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Original Article

Cellular Network Base Station Power Scheduling Using Machine Learning to Prevent Energy Wastage

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Abstract - *Energy conservation is crucial because of the growing need for cellular communication and energy usage. To address the issue of energy conservation, a number of green computing approaches have been proposed; however, the majority of these are less suitable and only achieve a small amount of energy savings in comparison to the anticipated level. This paper aims to develop and model a traffic-aware power-saving plan for cellular base stations. A Green Cellular Base Station Scheduling (GCBS) method is suggested. The training of a base station's historical traffic load is the first step in the GCBS technique. Next, forecast future traffic. The power of the base station will be adjusted based on the future traffic loads. A simulation has been conducted in this regard, and performance has been examined in terms of the base station's maximum energy requirements, actual energy requirements, and the quantity of energy saved by the suggested approach. The simulation results show that the GCBS approach can reduce the base station's energy consumption by 60%. The conclusion has finally been reached, and the plan for future extensions has been discussed.*

Keywords - *Cellular network, Machine Learning, Power Consumption, Proactive Power Scheduling, Workload Prediction.*

1. Introduction

In smart cities, numerous cutting-edge technologies related to networks, communication devices, and sensors are used. The primary objective of employing these technologies is gathering, processing, and managing resources and services [1, 2]. Moreover, this gathered information is used by the data-driven applications to deliver prompt responses to citizens and also in various life-threatening circumstances [3]. During the service execution and delivery of smart cities, the communication networks are playing an essential role. These networks heavily rely on electrical energy. Additionally, during the ideal times of the network, the communication infrastructure wastes a significant amount of energy. Therefore, the prevention of energy wastage is required because sustainability continues to be a key consideration in the creation of smart cities.

Minimizing electric energy waste, switching to green energy sources, reducing the number of bio-fueled vehicles, and developing methods to reduce energy waste are all crucial to addressing the sustainability issue of smart cities [4, 5]. Therefore, green technologies are essential to sustainability. Reducing waste that harms the environment is the goal of green technology [6, 7]. Green technologies are therefore creating ways to lower the use of non-renewable energy sources, such as biofuels. These crucial actions aid in preserving equilibrium between environmental preservation and modernization [8]. Thus, to reduce energy waste in cellular network base stations, an ML model is simulated to achieve sustainability. In this context, "A Machine Learning (ML) framework is contributed to demonstrate a less energy-consuming cellular network system".

Cellular communication is an extremely energy-intensive infrastructure among the many services of a smart city. This network keeps the administration, infrastructure, and residents of smart cities connected [9]. Therefore, it is acting as the backbone of the smart city to maintain service operations [10]. On the other hand, communication infrastructure usage is also growing daily. Thus, a large number of new base stations are deployed to maintain the network's service quality [11, 12]. The communication quality costs too much in electrical energy consumption. The number of users and applications connected through the base stations directly correlates with the electrical energy consumption [13, 14]. Additionally, the base stations are set up to handle their maximum traffic load. In this case, energy is wasted if the base station has little traffic [15]. Therefore, this paper presents a traffic-aware electrical energy scheduling method for cellular base stations and is called Green Cellular Base-station Scheduling (GCBS). The GCBS predicts the future traffic demand of the base station and is mapped to the power requirement of the base station. Further, the predicted energy demand is used to make decisions about the base station’s live resources. Thus, an algorithm is introduced to preserve the power of the base station by smart energy utilization. This technique is a type of proactive resource management system to achieve green computing. This section provides an overview of the proposed GCBS technique. The second section offers the details of the GCBS technique to reduce energy wastage in a cellular base station. The third section describes the performance analysis of the GCBS technique. The last section concludes the work conducted based on the preserved amount of energy.

2. Background

The initial study is motivated by the research article contributed by M. A. Rahman et al [16]. Where the author was focused on green composites processing utilizing a variety of naturally available resources in achieving green sustainable development. Additionally, the environmental impacts of different composite materials are examined. By motivation of this article, the study was moved towards green technology. In this context, we identified two noteworthy articles, the first of which was contributed by D. S. Olaleye [17]. The author explores the relation between environmental issues in communication systems and RF engineering. They discussed RF methods that support the design, implementation, and environmentally friendly infrastructure. They also support employment of renewable energy, prospects, and challenges. The second article is contributed by F. Ayaz et al [18]. In this article, a Digital-Twin (DT) was discussed, which uses Artificial Intelligence (AI) to estimate energy consumption of BSs and EVs and identifies their role as energy buyers or sellers. A Reinforcement Learning (RL) is used to make decisions in energy exchange. By using these two articles, it is concluded that energy preservation and appropriate utilization are key to sustainable development. Additionally, machine learning algorithms can play an essential role in preserving energy in communication systems. This statement is aligned with the contribution of S. Sangeetha et al [19]. They present a performance analysis of the Energy Aware Scheduling Algorithm (EASA). The aim is to improve the efficiency and energy consumption in communication systems. They focused on optimal resource utilization and minimizing energy consumption for 5G green communication systems. Similarly, M. H. Alsharif et al [20] support the eco-friendly IoT solutions. Thus, they examine energy-efficient practices and strategies in the sustainable and energy-efficient IoT. Furthermore, according to A. E. Amine et al [21], the huge deployment of small cells in 5G networks is an alternative way to meet the requirement of increasing mobile data traffic to the Base Stations (BSs). This is an increase in the energy consumption. To address this challenge, the author proposes a multi-level Sleep Mode (SM) for BS components. They consider a network where small cells can switch to different SM levels to save energy. In order to deal with the same issue, T. Pan et al [22] propose a base station sleeping control scheme based on reinforcement learning. That enables the base stations to dynamically enter into sleep modes, to minimize power requirements using double deep Q-learning.

More research efforts are available, where the same research problem of energy consumption has been addressed. For instance, N. Piovesan et al [23] describe a model for characterizing the power consumption of 5G BSs. This model is able to capture the benefits of energy-saving mechanisms and can optimize the network energy efficiency. Similarly, S. Sun et al [24] propose a multi-cell sleep strategy, which includes adaptive cell zooming, user association, and Reconfigurable Intelligent Surface (RIS). This technique is aimed at minimizing BS's energy requirements. Using this method, BSs can enter into sleep mode during low traffic. Additionally, adaptive cell zooming and user association properties are helping in coverage adjustment to balance traffic load, and data rates will be enhanced by using RIS. Moreover, V. Saleh et al [25] also worked on a similar kind of solution, which is named the Aerial Base Station (ABS) for energy optimization. In this model, the traffic is selectively offloaded for energy savings without violating quality-of-service. For this purpose, a Deep Deterministic Policy Gradient (DDPG) is used to optimize ABS positioning, GBS sleep mode scheduling, and resource allocation. As a conclusion, sustainability is initiated with green technologies and by reducing carbon footprints. However, there are many ways and methods to achieve sustainability. Among them, energy preservation is also a feasible and effective way for sustainability. In this context, sustainability is prominent in smart city development, where the communication requirements are increasing day by day. This also increases the high volume of energy consumption as well as energy wastage. This issue is addressed in recent literature and is also solved by using machine learning and deep learning approaches. These techniques are promoting energy efficiency and sustainability in future communication technology development.

3. Proposed GCBS Technique

Existing techniques that are utilized to reduce the energy consumption in the base station are less accurate. In addition, these techniques do not consider the behavioral dissimilarity between the base stations, which are located in different geographical locations, during the design of the energy-saving model. Thus, these techniques are less appropriate to preserve beneficial amounts of energy. The GCBS technique aims to preserve the energy wastage of the cellular base stations by making smart decisions using ML techniques during less traffic time. The GCBS technique considers the behavior of base station traffic. Thus, a solution has been formulated by using ML-based prediction. The proposed solution is described as the GCBS technique. Additionally, its working is demonstrated in Figure 1.

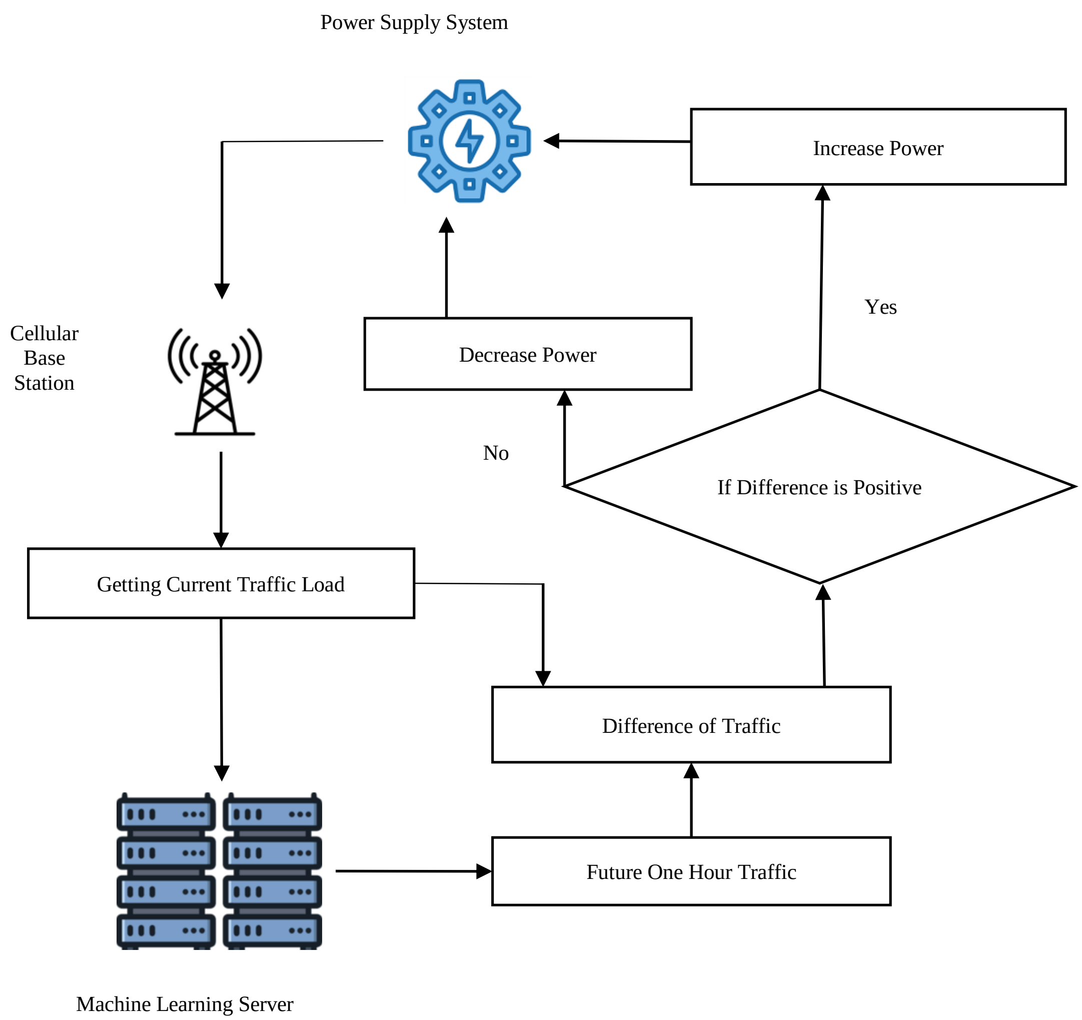


Fig. 1 Flow diagram of the GCBS technique

The GCBS technique concentrates on an individual base station. It captures and stores the hourly traffic of the base station. This recorded traffic data is analyzed by using an ML server. This server is the main component of the GCBS technique. This server computes and predicts future hour traffic load on the base station. The Difference between the future predicted traffic load and the current load on the base station is used for decision-making and preventing electrical energy wastage. The given system calculates the amount of energy supply increase or decrease for the base station components. Next, a detailed discussion on individual GCBS components is described as follows:

3.1. Machine Learning Server

The machine learning server is an essential component of the model. The server utilizes ML algorithms. These algorithms are performing analysis of the cellular base station traffic patterns and then predicting the future traffic load. The required model for performing the base station's future traffic prediction is demonstrated in Figure 2. This model starts with a component "Historical base station traffic load". This component stores the previous records of base station traffic on an hourly basis. In this experiment, the cellular base station's per-hour traffic load is taken in the form of a dataset. That dataset is obtained from Kaggle [26]. The dataset consists of four attributes. These attributes are the base station's identity, time, and traffic. The details of the dataset attributes are given in Table 1. The dataset consists of a total of 497544 samples. The dataset consists of workload data for 57 base stations. The one-year traffic data in one-hour intervals is defined in this dataset. Each row of the dataset describes the amount of data served by the base station. For example, if a base station serves 10 users and each user consumes 10 MB of data each hour, then the total traffic of the base station for that hour is 10*10 = 100 MB. The GCBS model is working on an individual base station; therefore, the traffic data of a single base station ID "Cell_003781" has been considered.

Table 1. Details of attributes

Attribute	Values
Date	23-Oct-2017 to 22-Oct-2018
Hour	0 and 23
Cell Name	57 unique values
Traffic	0 to 3904.19337 MB

The base station is selected randomly for performing the simulation. Next, the data only belonging to base station ID "Cell_003781" is separated from the entire dataset and used. The individual base station's selected data is pre-processed. Thus, the "Cell Name" attribute is removed from the data. Then, two attributes, namely "Date" and "Hour" attributes, are combined to create a single attribute named "date time". The "date time" attribute is converted as the index attribute.

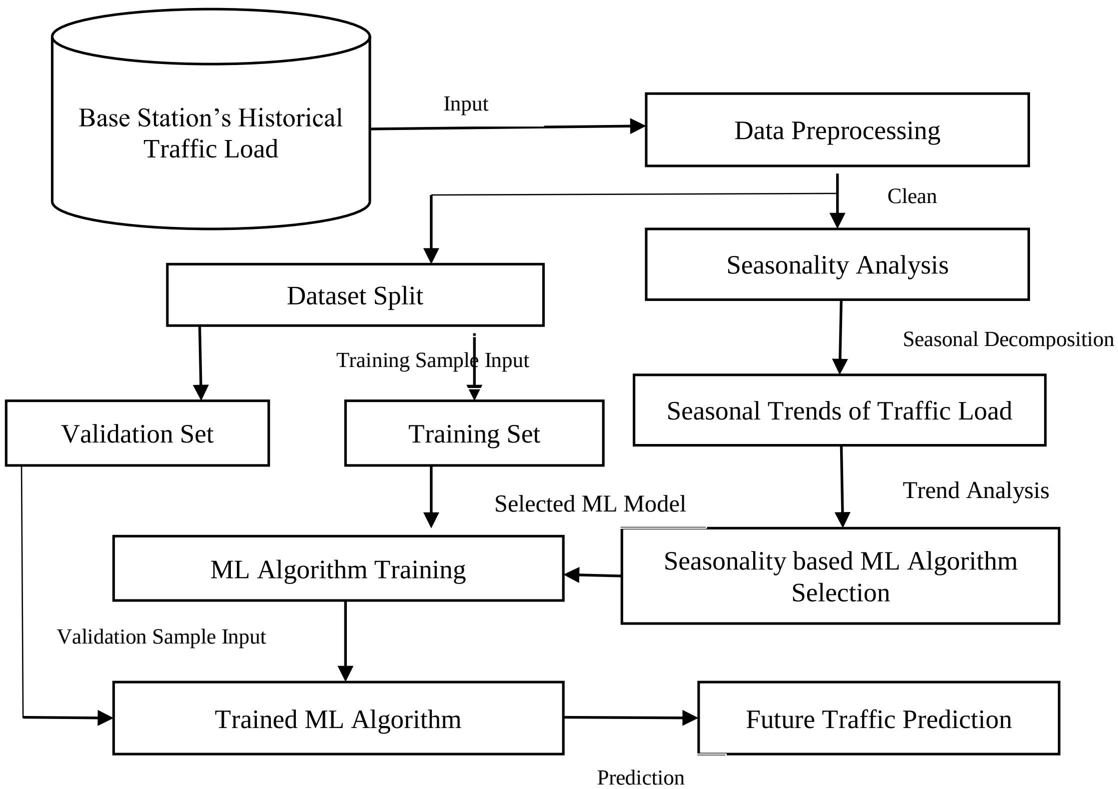


Fig. 2 Base station traffic load prediction model

This data is further used for the experiment; the pre-processed dataset is demonstrated in Figure 3. The traffic values are associated with the time; hence, the dataset is a time series dataset. Therefore, an investigation can be made for the different time-based patterns analysis.

The analysis aimed to provide an understanding of base station traffic for different time intervals, such as total hourly, daily, weekly, and monthly traffic patterns.

In this work, the hourly traffic patterns have been considered, and seasonal trends are investigated [27]. The seasonality analysis is used to identify the relationship between the time cycles and the dataset values. The seasonality analysis is a tool for time series data analysis. It helps to decompose a time series into its sub-components, namely the Trend component (T), Seasonal component (S), Cyclical component (C), and Noise component (N). There are two ways to combine these components, either additively or multiplicatively, as follows:

A. Additive model:

$$y_t = T_t + S_t + C_t + N_t \tag{1}$$

B. Multiplicative model:

$$y_t = T_t * S_t * C_t * N_t \tag{2}$$

The seasonal pattern analysis based on Hourly, Daily, Weekly, and Monthly traffic data was carried out. The hourly data seasonal decomposition is given in Figure 4. Based on this analysis, the dataset does not have a strong seasonal influence on the hourly data. Therefore, regression-based algorithms can provide accurate predictions. The analysis also demonstrates that the data is in a linear relation and shows fewer cyclic patterns. Thus, we can use regression-based algorithms like K-Nearest Neighbor (KNN) regressor, Support Vector Regression (SVR), and XGBoost regression for performing the prediction of future traffic.

datetime	Traffic
2017-10-23 00:00:00	557.98491
2017-10-23 01:00:00	0.86567
2017-10-23 02:00:00	2.00388
2017-10-23 03:00:00	1.00111
2017-10-23 04:00:00	0.97659

Fig. 3 Final dataset samples

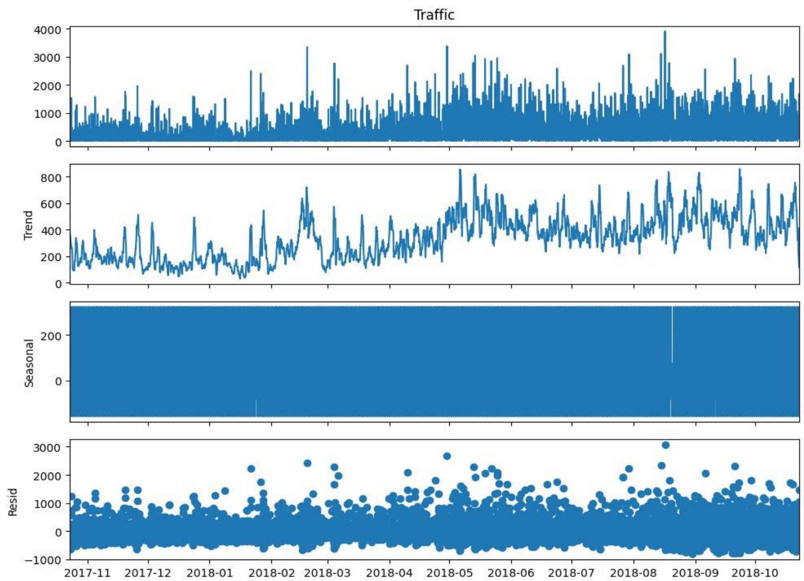


Fig. 4 Hourly data seasonal decomposition

A brief introduction of the considered algorithm of base station's traffic prediction is given as:

- K-Nearest Neighbor (KNN) regressor: It is employed in regression problems to predict continuous values. The KNN classifier is called the KNN regressor. Similar to the classification, it utilizes the k-neighbors to select similar instances and then, by averaging the results, the final prediction is performed [28].
- Support Vector Regression (SVR): It is the regression version of the SVM. The basic working principle of SVR is similar to the SVM classifier. First, the hyperplane has been identified similarly to the SVM, and then by averaging the outcomes, the final prediction is calculated [29].
- XGBoost Regression: It is a based ensemble learning algorithm. Bagging is used to enhance the performance of ML algorithms. The algorithm during training generates multiple decision trees and combines the results of all the decision trees for prediction. It allows them to learn more quickly than others. Therefore, it is good for datasets with a large number of features [30].

These three ML algorithms are tested on the prediction, and the most accurate algorithm is utilized for further implementation. The training of these models requires transforming time series data into a learnable pattern. Here, the daily traffic is used for training. The period of 24 previous hours of traffic data is used to predict the next hour of traffic. The training samples are demonstrated in Table 2.

Table 2. Training sample example

Input sequence (X)	Output (y)
$\{d_{t-23}, \dots, d_{t-1}, d_t\}$	d_{t+1}
$\{d_{t-22}, \dots, d_t, d_{t+1}\}$	d_{t+2}

Table 2 shows two vectors X(Input Sequence) and y(output). The X is a 2D vector of 8709 * 24 elements, and the y is a linear vector of outputs, which contains 8709 values. Next, both the vectors are divided into the training and testing samples, 70% of the total samples are used for training, and 30% samples are used for testing. Based on the predictions, a performance evaluation has also been done. To decide which ML algorithm provides accurate results. Thus, the Root Mean Square Error (RMSE) is calculated. The RMSE is calculated using:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}} \quad (3)$$

Where N is the number of samples for prediction.

Figure 5 demonstrates the RMSE of the implemented ML algorithms. According to the validation results, a minimum error with the SVR algorithm has been found. Additionally, the k-NN regressor and XGBoost algorithm show a higher error. Therefore, the SVR is the most accurate algorithm, which can be used in the development of the GCBS model.

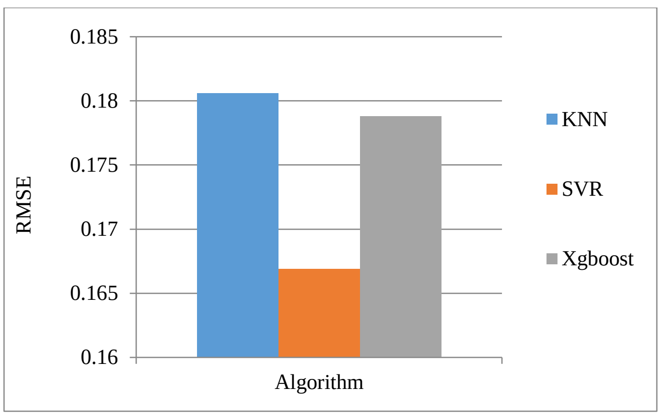


Fig. 5 RMSE of Prediction Algorithms

3.2. Other GCBS components

Based on the performance of the SVR model. The SVR model has been selected for making predictions of the traffic load. Let the SVR utilize a function that predicts a continuous value and can be defined as:

$$f(x) = predict(x_1, x_2, \dots, x_{24}) = L_p \quad (4)$$

Where, $x = (x_1, x_2, \dots, x_{24})$ the traffic samples of the last 24 hours, and L_p is the predicted next hour traffic load, based on the input x. The future one-hour traffic load of the base station L_p and the actual traffic or current traffic load L_cBoth are used to make decisions about the increasing and decreasing amount of power supply. In order to understand this process, first, an assumption has been made.

Assumptions: Let,

1. The base station has E amount of electric energy consumption when it is functioning in its full capacity.
2. The base station is serving U number of users when serving in full capacity. Additionally, U number of users can produce L maximum traffic [30].

Next, after the prediction of the future load of the base station, the Difference ΔL between the predicted traffic L_p and the actual current load L_c has been measured. The Difference can be calculated by:

$$\Delta L = L_p - L_c \quad (5)$$

In Equation (5), the ΔL can be positive (+) or negative (-). Here, the positive sign describes the increasing load, and the decreasing load is demonstrated by the negative sign. Now, when it is required to decide to increase or decrease power in the base station, according to the changing traffic load. A threshold T is required to consider, which helps in decision-making tasks. In this situation, if the measured difference ΔL is positive and it is higher than the threshold T, then it is required to increase the power of the base station to fulfill the power requirement. Similarly, if the value of ΔL is less than the threshold T, it is required to reduce the amount of power supply. To calculate the threshold value, the total traffic load of the last 24 hours has been considered. Additionally, the mean of predicted and actual traffic Load (L) has been measured. That can be calculated using Equation (6):

$$L_n = \frac{1}{N}\sum_{i=1}^{N}\frac{L^i{}_p + L^i{}_c}{2} \quad (6)$$

Where N is the total number of samples to consider in threshold calculation, and in this experiment, N=24, $L^i{}_p$ is the predicted traffic of the i^{th} hour, and $L^i{}_c$ is the actual current load of the i^{th} hour. The mean load L can be directly used as a threshold. Here, we have considered 5% of additional traffic load L_n. This additional amount of traffic load offers flexibility to manage and transfer traffic load, and it is defined as L_f. In this experiment L_f=5% of L_n. That can also be helpful in dealing with the delay in turning the power supply on or off to the base station. Hence, the value of L is working as a soft threshold. Additionally, the final threshold value can be defined using Equation (7):

$$T = L_n * L_f \quad (7)$$

However, the error in prediction also needs to be considered; we need to increase the margin of the threshold. Therefore, an additional 5% has been added to the threshold calculation. This increase in threshold is denoted as L_e. Based on this influence of error, Equation (7) is updated as given in Equation (8).

$$T = L_n * (L_e + L_f) \quad (8)$$

After the calculation of threshold T, it is required to utilize this to make a decision. Therefore, a decision function is needed to define, which can accept the traffic difference and result in the amount of energy to increase or decrease. In order to calculate the amount of energy to supply, we use our first assumption. According to our first assumption, E amount of energy is needed to serve U number of users. These U users will increase the traffic L. Thus, first, it is required to calculate the amount of energy required to serve a single user. The amount of energy increased by a single user is denoted as I_E. The amount of increase in energy by a single user is given by Equation (9):

$$I_E = \frac{E}{U} \quad (9)$$

Similarly, a single user also increases the traffic load. This amount of increase in traffic load is given by I_T Moreover, it can be expressed using Equation (10):

$$I_T = \frac{L}{U} \quad (10)$$

A single user will increase the total traffic I_T. Similarly, the total electrical energy demand I_E required to serve a single user. Therefore, if the total Difference of traffic load is ΔL, then the total increase in energy IE is given by Equation (11):

$$IE = I_E * \Delta L \quad (11)$$

Equation (11) describes the amount of energy to be increased or decreased in the base station power supply by using the Difference in traffic load. In this situation, two cases are possible:

Case 1: when the ΔL is positive
Increase the energy by:

$$IE + T \quad (12)$$

Case 2: when the ΔL is negative
Decrease the energy by:

$$IE - T \quad (13)$$

In this section, the proposed GCBS technique has been explained. Now, we are summarizing the steps of power supply optimization. In this context, Table 3 provides the required algorithm of the proposed GCBS algorithm. The algorithm described in Table 3 shows the simple steps to preserve energy in the base station.

The algorithm accepts the last 24-hour traffic x of the considered base station. Additionally, increase and decrease a certain amount of energy supply. In the first step, the input x is used with the trained ML algorithm, namely SVR. The SVR uses this input to predict the next hour's traffic load. L_p. In the second step, the Difference ΔL between the current L_c and predicted L_p The traffic load has been calculated.

Table 3. Proposed GCBS algorithm

Input: Last 24-hour traffic load x Output: Increase or Decrease Power Supply

Process:
1. $L_p = SVR.predict(x)$
2. $\Delta L = L_p - L_c$
3. Calculate $T = L_n * (L_e + L_f)$
4. $if(\Delta L > T)$
    a. Increase the energy by: $IE + T$
5. Else
    a. Decrease the energy by: $IE - T$
6. End if

In the third step, the threshold T is calculated, and if the ΔL is larger than the threshold, then the amount of power supply has been increased; else, the amount of energy has been reduced in the supply.

After the successful formulation of the GCBS model, in the next section, the implementation of this technique has been performed, and its results have been measured and discussed.

4. Simulation and Results

In this work, a single base station unit has been considered for preparing the simulation and conducting the experiment. The GCBS technique is an energy saver for the base station. The concept of GCBS is influenced by proactive energy management. This technique is simulated using Python and the cellular traffic workload dataset [26].

After the implementation of the GCBS-based simulation, the performance has been measured in terms of Root Mean Square Error (RMSE). The RMSE is given in Table 4. In addition, Mean Squared Error (MSE) and Mean Absolute Error (MAE) are also included.

The RMSE of the SVR algorithm is found to be 0.1358, which is acceptable for use with the GCBS system. The prediction using the SVR algorithm has been performed. Additionally, the comparison between predicted traffic and actual traffic has been done.

Table 4. RMSE of ML algorithms

Algorithms	KNN	SVR	Xgboost
RMSE	0.1806	0.1669	0.1788
MSE	0.0326	0.0278	0.0319
MAE	0.1444	0.1335	0.1430

In this context, there are two scenarios that have been considered for simulation:

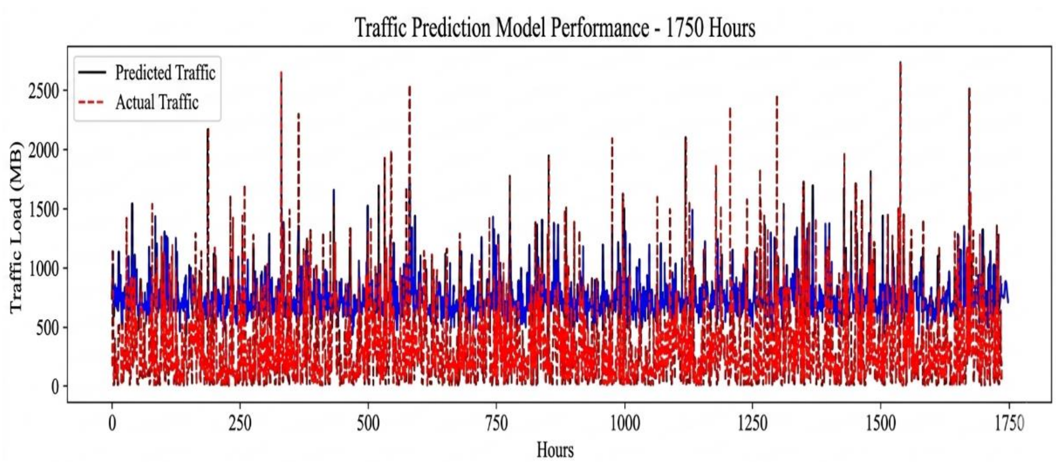
1. In the first scenario, the traffic and energy relationship has been discussed. In this context, predicted traffic and actual traffic, the Difference between actual and predicted traffic, and predicted and actual energy requirements are simulated.
2. In the second scenario, the aim is to demonstrate the energy saving by implementing the described methodology. In this context, Actual energy requirements, Difference in predicted energy demand and actual energy demand, and Overall energy saving using a traffic-aware power scheduling are discussed.

4.1. Simulation Scenario A

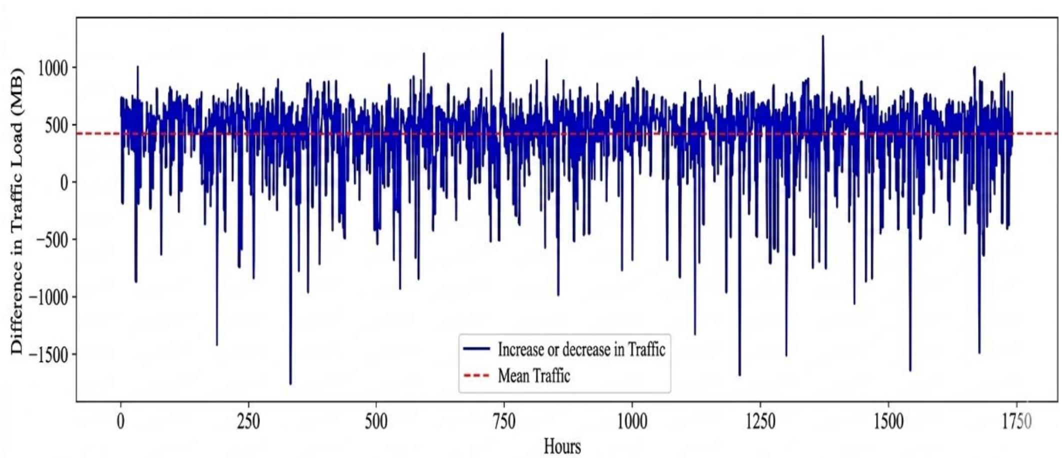
Figure 6(a) shows the validation results of the GCBS model in terms of traffic prediction. The red line in this diagram shows the actual traffic load, which is formulated using. L_c. The blue line shows the predicted traffic, which is represented by using. L_p. According to the results, the predicted traffic load is mostly higher than the actual traffic load. Therefore, there are fewer chances for misbehavior or degradation of the GCBS in terms of service quality. In Figure 6(B), the traffic difference ΔL is demonstrated. The ΔL is calculated between predicted traffic and actual (current) traffic. Additionally, the mean traffic difference L is also highlighted in this diagram.

Basically, the Difference between predicted traffic and actual traffic shows the error in prediction, which is required to adjust for the calculation of the predicted actual value. In the simulation, it is found that there is a 406.42 MB mean traffic difference in per-hour traffic data. The traffic difference ΔL between actual (current) traffic L_c and predicted traffic L_p.

For this purpose, Equation (5) has been used. This traffic difference is needed to transform into the energy demand. In this context, Equation (12) has been used to calculate the IE. Therefore, in Equation (10), the maximum energy demand is assumed as 100%. Additionally, the maximum traffic value calculated from the dataset has been found to be 3904.19337 MB of traffic. Based on these two values, the remaining results have been calculated.



(a)



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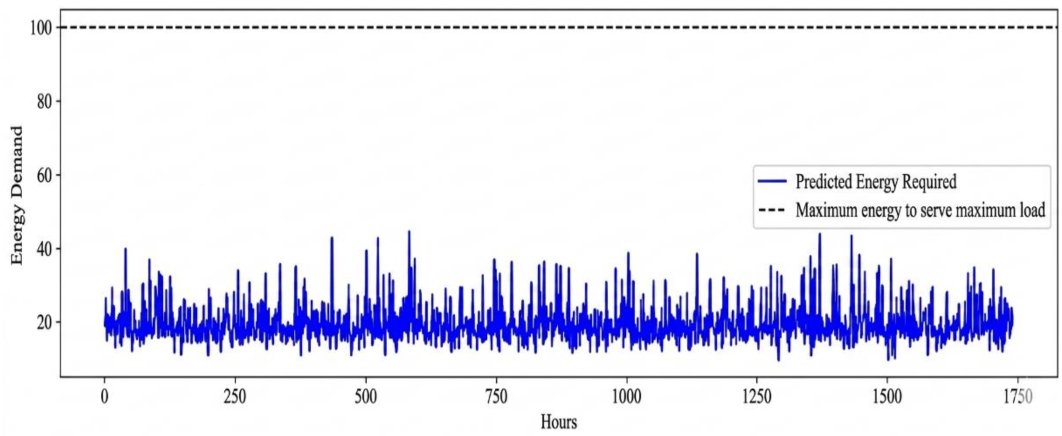


(c)

Fig. 6 (a)Predicted and actual traffic, (b)Difference between actual and predicted traffic with the mean Difference of traffic load, and (c)Predicted demand of energy.

Figure 6(c) shows the energy demand for the predicted scenario of the GCBS. The prediction of traffic load is converted into the energy requirement of the base station. Additionally, the maximum energy requirement is also given using the red dotted line.

Based on predicted traffic, the demand for energy in the base station is very low. There is a significant difference between the maximum amount of energy supply and the actual utilization of energy. Therefore, the ideal base station may waste more than 60% of electrical energy. Because if base stations are working at their full capacity, then the maximum amount of energy is supplied.

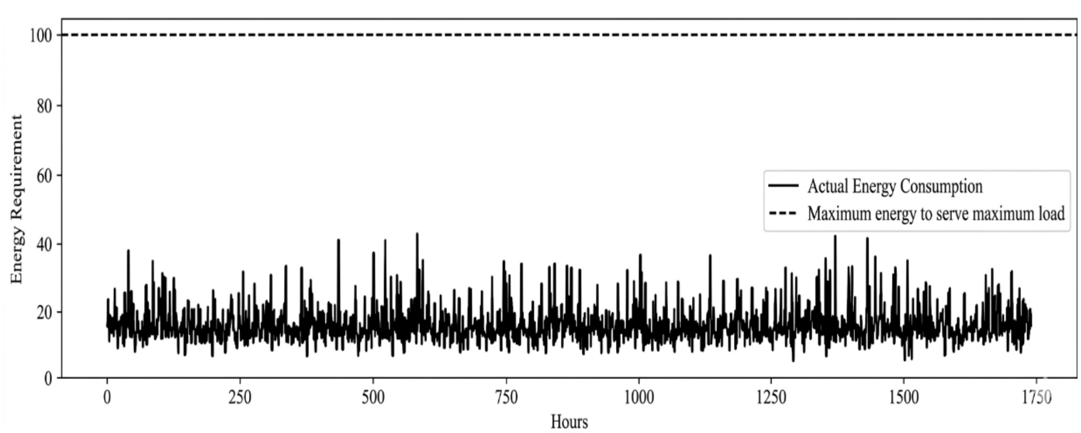
4.2. Simulation Scenario B

In this context, a demand-aware energy management technique is required, which can preserve the energy. Similarly, the actual requirement of energy of the base station has also been measured. This measurement is performed by using the validation dataset samples. The actual energy demand of the base station is shown in Figure 7(a).

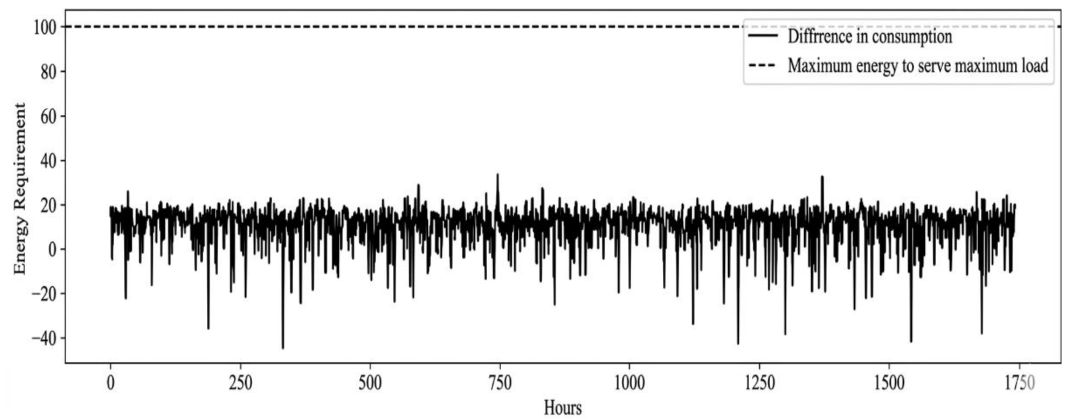
In this figure, the X-axis shows the hours, and the Y-axis shows the energy demand.

According to the measured Difference between actual energy demand and maximum energy requirement, the Difference between them is so much higher. In the utilized validation dataset, on average, 73% of electrical energy has gone to waste or is unutilized. The Difference between predicted energy demand and actual energy demand has also been measured. The measured Difference is reported in Figure 7(b). In this diagram, the X axis shows the hours of prediction, and the Y axis shows the Difference between the predicted and actual energy requirement.

This Difference in energy demonstrates the amount of energy required to increase or decrease in the base station. Therefore, as the Difference is found to be positive, then it is required to increase the amount of energy to the base station, and when the Difference is negative, then the algorithm reduces the energy supply.



(a)



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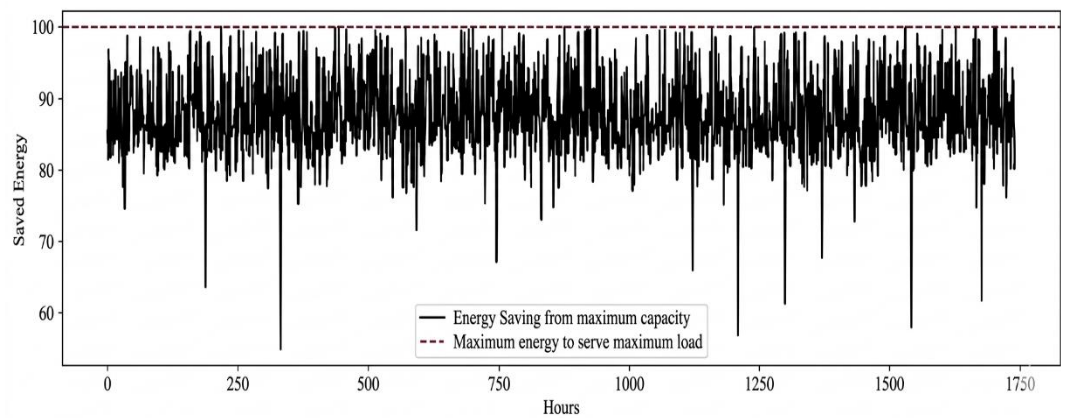

(c)

Fig. 7(a) Actual energy requirements, (b) Difference in predicted demand and actual demand, and (c) Overall energy saving using a traffic-aware power scheduling.

Finally, we have calculated the results in terms of total saved energy.

$$IE + M_e + T \tag{14}$$

The entire formulation, simulation, and results analysis have been done to save the energy of the base station. The amount of energy saved is shown in Figure 7(c). During this simulation, it is found that the power saving and prediction accuracy are highly correlated. Because the Difference between traffic on the base station (i.e., predicted and actual) is a type of error (M_e). In this condition, if the Difference is positive, then it negatively impacts the service quality of the application. Therefore, we need to update Equations (12) and (13) to achieve high service quality. Hence, Equation (13) has become:

$$IE + M_e - T \tag{15}$$

Let the currently supplied amount of energy be E_t, then the final amount of energy needed to supply at the time $T + 1$ is given by:

$$E_{t+1} = E_t + (IE + M_e \pm T) \tag{16}$$

If the IE is replaced by Equations(11) and (16) as:

$$E_{t+1} = E_t + (I_E * \Delta L + M_e \pm T) \tag{17}$$

Additionally, by replacing the value of threshold T using Equation (8), the final amount of energy to supply is given by Equation (18).

$$E_{t+1} = E_t + \left(I_E * \Delta L + M_e \pm \left(L_n * \left(L_e + L_f\right)\right)\right) \tag{18}$$

However, the employment of Equation (18) in simulation increases the energy consumption of the base station. In this condition, the GCBS model is only able to preserve 56% of the overall energy compared to the ideal base station. Service quality of cellular networks and energy preservation is a type of optimization problem.

Therefore, continuous learning of the GCBS model will help to find the optimal performance. However, in the worst conditions, a traffic-aware system will help to reduce energy consumption by approximately 50% from the ideal state of the base station.

Table 5. Energy saving by the GCBS technique by using different ML algorithms

Energy saving	KNN	SVR	XgBoost
Maximum	51%	56%	52%
Minimum	38%	43%	40%

Table 5 demonstrates the effectiveness of the proposed GCBS model by using three machine learning algorithms. Additionally, the energy saving of the algorithms was measured in terms of the minimum and maximum energy saving in terms of percentage. That shows the prediction of traffic may help to reduce the energy wastage.

5. Discussion

The presented GCBS technique was developed to analyze the base station traffic and, according to the possible traffic, manage the resources for optimal energy consumption. Therefore, it is recommended to deploy this model into an individual base station. Therefore, the GCBS model is scalable and has less behavioral influence on prediction. But, the GCBS model is highly dependent on the accuracy of the employed machine learning model; if the accuracy is not acceptable, then the GCBS is violating the energy demands positively and/or negatively. However, if the appropriate ML model is selected, then an effective and high-energy model can be implemented.

6. Conclusion

In a smart city, cellular base stations are increasing day by day to fulfill the increasing demands. However, in these base stations, increasing energy consumption and energy wastage are the key problems. In this paper, a proactive energy management technique has been proposed. The aim is to improve the energy efficiency of the base stations by reducing energy wastage. This technique utilizes the ML technique to predict the next hour's traffic load on a base station. The prediction is used to decide the amount of power supply for the base station. To predict the traffic, the SVR algorithm has been used. Additionally, to select the appropriate algorithm, three popular algorithms, namely KNN, SVR, and XGBoost, have been compared. Based on the RMSE of the SVR algorithm, it is found that SVR is more accurate than the other two algorithms. Thus, the GCBS technique utilizes the SVR algorithm. The simulation has been done, and the performance has been analyzed. Based on the performance, the proposed GCBS technique can preserve more than 50% of electricity wastage compared to ideal and traditional base stations.

Conflicts of Interest

On behalf of all the authors, the corresponding author states that there is no conflict of interest to declare that is relevant to the content of this article.

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