleep depth. Further optimization of the sleep mode is obtained through two different algorithms, i.e. random sleeping and strategic sleeping algorithm. With increased wireless network traffic and performance improvement of the network, green communication is gaining attention. The work done in [5], [6] endeavoured to reduce a significant chunk of the overall energy consumption by minimizing the power consumption at each BS. Optimizing the user connection reduces BS power consumption, improving green energy utilization efficiency [5]. Han et al. [6] minimized the communication overhead between the user and BS by dispensing the traffic load. The proposed method considerably reduced the power consumption of the network.

The next-generation cellular network analysis for green communication is carried out in [7]. The authors presented the research approach of BS switching that deliberates the impact on users' quality of service. F. Han et al. [21] presented a broad survey of BS switching techniques for green communication in 5G. The authors presented optimization objectives, constraints for BS switching design, and various BS switch-off strategies. In previous studies, authors did not consider the delay factor, so to overcome the delay problem, authors in [9] proposed a study in which BS sleep control and power match for a single cell. Further analysis of total power consumption and the average delay is carried out.

Yang et al. [10] proposed a scheme to reduce the number of active/on BSs, during low traffic periods authors also ensured the QoS of users by addressing the energy consumption reduction problem in their study. In [11],[12], various switching strategies are adopted for the total power consumption of a network by analyzing the user traffic associated with the network. In [11] energy saving problem of BSs is formulated. In the proposed study, the levels of power transmission during various traffic load is determined. Further, the total energy cost is reduced for active BSs. In [12], the number of active BSs is determined during peak traffic hours to ensure desired quality service to users; during idle periods, several of the BSs continue to be active, whereas the remaining BSs are switched off to reduce power consumption.

Studies in [13]-[15] are concerned with minimizing the energy consumption of BS by analyzing various factors like user traffic load and user mobility. The study in [13] considered user distribution patterns as analyzing parameters to minimize the power consumed by heterogeneous networks. When the users are evenly distributed, the system considers the optimum operational policy by considering the BS location. If the users are distributed non-uniformly, BS location and user density are considered for the BS switching decision. After that, Feng et al. [14] proposed a method in which energy efficiency is maximized using the game theoretical approach. A switching strategy is proposed by exploring the correlation between a user request strategy and BS switching cost. Gao et al. [15] also proposed a switching scheme wherein the parameters like the time taken to reach a specific BS and user mobility are considered to increase energy efficiency.

Table 1. Different Sleep Modes with Wake-Up Times and Power Consumptions

Sleep Mode/State	Wake-up Time (s)	Power Consumption
On mode	0	100%
Stand-by/light sleep mode	0.5	50%
Sleep/Deep sleep mode	10	15%
Off mode	30	0%

The studies in [16]-[19] focus on designing the optimization problem for BS switching using various optimization techniques. Gunhee Jang et al. [16] proposed a BS sleep mode optimization for BS switching. The authors predicted the user traffic using LSTM based model for multiple time slots. Using predicted user traffic, the BS sleep mode optimization problem is formulated. Further, Lypunov optimization is used to solve the optimization problem. Bart P. et al. [17] analyzed the tradeoff between power consumption through BS switching and user performance. The user performance is optimized by applying the load-balancing user association method. James J. Q. et al. [18] proposed a binary social spider algorithm for BS sleep mode selection. A penalty function is used to formulate the optimization problem. Min W. et al. [19] proposed an energy-saving scheme for BS in 5G networks. Two types of data traffic are considered in the proposed study, i.e. high, and low data traffic; separate data and control planes are used to manage the two types of traffic. The optimization problem is formulated for energy saving, and Particle Swarm optimization is used to solve the problem.

A power consumption model of a minor cell BS is presented in [22], which comprises three interrelated blocks, i.e. i) microprocessor, ii) power amplifier and radio frequency transmitter, iii) Field Programmable Gate Array. These blocks consume the maximum portion of power as they are responsible for signal transmission. The total power consumption of a small cell BS is the sum of the power consumed in these three blocks.

Referring to the above-discussed power consumption model, the BS modes are classified as on, standby, sleep and off mode [16]. The various sleep modes and their respective wakeup times are presented in Table 1.

In this section, the existing work is discussed. However, the existing work does not consider the real-time network traffic variations and does not guarantee sufficient coverage of user traffic during the BS switching, which makes incorporating the study into real systems challenging. Additionally, in the existing work, network traffic forecasting is carried out for the short term. These are the gaps that are identified after reviewing the existing work. In the proposed work, these issues are solved by implementing long-term network traffic prediction on the large real-time database, which will help implement the BS switching techniques more precisely. The transmit power variations to varying traffic conditions are also considered in the proposed power consumption model. The following section discusses the user traffic prediction model.

3. User Traffic Prediction Model

This section discusses the description of the dataset, prediction model and evaluation metric.

3.1. Dataset Description

The dataset used in the proposed model is obtained from Kaggle. The dataset consists of the downlink traffic (in Kbps) information of 4G LTE cells. The data is collected from 57 LTE cells for 365 days.

3.2. Prediction Model

The LSTM model is used for network traffic prediction in the proposed work. LSTM models are types of recurrent neural networks (RNNs). The important feature of LSTM is; it can effectively capture the pattern from the time series. Hence it provides more accurate results for prediction. BS On/Off strategies. The LSTM model is a variation of the Recurrent Neural Network model, which can capture the pattern from the time-series data.

The data obtained from the dataset is first pre-processed to check missing data and null fields. Further, the pre-processed data is provided to the LSTM model as training data. During the training process, the model checks validation loss after every epoch.

The performance of the proposed model is evaluated with the Root Mean Squared Error (RMSE) metric

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\widehat{Ri} - Ri)^2}{n}} \quad (1)$$

The predictions made by the LSTM model are then used in the BS switching algorithm, which is discussed in section 4.

4. Base Station Switching

The BS switching technique involves three processes sleep mode selection, user relay and BS switching.

4.1. BS Sleep Mode Selection

This process involves selecting one of the BS modes mentioned in table 1 according to the predicted traffic load.

4.2. User Relay

This process involves handling users when the BS is switched to sleep mode.

4.3. BS Switching

This process involves switching the BS mode from current to the mode that is selected with the help of the BS mode selection process.

The complete flow of the BS switching is presented in figure 1.

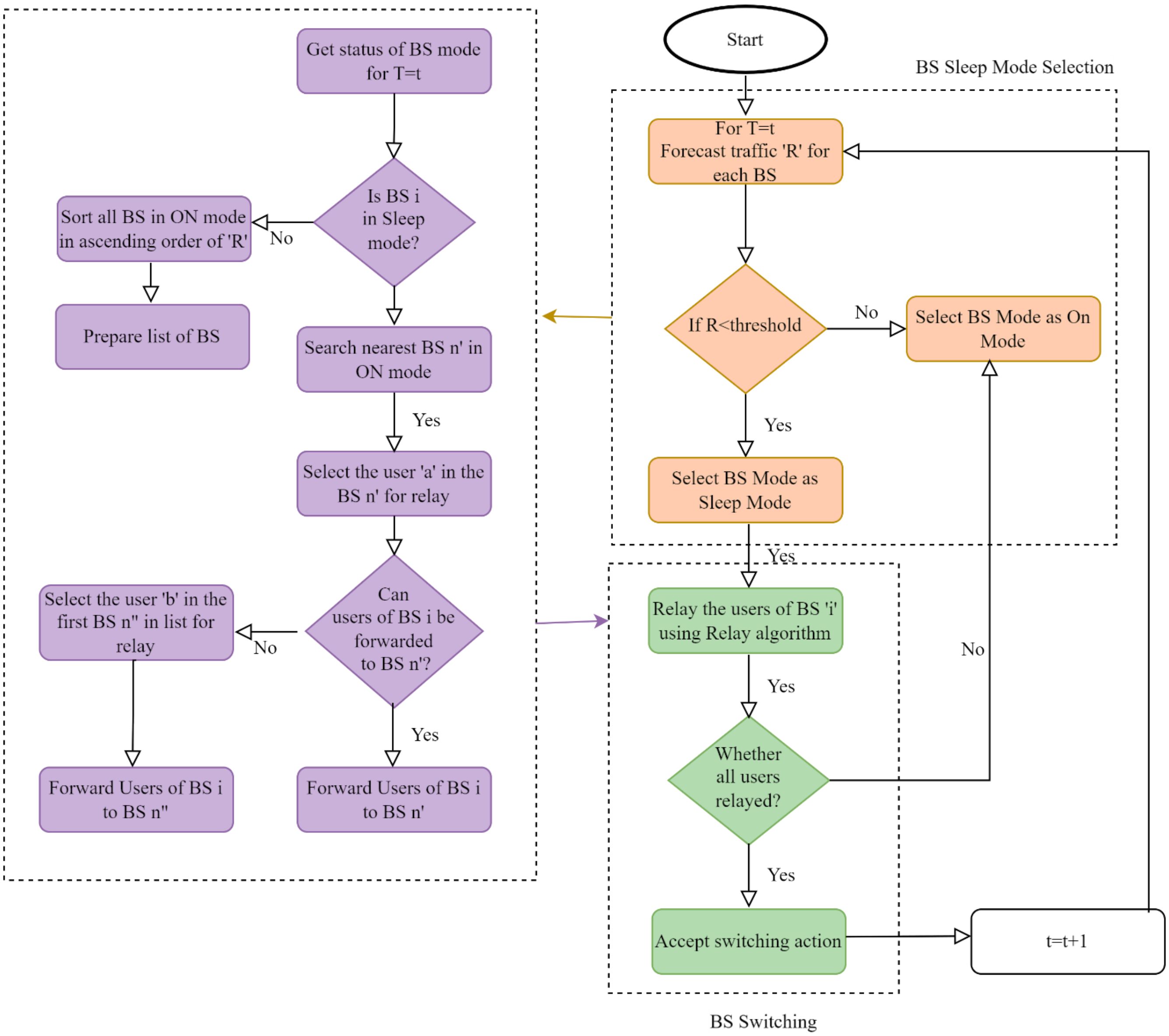

Fig. 1 System Flowchart

In the proposed system BS switching strategy is implemented by taking the predicted traffic load per base station as a deciding factor for selecting the BS mode. The predicted traffic load will help the BS select an appropriate mode to reduce power consumption during low-traffic periods. The power consumption model of the proposed system is presented in section 5.

5. System Model

In this section, the system model for formulating the BS switching problem and calculating the power consumption of BS is introduced. It is critical to cover the user traffic sufficiently while switching the base station into sleep/ dormant mode. To acknowledge this problem, we first define the system parameters as follows:

The Base Station (BS) is represented as Bi,
Where i= 1,2,3,…..,n
The capacity of BS Bi is represented as Ci,
Where i= 1,2,3,…..,n
The predicted/ forecasted traffic load of Bi is represented with Ri,
Where i= 1,2,3,…..,n

In our study, we are considering four BS sleep modes, and these modes are defined as:
M_{on}: on mode;

M_{sb}: standby/light sleep mode;
M_{sl}: sleep mode/deep sleep mode
M_{off}: off mode

The States of the Base Station is defined as,

$$M_{off(i)} = \begin{cases} 1 & BSi\ is\ in\ Off\ state \\ 0 & Otherwise \end{cases} \quad (Ri < 0.1) \tag{2}$$

$$M_{sb(i)} = \begin{cases} 1 & BSi\ is\ in\ Standby\ \ state \\ 0 & Otherwise \end{cases} (0.3 < Ri < 0.7) \tag{3}$$

$$M_{sl(i)} = \begin{cases} 1 & BSi\ is\ in\ Sleep\ state \\ 0 & Otherwise \end{cases} (0.1 < Ri \leq 0.3) \tag{4}$$

$$M_{On(i)} = \begin{cases} 1 & BSi\ is\ in\ On\ state \\ 0 & Otherwise \end{cases} \quad (Ri \geq 0.7) \tag{5}$$

Let Xi, Yi, and Zi be the notations related to state transitions and the values of them are defined as,

$$Xi = \begin{cases} 1 & BSi\ switches\ between\ On - Off\ state \\ 0 & Otherwise \end{cases} \tag{6}$$
where $(i = 1,2,3, \dots \dots, n)$

$$Yi = \begin{cases} 1 & BSi\ switches\ between\ On - Sleep\ state \\ 0 & Otherwise \end{cases} \tag{7}$$
$$where\ (i = 1,2,3, \dots \dots, n)$$

$$Zi = \begin{cases} 1 & BSi\ switches\ between\ On - Standby\ state \\ 0 & Otherwise \end{cases} \tag{8}$$
$$where(i = 1,2,3, \dots \dots, n)$$

The objective function is the summation of power consumption by all BSs in a network $\sum_{i=1}^{n} P(i)$ and power consumption due to switching between different states, $P_{switching}$ and it is denoted as P_{total}

$$P_{total} = \sum_{i=1}^{n} (P(i) + P(i)_{switching}) \tag{9}$$

The power consumption of a BSi, $P(i)$, is obtained as,

$$P(i) = M_{on}(i) * (P_f^1 + \rho_s * P_D(i) + M_{sl}(i) * P_f^2 + M_{sb}(i) * P_f^3 \tag{10}$$

Where,
P_f^1, P_f^2, P_f^3 are the fixed power consumption of BS in on, sleep and standby modes, respectively.

ρ_s is the slope of load-dependent power consumption.

The connection between BS i and User j is denoted as $a_{i,j}$, and the value of it is defined as,

$$a_{i,j} = \begin{cases} 1 & If\ user\ j\ is\ connected\ with\ Bi \\ 0 & Otherwise \end{cases} \tag{11}$$
$$where(i = 1,2,3, \dots \dots, n\ and\ j = 1,2,3, \dots \dots, m)$$

The data traffic demand of User j is denoted as d_j, and the value of it is defined as:

$$d_j = \begin{cases} 1 & If\ user\ j\ requires\ data\ service \\ 0 & Otherwise \end{cases} \tag{12}$$
$$where(j = 1,2,3, \dots \dots, m)$$

Load-dependent power consumption $P_D(i)$ is defined as

$$P_D(i) = P(i)^{max} * \sum_{j=1}^{m} d_j * a_{i,j} * \frac{\bar{C_i}}{C_i^{max}} \tag{13}$$

Also, the power consumption of state transitions of BS, $P_{switching}$, is obtained as,

$$P_{switching} = \sum_{i=1}^{n} (X_i * P_{on-off} + Y_i * P_{on-sleep} + Z_i * P_{on-standby}) \tag{14}$$

It is assumed that the maximum power consumption of BS is P_{max}. The power consumption of BSi should be smaller than or equal to P_{max}

$$P_i \leq P_{max} \tag{15}$$

5.1. Problem Formulation

Based on constraints defined in the system model, the optimization problem of the proposed energy-saving scheme can be formulated as,

$$f(\mathrm{n}) = \min P_{total}$$

$$f(n) = min \sum_{i=1}^{n} (P(i) + P(i)_{switching}) \tag{16}$$

Where $(P(i)$ and $P(i)_{switching}$ are given in equations 11 and 15, respectively.

The main goal of the proposed system is to minimize the total power consumption of the BSs, along with satisfying user data requirements. First, the traffic load prediction of BS is carried out, which is used to select the BS sleep mode. Further power consumption of each BS is calculated and compared with the standard power consumption of BS. The results of the proposed system are presented in section 6.

6. Simulation Results

Simulation results of the performance evaluation of network traffic prediction are presented in this section. The LSTM model is used for the prediction.

The details of the parameters selected for the simulation of the LSTM model are given in table 2.

Table 2. Hyperparameter Selection

Number of Layers	3 (2 LSTM layers + 1 output layer)
Number of Hidden Units	500
Error Function	Root Mean Squared Error
Training Algorithm	Adaptive Moment Estimation
Training Data Split	70% for taring, 30% for testing
Training Stop Rule	300 epochs
Batch Size	50

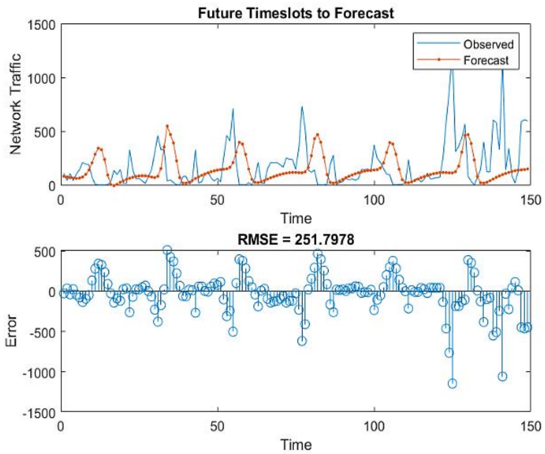

Fig. 2 RMSE loss before updating network state

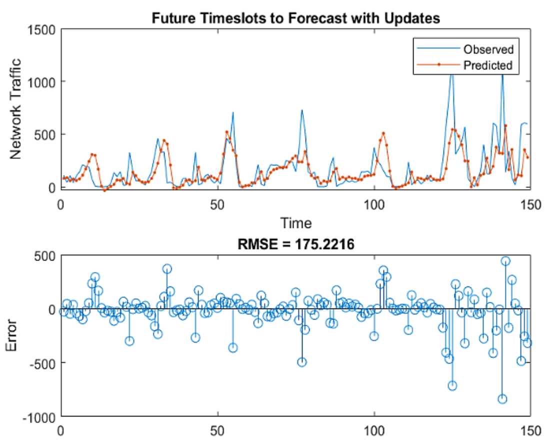

Fig. 3 RMSE loss after updating network state

To evaluate past dependencies, future traffic predictions are conducted for 150-time slots. With the proposed model, the prediction loss RMSE of 251 Kbits is obtained, as shown in figure 2.

In order to reduce the prediction loss, we further updated the LSTM network with forecasted values. The results show that after updating the network with forecasted values, the prediction loss is decreased to 175 Kbits. The results are shown in figure 3.

The improved RMSE shows that the learning of the model is improved when the network is updated with the forecasted values. This improved learning of the network results in the improved accuracy of prediction.

Further, the training data size varies to check the effect on RMSE. The training data sizes are datasets of 3 months, 6 months, 9 months and 12 months. Figure 4 shows the RMSE loss for different training data sizes. Results show that the network's learning increases as the training data size increases; low RMSE is obtained for large data sizes. Further, the RMSE loss is significantly reduced after updating the network state for a large dataset.

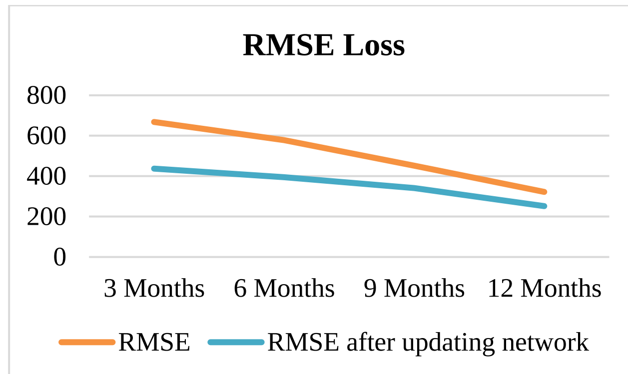

Fig. 4 RMSE loss for different training data sizes

The predicted traffic load is used to select the BS sleep modes. For BS switching, the system parameters considered are shown in table 3.

Table 3. Parameter Considered for Bs Switching

Parameter	Type/ Value
Network	Homogeneous
BS Type	Macro BS
No. of BS	5
Standard Power consumption per BS	1500 Watt
Fixed power consumption of BS	600 Watt
Service Rate	100 Mbps

Based on the predicted traffic load, 5 case scenarios are presented in this paper. The traffic load per BS is forecasted for five future time slots, which is used to decide BS sleep mode. The probable BS modes based on predicted traffic load are given in table 4.

Table 4. Predicted Traffic Load For Various Bs

Predicted Traffic Load	Case 1 t=t1	Case 2 t=t2	Case 3 t=t3	Case 4 t=t4	Case 5 t=t5
BS1	Low	High	High	Low	Low
BS2	High	Low	Low	Low	High
BS3	High	Low	Low	High	Low
BS4	Low	High	High	High	High
BS5	High	Low	Low	High	High

Time slot t1: The BS1 and BS4 possess low traffic load and can be switched to sleep mode. Whereas BS 2, BS 3 and BS5 have high traffic load and are kept in on mode.

Time slots t2 and t3: BS2, BS3 and BS5 can be switched to sleep mode as they have a relatively low traffic load than BS 1 and BS 4. In this case, BS 1 and 4 are switched to on mode. If the traffic of BS 2,3, and 5 are sufficiently covered by BS 1 and 4, then the decision is continued; another BS in sleep mode is switched to on mode to cover the user traffic.

Time slot t4: BS 1 is switched to sleep mode during this time slot, whereas BS 2 is kept in sleep mode as the previous mode. BS 3,5 are switched to on mode, and the mode of BS 4 is continued to on mode.

Time slot t5: During this time slot, BS 2 and 3 switched to different modes than the previous time slot as the traffic load changed. BS 1,4 and 5 continued with the same mode since they have similar traffic loads.

Implementing these case scenarios in the proposed power consumption model, the consumed power by each BS for each time slot is calculated using equation 9 and further compared with the standard power consumption of the network, i.e. without implementing the BS sleep modes. The power consumption of the network without BS switching and power consumption with BS switching is shown in figure 5. Results show that the power consumption network is reduced significantly when the BS switching strategy is applied to the system.

Predicting future traffic load helps BS manage its resources properly per the variation in user traffic. The prediction helps BS avoid frequent BS switching during various time slots. If the traffic load of BS 2 from table III is observed in table 5, it is seen that the traffic of BS 2 is low for three consecutive time slots. In such a case, the switching of BS from sleep mode to standby mode is avoided, and the BS's power consumption is further reduced.

The comparison of the power consumption of BS with BS switching and the reduction of frequent switching is presented in fig. 6.

Results show that the power consumption of BS is reduced by approximately 27%, which is more when compared to existing work [16]. It is observed that in the proposed work, by predicting the traffic load of BS, the power consumption of BS is reduced significantly.

Table 5. Traffic Load Scenario of Bs 2

	Case 1 t=t1	Case 2 t=t2	Case 3 t=t3	Case 4 t=t4	Case 5 t=t5
BS2	High	Low	Low	Low	High

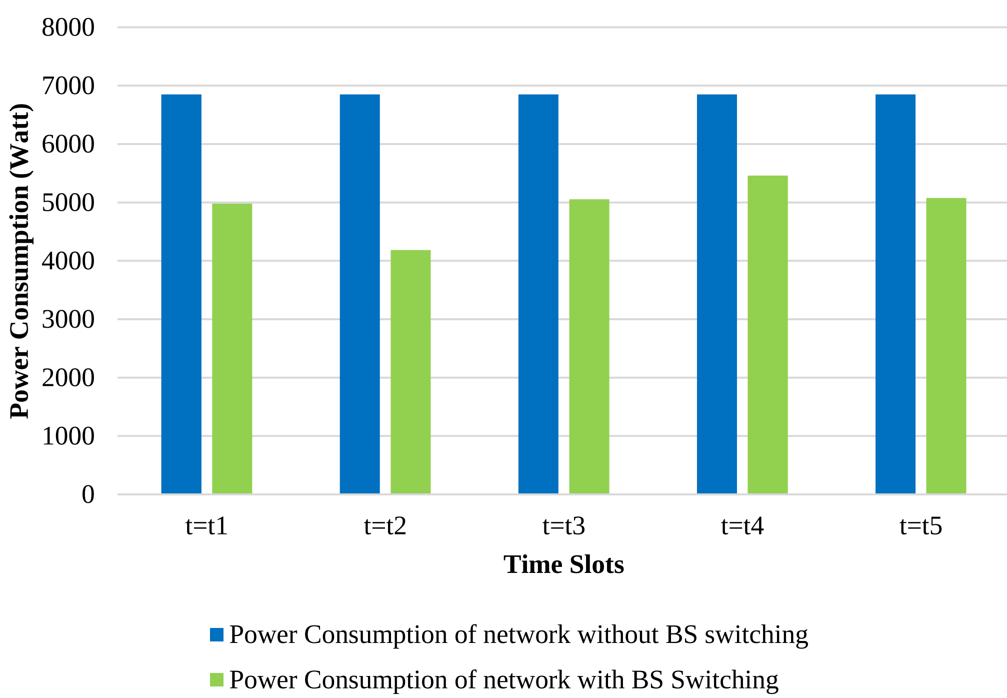

Fig. 5 Power consumption of network

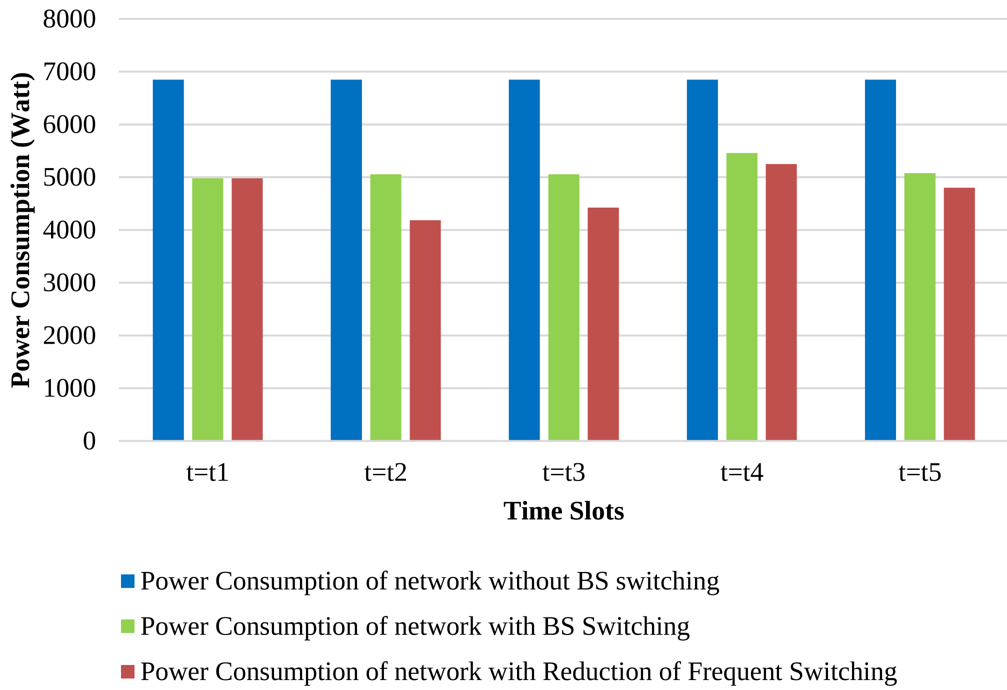

Fig. 6 Power consumption of network

7. Conclusion

This paper proposes the BS switching and power consumption reduction technique. In the proposed system, an LSTM-based network traffic prediction model is used. By utilizing past communication information from users, LSTM-based network traffic prediction models predict network traffic in the future. With the help of the forecasted traffic using the LSTM-based prediction model, the system can reduce the overhead that occurs during synchronizing traffic information between users and BSs. With the help of the predicted network traffic, a BS sleep mode selection criterion is proposed. Subsequently, the power consumption model is presented to measure the power consumed by the BS in the selected sleep mode. The simulation results of a network traffic load prediction using LSTM based model are presented in the paper.

Further, we attempted to reduce the RMSE loss by updating the network state. The prediction on different sizes of datasets is carried out; the results show a significant reduction in the RMSE loss than RMSE loss before network updation for large datasets. With the proposed BS sleep mode selection technique and power consumption model, a significant reduction in network power consumption is achieved while providing adequate coverage for user traffic. The prediction of traffic load helps BS to avoid the frequent switching of BS, further reducing power consumption. With the proposed BS switching technique, the total power consumption of the network is reduced by approximately 27%. Therefore, our proposed model resolves the shortcomings of existing models regarding traffic handling and data synchronization overhead. In future, the proposed BS sleeping strategy model can be implemented for heterogeneous network models in real-time systems.

References

[1] Y. Xu and J. Chen, "An Optimal Load-Aware Base Station Sleeping Strategy in Small Cell Networks Based on Marginal Utility," *2017 3rd International Conference on Big Data Computing and Communications (BIGCOM)*, pp. 291-296, 2017. Crossref, https://doi.org/10.1109/BIGCOM.2017.65

[2] J. Wu, Y. Zhang, M. Zukerman and E. K. N. Yung, "Energy-Efficient Base-Stations Sleep-Mode Techniques in Green Cellular Networks: A Survey," in *IEEE Communications Surveys & Tutorials*, vol. 17, no. 2, pp. 803-826, 2015. Crossref, https://doi.org/COMST.2015.2403395

[3] Syed Waqas Haider Shah, Ahmad Talal Riaz and Zahoor Fatima, "Energy-Efficient Mechanism for Smart Communication in Cellular Networks", 2019 Crossref, https://doi.org/10.48550/arXiv.1809.07855

[4] Hernan X. Cordova J., "Energy-Efficiency (EE) Performance for 5G Wireless Systems under the Presence of Hardware Impairments," *SSRG International Journal of Electronics and Communication Engineering*, vol. 6, no. 8, pp. 31-37, 2019. Crossref, https://doi.org/10.14445/23488549/IJECE-V6I8P105

[5] B. Wang, Q. Kong, W. Liu, and L. T. Yang, "On Efficient Utilization of Green Energy in Heterogeneous Cellular Networks," *IEEE System Journal*, vol. 11, no. 2, pp. 846–857, 2017. Crossref, https://doi.org/10.1109/JSYST.2015.242736

[6] T. Han and N. Ansari, "A Traffic Load Balancing Framework for Software Defined Radio Access Networks Powered by Hybrid Energy Sources," *IEEE/ACM Transactions on Networking*, vol. 24, no. 2, pp. 1038–1051, 2016. Crossref, https://doi.org/10.1109/TNET.2015.2404576

[7] H. Ghazzai, E. Yaacoub, A. Kadri, H. Yanikomeroglu, and M.S. Alouini, "Next-Generation Environment-Aware Cellular Networks: Modern Green Techniques and Implementation Challenges," *IEEE Access*, vol. 4, pp. 5010–5029, 2016. Crossref, https://doi.org/10.1109/ACCESS.2016.260945

[8] G. V. Ramanaiah, L. Krishna kavya, P. V. Rajya Lakshmi, V. Sai Kumar and Sk. Shahed Ali, "Optimal Energy Efficiency Through DPSN Based 5G Network," *SSRG International Journal of Electronics and Communication Engineering*, vol. 7, no. 3, pp. 29-34, 2020. Crossref, https://doi.org/10.14445/23488549/IJECE-V7I3P105

[9] J. Wu, Y. Bao, G. Miao, S. Zhou, and Z. Niu, "Base-station Sleeping Control and Power Matching for Energy-Delay Tradeoffs with Bursty Traffic," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 5, pp. 3657–3675, 2016. Crossref, https://doi.org/10.1109/TVT.2015.2434381

[10] Y. Yang, L. Chen, W. Dong, and W. Wang, "Active Base Station Set Optimization for Minimal Energy Consumption in Green Cellular Networks," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 11, pp. 5340–5349, 2015. Crossref, https://doi.org/10.1109/TVT.2014.2385313

[11] N. Yu, Y. Miao, L. Mu, H. Du, H. Huang, and X. Jia, "Minimizing Energy Cost by Dynamic Switching ON/OFF Base Stations in Cellular Networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 11, pp. 7457–7469, 2016. Crossref, https://doi.org/10.1109/TWC.2016.2602824

[12] C. Peng, S.B. Lee, S. Lu, and H. Luo, "GreenBSN: Enabling Energy Proportional Cellular Base Station Networks," *IEEE Transactions on Mobile Computing*, vol. 13, no. 11, pp. 2537–2551, 2014. Crossref, https://doi.org/10.1109/TMC.2014.2307322

[13] S. Cai, Y. Che, L. Duan, J. Wang, S. Zhou, and R. Zhang, "Green 5G Heterogeneous Networks Through Dynamic Small-Cell Operation," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 5, pp. 1103–1115, 2016. Crossref, https://doi.org/10.1109/JSAC.2016.2520217

[14] M. Feng, S. Mao, and T. Jiang, "BOOST: Base Station ON-OFF Switching Strategy for Energy Efficient Massive MIMO HetNets," in *Proceedings of IEEE INFOCOM-35th Annual IEEE International Conference on Computer Communications*, pp. 1-9, 2016. Crossref, https://doi.org/10.1109/INFOCOM.2016.7524485

[15] J. Gao, Q. Ren, P. S. Gu, and X. Song, "User Association and the Small-Cell Base Station On/Off Strategies for Energy Efficiency of Ultra Dense Networks," *Mobile Information Systems*, vol. 2019, pp. 1–12, 2019. Crossref, https://doi.org/10.1155/2019/6871378

[16] G. Jang, N. Kim, T. Ha, C. Lee and S. Cho, "Base Station Switching and Sleep Mode Optimization with LSTM-Based User Prediction," in *IEEE Access*, vol. 8, pp. 222711-222723, 2020. Crossref, https://doi.org/10.1109/ACCESS.2020.3044242

[17] Post, Bart, Borst, Sem and Berg, Hans, "A Self-Organizing Base Station Sleeping and User Association Strategy for Dense Cellular Networks," *Wireless Networks*, vol. 27, pp. 1-16, 2021. Crossref, https://doi.org/10.1007/s11276-020-02383-3

[18] J. J. Q. Yu and V. O. K. Li, "Base Station Switching Problem for Green Cellular Networks with Social Spider Algorithm," *2014 IEEE Congress on Evolutionary Computation (CEC)*, pp. 2338-2344, 2014. Crossref, https://doi.org/10.1109/CEC.2014.6900235

[19] Kang M.W and Chung Y.W, "An Efficient Energy Saving Scheme for Base Stations in 5G Networks with Separated Data and Control Planes Using Particle Swarm Optimization," *Energies*, vol. 10, no. 9, pp. 1417, 2017. Crossref, https://doi.org/10.3390/en10091417

[20] Mohammed Yesuf Mohammed, "Green Energy Technique for Seven Cell Long Term Evolution (LTE) Cellular Network," *SSRG International Journal of Electronics and Communication Engineering*, vol. 6, no. 3, pp. 18-22, 2019. Crossref, https://doi.org/10.14445/23488549/IJECE-V6I3P104

[21] F. Han, S. Zhao, L. Zhang, and J. Wu, "Survey of Strategies for Switching Off Base Stations in Heterogeneous Networks for Greener 5G Systems," *IEEE Access*, vol. 4, pp. 4959–4973, 2016. Crossref, https://doi.org/10.1109/ACCESS.2016.2598813

[22] C. Liu, B. Natarajan and H. Xia, "Small Cell Base Station Sleep Strategies for Energy Efficiency," in *IEEE Transactions on Vehicular Technology*, vol. 65, no. 3, pp. 1652-1661, 2016. Crossref, https://doi.org/10.1109/TVT.2015.2413382