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Energy Optimization for Mtn Green Communication Networks Using Artificial Neural Network

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Abstract- Artificial Neural Networks (ANNs) have emerged as an effective approach to improve energy efficiency in cellular communication networks. Cellular base stations account for over 70% of the energy consumed in cellular communication networks. Reducing the power consumed by these stations while maintaining Quality of Service (QoS) is needed to ensuring the sustainability of mobile communication networks. An ANN-based model was created to optimize the energy consumption of MTN green communication networks. The model was created using MATLAB/Simulink that would predict the power demand of cellular base stations based on several input variables. The model adapts base station operation to use energy optimally while ensuring continuous network coverage and QoS. To accomplish this, the model is built using base station operating data from MTN, Nigeria, which was trained, validated and evaluated under different traffic load conditions. Performance was compared with the conventional base station operation and Model Predictive Control (MPC) approach. Simulation results show that the conventional system consumes an average power of 2955 W while the ANN model achieves a reduction to 2847 W, representing 3.65% energy savings. Also, the MPC approach achieved a further reduction to 2747 W representing 7.04%. Although the MPC achieved the least energy consumption, the ANN has a good prediction accuracy coupled with adaptive learning which makes it have low computational complexity. The study concludes that ANN is a reliable method for improving the efficiency of energy usage within the network, reducing the amount of greenhouse gas emissions that are released into the atmosphere, reducing the costs of operating the network and improving the overall sustainability of green communication networks.

Keywords: artificial neural network, base station, energy optimization, green communication network, mtn, quality of service. renewable energy.

I. INTRODUCTION

The rapid expansion of mobile communication technologies and the increasing demand for high-speed data services have increased the energy consumption of cellular communication networks. The progress from 2G to 5G and beyond has increased the number of macro, micro and small-cell base stations that are deployed worldwide to meet the demand for cellular voice, video streaming, IoT, cloud computing and broadband internet services. Though these technologies have greatly improved communication quality and network ability, they have also led to an increase in electrical energy consumption and greenhouse gas emissions. For these reasons, the telecommunication industry is prioritizing improving the energy efficiency of mobile communication networks (Elghamrawy et al., 2024; Binzagr et al., 2024). Among all of the components of a cellular communication network, the Base Transceiver Station (BTS) consumes the highest proportion of electrical energy. The base stations consume between 60% and 80% of the total electrical energy used by a cellular communication network. These components continue to operate continuously throughout the day and even during periods of low cellular communication network utilization. This results in unnecessary electrical energy consumption during these periods (Hossain et al., 2020). For companies like MTN Nigeria, which manages thousands of cellular base stations across the country, energy efficiency is both an economic and environmental necessity.

Green communication networks have emerged as an effective solution to reduce energy consumption while maintaining the reliability of communication networks. These green networks incorporate intelligent energy management, renewable energy sources, adaptive power control, efficient radio resource allocation and artificial intelligence techniques to minimize energy consumption while maintaining QoS. These technologies contribute to lower carbon emissions, improved operational efficiency and sustainable telecommunication infrastructure (Ozturk et al., 2021). Artificial Intelligence (AI) has become one of the most promising technologies to solving complex optimization problems in wireless communication systems. Among AI techniques, Artificial Neural Networks (ANNs) have demonstrated remarkable capabilities in modeling nonlinear relationships, learning from historical data, forecasting traffic demand and making intelligent decisions under uncertain operating conditions. ANNs learn the behaviour of communication networks directly from the training data and can use this knowledge to optimize network performance in real-time.

An Artificial Neural Network (ANN) is composed of interconnected neurons within the input, hidden and output layers of the ANN. The ANN uses the backpropagation algorithm to learn from supervised data, adjusting the weights of the connections between the neurons to minimize errors between the output of the ANN and the actual output of the ANN's data. As such, the ANN is well-suited for tasks that involve predicting the communications traffic within the communications network, predicting the amount of energy that will be required by consumers of that network and determining the best allocation of power to the base stations within the cellular communications network (Chang, 2012). The demand for communication networks from users of MTN communications networks varies throughout the day due to the nature of their mobility, their internet usage, their business activities and their use of multimedia services. During the peak hours of the day, the amount of power required to maintain communication network performance is high, whereas during the off-peak hours of the day, the amount of power that is required from the network is low. Therefore, it is not possible for communication networks to be powered by fixed-power systems alone. Instead, it is possible to power communication networks using artificial neural networks (ANNs) that can learn how to adjust the operating parameters of the base stations to reduce the amount of power required to communicate with users.

Several researchers have proposed different methods of improving the energy efficiency of communication networks. For example, Bonthu, (2019) investigated the use of hybrid renewable energy systems in green cellular networks, which resulted in the reduction of the costs of running these networks. Similarly, Ozturk et al. (2021) developed a traffic-aware cell-switching strategy for reducing the energy consumption of ultra-dense radio access networks while maintaining coverage of the network. The paper of Chen et al. (2022) introduced an energy-efficient federated learning structure for heterogeneous mobile devices. Also, the paper of Binzagr et al. (2024) discussed energy-efficient techniques for Beyond-5G (B5G) and Sixth-Generation (6G) wireless networks using Non-Orthogonal Multiple Access (NOMA). Recent advances in deep learning have enabled the application of ANN in communication systems. ANN are being used in traffic prediction, adaptive resource allocation, interference mitigation, renewable energy forecasting, changing sleep mode management and intelligent power allocation. These capabilities enable communication systems to automatically respond to changes in the communication system while minimizing the energy consumption of the system (Chung, 2017). Despite these advances in energy optimization for mobile networks, several existing techniques for optimizing the energy consumption of mobile networks remain computationally intensive. Techniques like Model Predictive Control, genetic algorithms, particle swarm optimization and mixed-integer programming are examples of techniques that require important computational resources and accurate models of the mobile communication systems. However, Artificial Neural Networks can be used to optimize energy consumption in mobile networks by learning the relationships between the energy consumption of the mobile network and its operational data. Although several studies have investigated the use of artificial neural networks (ANNs) in wireless communications, relatively few have investigated the use of ANNs to optimize the energy usage of MTN green communication networks. This research gap is especially relevant within developing countries, as the cost of electricity is high and diesel engines contribute to high levels of carbon emissions.

The study aims to use an Artificial Neural Network (ANN) to optimize the energy consumption of MTN's green communication networks. The ANN will be able to predict the best power consumption of MTN's green

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communication networks based on parameters like the traffic demand of the network, the power used for transmitting data, the processing power used for communication, the availability of renewable energy sources for the communication network, the ambient temperature of the area and the density of users that are active within the communication network. The ANN model will be implemented using MATLAB/Simulink and will be compared with the conventional operation of MTN's communication networks and Model Predictive Control (MPC) techniques.

The major contributions of this research include: Development of an ANN-based energy optimization model for MTN base stations, Integration of renewable energy into intelligent base station power management, Reduction of energy consumption while maintaining Quality of Service (QoS), Comparative performance evaluation of Conventional, ANN and MPC control operations, Provision of a practical structure for green communication networks of MTN. The outcomes of this research are expected to contribute to the reduction of operational costs, the minimization of greenhouse gas emissions, the improvement of energy efficiency and the support for the realization of intelligent green communication systems in wireless networks of the future.

II. MATERIALS AND METHODS

This study developed an Artificial Neural Network (ANN)-based energy optimization structure for selected MTN Nigeria cellular base stations operating in both urban and suburban environments. The data for the study was collected from MTN cellular base stations in Enugu State, Nigeria. The data collected included variables such as traffic load, number of users, transmission power, power amplifier consumption, processing power, cooling system power, renewable energy contribution, battery state of charge, ambient temperature and total power consumption of the base station. These data elements were used to train and validate the ANN model to reduce the energy consumption of the base stations while maintaining the required Quality of Service (QoS).

The study was implemented using MATLAB R2024a with the Neural Network Toolbox and Simulink. More materials included a personal computer (Intel Core i7, 16 GB RAM), a digital power/energy meter, a range analyzer, solar photovoltaic and battery storage models, an ambient temperature sensor and network traffic datasets. The ANN model was implemented to analyze the collected parameters to determine the best energy management strategies for a cellular base station.

Fig. 1 shows the block diagram of energy consumption dynamics of an MTN green communication network using ANN theory.

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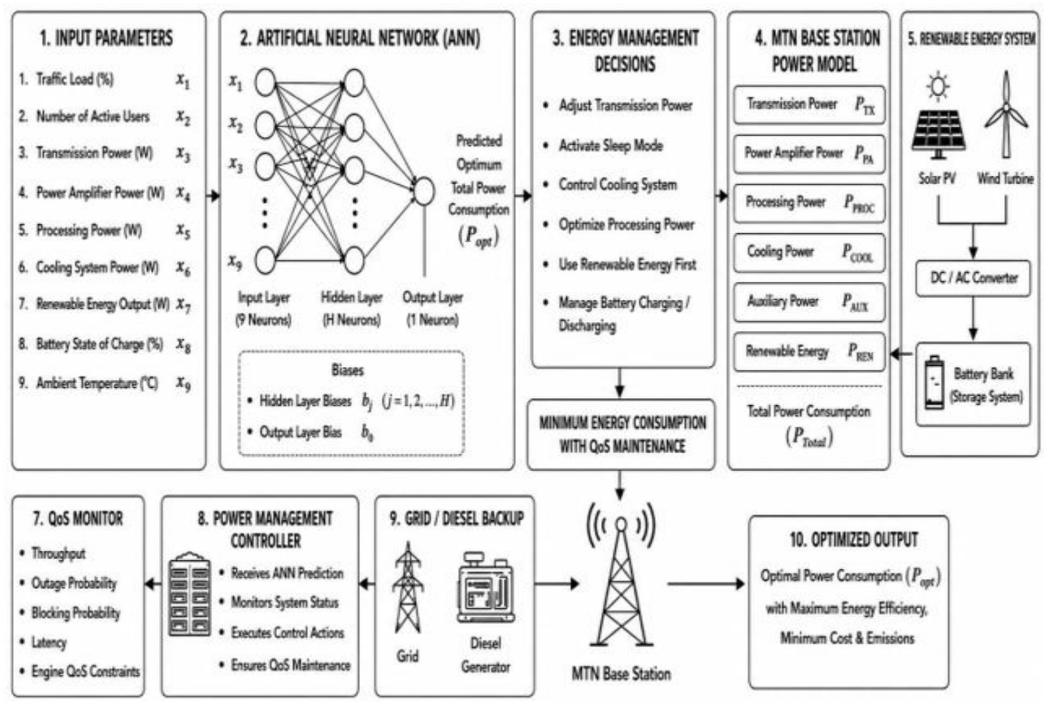

Figure 1. Block Diagram of Energy Consumption Dynamics of MTN Green Communication Network Using ANN Theory (Wang, 2018)

As shown in fig. 1, the artificial neural network (ANN) was developed based on the back-propagation learning algorithm to predict the power consumption of MTN base stations. The ANN consists of an input layer, a hidden layer and an output layer. The input layer takes inputs such as traffic load, number of active users, transmission power, power amplifier consumption, cooling power, processing power, renewable energy output, battery state of charge and ambient temperature. The hidden layer applies sigmoid activation functions to the inputs to capture the nonlinear relationships among them. The output layer predicts the power consumption of the base station.

2.1 The Mathematical Model of ANN

2.1 ANN Neural Network

Eq. 1 gives the hidden layer neuron j:

$$net_j = \sum_{i=1}^{n} w_{ij}\ x_i\ +\ b_j \tag{1}$$

$$aij\ =\ f(net_j) = \frac{1}{1+e^{-netj}} \tag{2}$$

Eq. 3 gives the output network k:

$$net_k = \sum_{j=1}^{H} v_{jk}.a_j + b_k \tag{3}$$

$$y_k = f(net_k) = net_k \ (linear\ output) \tag{4}$$

Where:
x_i = input variable
w_{ij} = weights between input and hidden layer
v_{jk}= weights between hidden and output layer
b_j, b_k= bias terms
a_j = activation of hidden neuron
y_k= predicted output (optimal power)

2.2 MTN Green Base Station Power Model
Eq. 5 gives the total power consumption at the base station

$$P_{TOTAL} = P_{TX} + P_{PA} + P_{PROC} + P_{COOL} + P_{AUX} - P_{REN} \tag{5}$$

Where:
P_{TX} = Transmission power (W)
P_{PA} = Power amplifier power (W)
P_{PROC} = Processing power (W)
P_{COOL} = Cooling system power (W)
P_{AUX} = Auxillary power (W)
P_{REN}= Renewable energy contribution (W)

2.3 Renewable Energy Model
Eq. 6 gives the available renewable energy at time (t)

$$P_{REN}(t) = \eta_{pv} P_{pv}(t) \ + \ \eta_w P_w(t) \tag{6}$$

Where:
η_{pv}, η_w are coefficient of PV and wind

2.4 Battery State Update Model
Eq. (7) gives the battery state of charge (SOC) at time (t)

$$SOC(t+1) = SOC(t) + \frac{\eta_{ch(t)} - \frac{P_{dis}(t)}{\eta_{dis}}}{E_{bat}} . \Delta t \tag{7}$$

$$0 \leq soc(t) \leq 1 \tag{8}$$

Where:
P_{ch}, P_{dis} = charging and discharging power (W)
η_{ch}, η_{dis} = charging and discharging efficiency

E_{bat} = battery capacity (Wh)
Δt = time step (h)

2.5 Energy Optimization Problem
Eq. 8 gives the energy optimization problem
Objectives: minimize total power consuption

$$\mathrm{j} = \sum_{i=1}^{\tau} P_{TOTAL}\,(t) \tag{8}$$

Subject to:

$P_{TX,min} \leq P_{TX}(t) \leq p_{TX,max}$

$0 \leq P_{PROC}(t) \leq P_{PROC,max}$

$0 \leq P_{COOL}(t) \leq P_{COOL,max})$

$SOC_{min} \leq SOC(t) \leq SOC_{max}$

$P_{out}(t) \geq P_{demand}(t)\ (Q_oS\ is\ constant)$

Where:
$T =$ prediction horizon
$P_{out}(t)$ = output power
$P_{demand}(t)$ = required power based on traffic demand

2.6 Energy Optimization Problem
Eq. (9) gives the sustainable renewable energy

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2 \tag{9}$$

Eq. (10) gives the Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2} \tag{10}$$

Eq. (11) gives the Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{11}$$

Eq. (12) gives the prediction accuracy

$$Accuracy = \left(1 - \frac{|y_i - \hat{y}_i|}{y_i}\right) X\ 100\% \tag{12}$$

Eq. (13) gives the back-propagation (weight update)

$$w_{new} = w_{old} - \frac{\eta \partial MSE}{\partial w} \tag{13}$$

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Eq. (14) gives the bias update

$$b_{new} = b_{old} - \frac{\eta \partial MSE}{\partial b} \tag{14}$$

Where:

η = learning rate

y_i = actual output

$\hat{y}$ = predicted output

N =number of sample

2.7 Performance Metrics

The performance metrics with the equations for energy optimization for MTN green communication network using ANN are listed as follow

- Average Power Consumption (N)
- Energy Saving (%)= $\left(\frac{P_{conventional} - P_{optional}}{P_{conventional}}\right) X100\%$ (15)
- Renewable Energy Utilization (%) = $\left(\frac{P_{ren,used}}{P_{ren,available}}\right) X100\%$ (16)
- Quality of Service (throughput, outage and blocking)
- MSE, RMSE, Accuracy

2.8 Energy Optimization Procedure

The ANN continuously predicts future energy demand based on changing traffic conditions. Depending on the predicted load, the controller performs the following actions:

- Activates sleep mode during low traffic periods.
- Adjusts transmission power according to user demand.
- Prioritizes renewable energy utilization before grid supply.
- Minimizes cooling system power when thermal conditions permit.
- Optimizes processing power without affecting QoS.
- Allocates communication resources dynamically.

Fig. 2 shows the block diagram of ANN green techniques to optimize energy in MTN base station.

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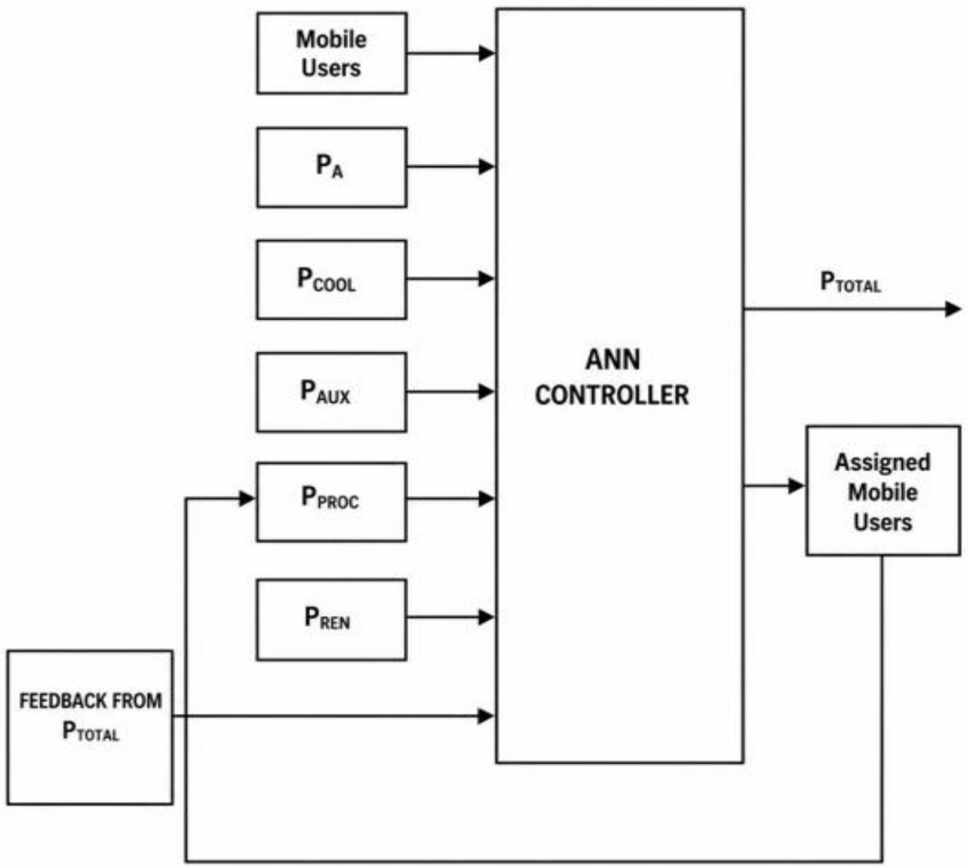

Figure 2. Block Diagram of ANN Green Technique to Optimize Energy in MTN Base Station.

As shown in fig. 2, the ANN-based green technique optimizes base station energy consumption by predicting power demand, allocating energy efficiently, and managing user activity in real time. Key components include: Mobile Users represent user demand and bandwidth requirements as dynamic inputs. Power for Amplification is energy use in RF transmission, optimized to avoid waste. Power for Air Conditioning (HVAC load) is energy managed by ANN to reduce thermal energy costs. Processing Power is energy for signal processing, minimized without affecting service quality. Power from Renewable Energy is solar or hybrid source prioritized before grid power. ANN Controller is the core optimizer calculating total power, allocating resources, and maintaining QoS. Assigned Mobile Users is the allocation of users within energy limits to balance efficiency and demand. Feedback is a closed-loop system that updates ANN decisions by comparing predicted and actual performance. Fig. 3 shows the simulink model for energy optimization of base station power consumption using ANN.

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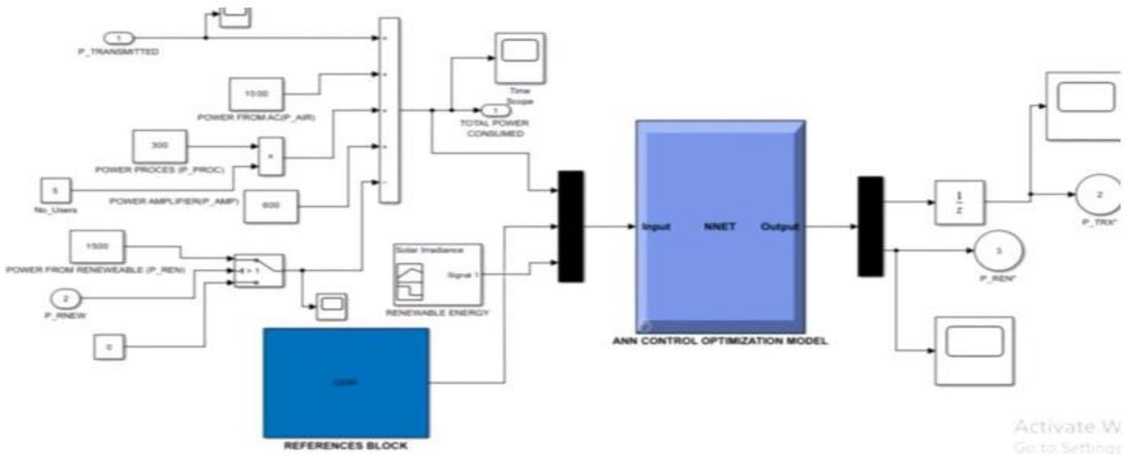

Figure 3. Simulink Model of a Base Station for Energy Optimization Using ANN

As shown in fig. 3, the ANN model was implemented using MATLAB and Simulink to optimize the energy consumption of MTN's base stations. The ANN model was trained using the Levenberg - Marquardt algorithm. The model's performance was evaluated using various metrics, such as the power consumption of the base station, the energy savings for the base station, the accuracy of the base station's power consumption predictions, the Mean Squared Error, the Root Mean Squared Error, the Mean Absolute Error, the Quality of Service and the utilization of renewable energy by the base station. The performance of the ANN model was compared to the performance of both the conventional base station and a Model Predictive Control (MPC) model to evaluate its effectiveness. Fig. 4 shows the simulink Model of a Base station for energy Optimization using Model Predictive Control (MPC).

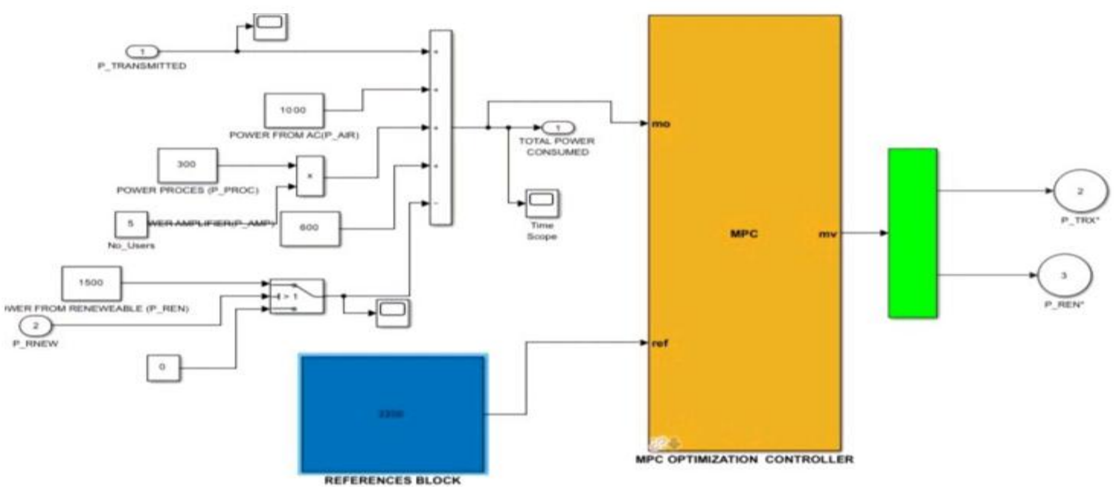

Figure 4. Simulink Model of a Base Station for Energy Optimization Using MPC

Fig. 5 shows the flow chart of energy Optimization of a Base station using ANN.

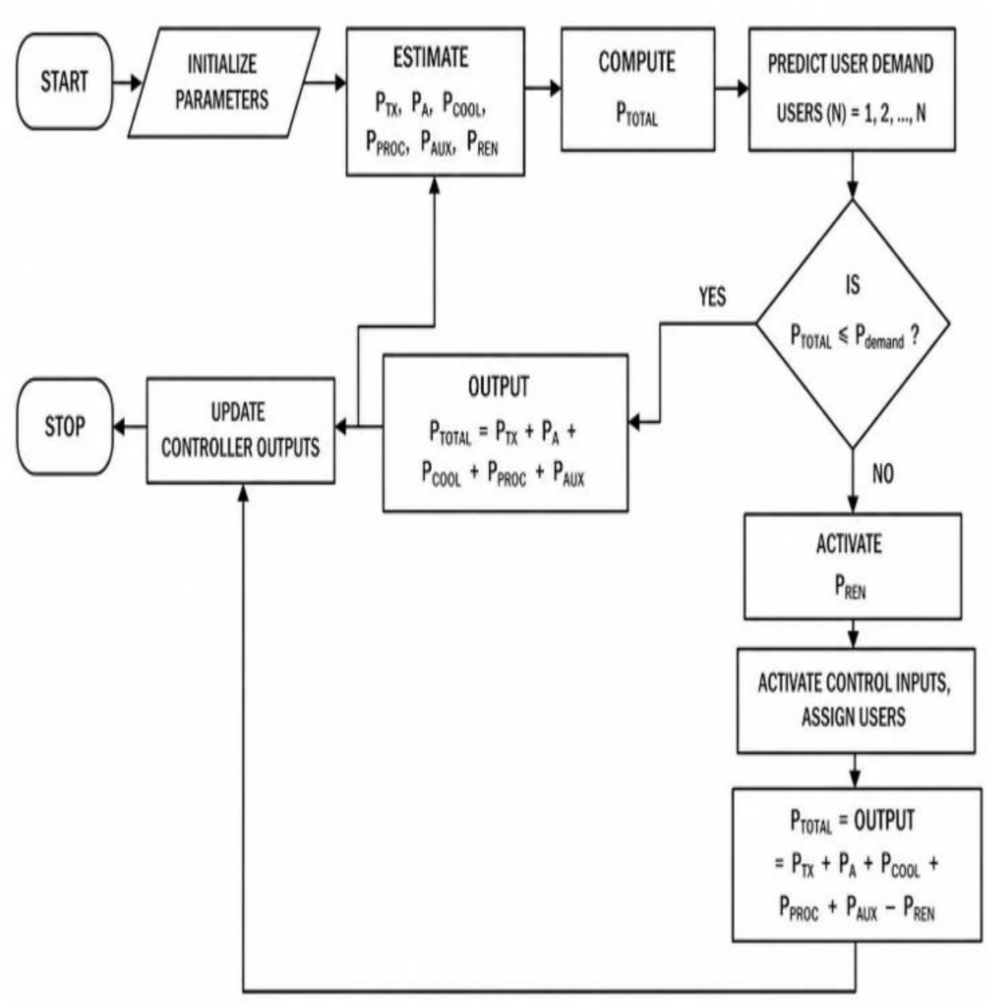

Figure 5. Flow Chart of Energy Optimization of a Base Station Using ANN

III. RESULTS AND DISCUSSION

3.1 ANN Training Performance

The ANN model was implemented within MATLAB using the Levenberg - Marquardt backpropagation algorithm and using operational data from MTN's base stations. The dataset was split into 70% for training, 15% for validation and 15% for testing the model. The training process for the ANN model was completed within a low number of epochs, with the Mean Squared Error of the validation data showing low error within the model. Also, the regression analysis of the model indicated strong connection between the predicted and measured power consumption of the cells. Table 1 shows simulation parameters for MTN green communication network using ANN

Table 1. Simulation Parameters for MTN Green Communication Network Using ANN

S/N	Parameters	Value
1	User 1 Radio Freauency	1711 MHz
2	User 2 Radio Frequency	1712 MHz
3	User 3 Radio Frequency	1713 MHz
4	User 4 Radio Frequency	1714 MHz
5	User 5 Radio Frequency	1715 MHz

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6	Simulation Time	0 – 24 hrs
7	Traffic Load	10 – 90 %
8	Transmission Power (P_{TX})	800 – 1800 W
9	Amplification Power (P_A)	900 W
10	Processing Power (P_{proc})	450 W
11	Cooling Power (P_{COOL})	500 W
12	Auxiliary Power (P_{AUX})	305 W
13	Renewable Energy Contr.	0 – 40 %
14	Battery Capacity	20 KWh
15	ANN Hidden Neurons	15
16	ANN Learning Rate	0.01
17	Maximum Epochs	1000
18	Training Algorithm	Levenberg – Marquardt
19	Bandwidth Per User	1 MHz

3.2 Hourly Power Consumption of MTN Base Station

Table 2 shows the energy consumed every 3 hours in Watts by Conventional, ANN and MPC model.

Table 2. Hourly Energy Consumption Profile

S/N	Traffic Load (%)	Conventional Power (W)	ANN Power (W)	MPC Power (W)	Operational Mode	Time (hrs)
1	15	2620	2525	2445	Deep Sleep	00:00-03:00
2	20	2700	2605	2525	Light Sleep	03:00-06:00
3	50	3000	2895	2805	Active	06:00-09:00
4	75	3300	3185	3075	Active	09:00-12:00
5	90	3500	3370	3255	Active	12:00-15:00
6	80	3350	3235	3125	Active	15:00-18:00
7	65	3100	2985	2880	Light Sleep	18;00-21:00
8	35	2870	2765	2665	Light Sleep	21:00-00:00

The experimental results of table 2 show that the power consumption varies with the traffic demand. Both the artificial neural network and the model predictive control method can reduce the power consumption compared with the existing method. The model predictive control method can reduce the power consumption to the lowest level due to predictive optimization. The artificial neural network method can provide the energy saving efficiently with lower computational complexity.

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Fig. 6 shows the base station (conventional) power consumption with renewable energy integration

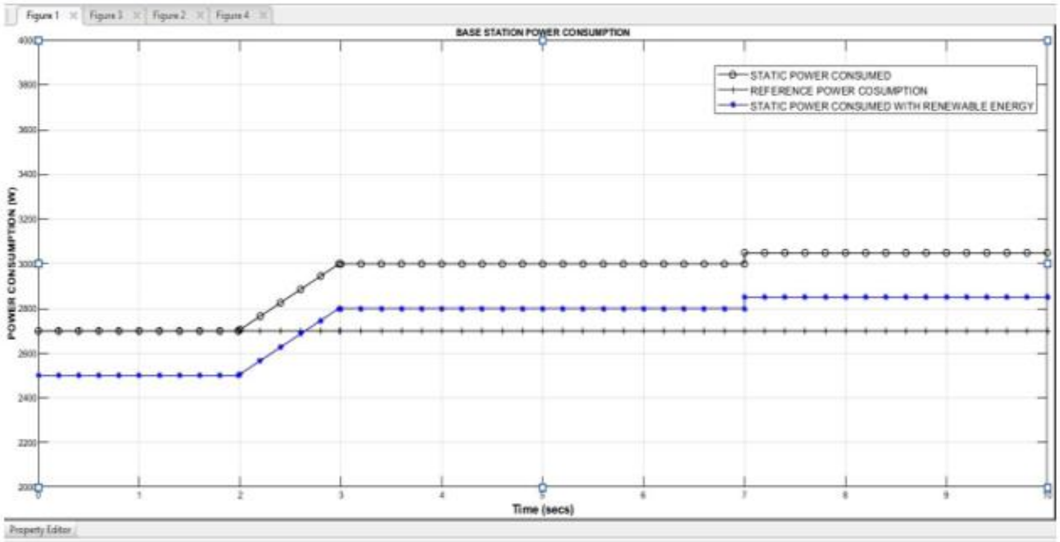

Figure 6. Base Station Power Consumption with Renewable Energy Integration

Fig. 6 shows that the integration of renewable energy into a cellular network reduces the power consumption of the base station by around 200 W throughout the 10-second simulation. Although the power consumption of the base station does increase at 2 and 7 seconds, the integration of renewable energy into the base station results in the base station consuming less energy overall than the static power consumption of the base station alone.

Fig. 7 shows the base station power consumption with MPC and ANN models.

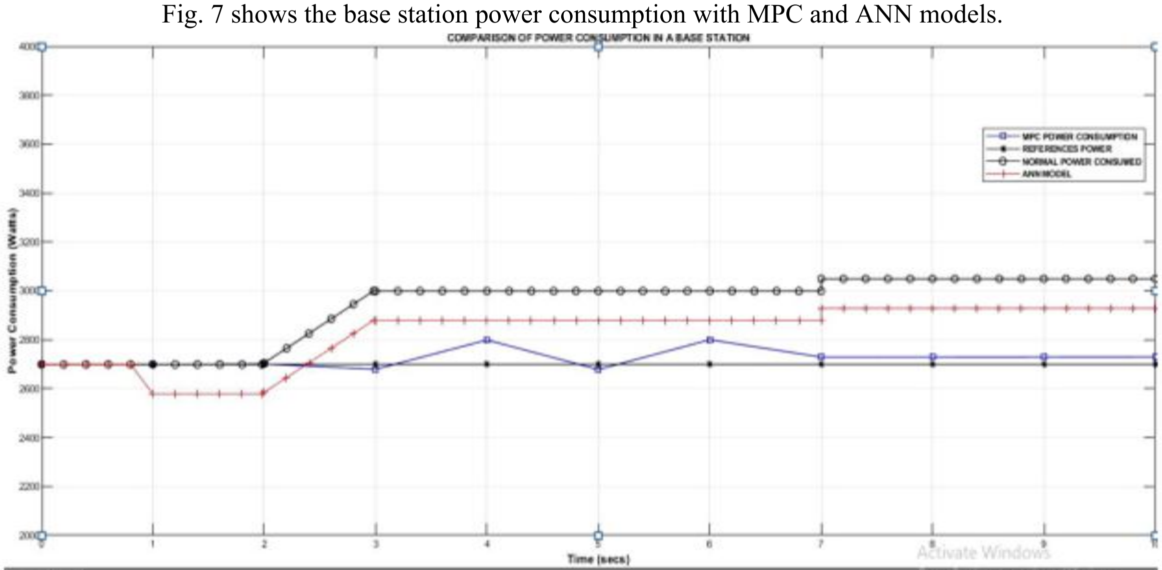

Figure 7. Base Station Power Consumption with MPC and ANN

Figure 7 presents the results of the simulations of both the ANN and MPC models compared to the baseline (conventional approach). The ANN model reduced the average power consumption of the base station by 108 W (3.65%) through intelligent energy management, while the MPC model achieved the greatest reduction in power consumption of 208 W (7.04%) through the use of predictive optimization and changing resource

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allocation. The average power consumption of the base station over the 10-second simulation was 2955 W (baseline), 2847 W (ANN) and 2747 W (MPC).

3.3 Calculation of Percentage Power Reduction
ANN Power Consumption with Normal Power Consumption:

$$percentage\ reduction = \frac{(Normal\ Power\ Consumed - ANN\ Model\ Power\ Consumption)}{Normal\ Power\ Consumed} \times 100 \quad (16)$$

$$percentage\ reduction = \frac{(2955 - 2847)}{2955} \times 100 = 3.65\%$$

MPC Power Consumption with Normal Power Consumption:

$$percentage\ reduction = \frac{(Normal\ Power\ Consumed - MPC\ Model\ Power\ Consumption)}{Normal\ Power\ Consumed} \times 100 \quad (17)$$

$$percentage\ reduction = \frac{(2955 - 2747)}{2955} \times 100 = 7.04\%$$

3.4 Performance Evaluation of ANN
The predictive performance of the developed ANN model was evaluated using standard statistical indices.

Table 3.4 ANN Prediction Performance

S/N	Performance Metric	Value
1	Mean Squared Error (MSE)	0.0032
2	Root Mean Squared Error (RMSE)	0.0566
3	Mean Absolute Error (MAE)	0.0415
4	Regression Coefficient (R)	0.992
5	Prediction Accuracy	98.4%
6	Training Samples	70%
7	Validation Samples	15%
8	Testing Samples	15%

As shown in table 3, the high regression coefficient (R = 0.992) and prediction accuracy of 98.4% of the ANN shows that it can accurately predict the energy consumption of the MTN base station. The low error values also confirm the robustness and reliability of the model.

IV. CONCLUSION

The ANN model was developed to optimize the energy consumption of MTN's green communication network. The model successfully reduced the power consumption of the network's base stations by 3.65% from 2955 W to 2847 W. The ANN model was able to accurately predict the power consumption of each base station at a rate of 98.4% accuracy. Also, the model was able to increase the use of renewable energy sources to power the network, reduce the reliance on grid power and perform real-time management of the power consumption of the base stations.

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