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Optimization-Based Technique to enhance Energy Efficiency in a Telecommunication Company: A recent Approach

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Abstract

Utilizing technology that uses less energy to complete the same task is known as energy efficiency. Machine learning could be used to optimize energy efficiency and lower power consumption at communication base station (BTS) locations. In this procedure, relevant work is reviewed to look for flaws. Additionally, the cell site under investigation is characterized, its power consumption is calculated, a SIMULINK model is created, and the module is identified. Additionally, optimizing high power consumption entails creating a machine learning rule base to keep track of the module's power usage. Develop machine learning rules for ANN that are intended to cut cell power consumption and enhance network performance. The next step is creating the implementation algorithm, and the final step is creating a power consumption model for the network under study. According to the outcomes of a thorough simulation, machine learning reduces the maximum power typically used at the cell site from 5746 kW to 4733 kW. With the addition of machine learning, the system's performance increased by 8.9%, or 4731 kW.

Keyword: Optimized, energy efficiency, reduction of power consumption, telecommunication base transceiver station.

Introduction

One of the major issues facing wireless cell community vendors globally right now is the problem of power efficiency. Due to issues with energy efficiency, some cell network vendors in Nigeria have been impacted, forcing the closure of websites. To deal with this circumstance, which provides Green conversation techniques were introduced as a result of several processes that were adopted to reduce power consumption in base stations. Enhancing Power Amplifiers (PA) Due to the fact that they consume the largest portion of BSs' strength consumption, PAs have garnered a lot of attention. The energy amplifier in a macro phone's base station (BS) consumes the most energy in cellular communications, accounting for up to 65% of the total power boost through all BS components. The issue is that the power efficiency of PA can only be achieved with internal tools; external requirements, like not knowing how many users are simultaneously requesting access to the BS, are no longer acceptable. This alters the efficiency of the electricity used by the internal machinery. It is typical for high bit error rates to lead to subpar conversation performance [1]. On the other hand, [2] unquestionably highlights the necessity of incorporating ultra-capacitors into the device in order to increase energy efficiency. The author of Egalitarianism [3] stressed the importance of redefining wifi conversation in order to increase its efficacy. [4] Reiterated that multi-radio efficiency's primary function is increased throughput. There appear to be optimization problems for the majority or minimum values that a character can take. We learned how to solve specific optimization issues in the Absolute Extremes section. The function's maximum and minimum values for the interval are shown here. Artificial intelligence (AI) software known as machine learning enables systems to automatically learn and advance. Computer systems are taught through machine learning what people take for granted, or what they learn from experience. Machine learning algorithms, as opposed to using specific equations as a model, use computational techniques to quickly "learn" statistics from data. As there are more educational samples available, the algorithm adapts and enhances overall performance. The growth and changes that have recently occurred in business have entered a new stage concurrently with the advancement of computer technology, fuzzy logic, and, ultimately, a completely new field of synthetic intelligence. According to a study [5], Artificial Intelligence (AI) is expanding because of its controllable ability to be predictive and sourcing. When combined with other sources, such as biomass, renewable energy sources like wind and solar are particularly effective and environmentally friendly because of their indestructible properties. This is true especially in rural areas. Following the above-mentioned research goals, which have to do with the tabulation of the gathered data and characterization of the current telecommunications-based Transceiver under study [6], is how this work will be accomplished.

Aim of the work

In order to maximize energy efficiency, a base transceiver station for communications must reduce its power consumption

The goal of the study

The operations of the telecommunications company have been impacted by the high power consumption of a cell site's modules. This has made it necessary to implement optimized energy efficiency by lowering power consumption at a base transceiver station (BTS) site for telecommunications. The specific goals are listed as follows:

1. Use the data gathered to determine the power consumption of the cell modules that need to be optimized.
2. Reduce the established high power consumption by the cell's modules to a target level.
3. Create machine learning rules for the cell to use less energy, improving performance.
4. Train the ANN using the machine learning rules that were designed to use less energy at the cell site.
5. Create an algorithm to carry out the sequence.
6. Based on the outcomes of the algorithm's integration into the network under study, create a power consumption model for it.
7. Provide evidence to support and defend the percentage increase in energy efficiency at the cell site with and without the use of machine learning

A closer look at other research works

In wind farms, where the source of electricity is stochastic, the introduction of renewable energy sources can improve the diesel generators used in the base stations of all Nigerian carriers. The inefficiency of increasing the percentage efficiency of the mills to raise the production capacity of the industries that completely rely on the generator for their daily manufacturing is addressed with the help of strength efficiency upgrades of doubly fed induction generator mac. The length of time it takes to send data from the transmit point to the receive factor is a major issue in our communication

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network, so the power source needs to be dependable; Small-scale industries in the United States are experiencing financial difficulties as a result of the decrease in electricity supply; one major issue attributable to this is a lack of planning tools that can predict how much electricity will be needed to feed the entire population [8]. "With increasing pressure to overcome environmental and financial crises, renewable energy sources have dramatically increased both qualitative and quantitative improvements. Taking awareness of the fact that passing information or transferring data from one factor to another has become a chronic problem in our communication industry, energy efficiency techniques should be adopted, such as laptop learning, which should as well improve the Recent energy efficiency improvements have been made to strengthen demand-side management of power distribution systems. Optimised Genetic Algorithm (OGA) was used in the work of [10] to improve the supply of epileptic electricity from the national grid due to instability that has been a problem for power users. With the help of the introduction of an Optimized Genetic Algorithm, this instability in the power supply experienced in the energy distribution network should be reduced (OGA). Recent years have seen a rise in the popularity of voltage adjustments based on reinforcement learning and distribution analysis. The incorporation of renewable energy sources into the power mix has greatly improved distribution and energy satisfaction in light of the growing global demand for energy. Due to ecological, social, economic, and environmental factors like the widely used photovoltaic structures (PVs) and wind turbine systems (WTs), renewable energy systems (RESs) had been hastily developed [11]. According to research [12], Nigeria's electricity system faces a number of technical difficulties as a result of its long, radial, weak, and ageing transmission network. This paper introduces the concept of electricity conservation and related technologies, as well as options to help users avoid suffering the negative effects of increased electricity efficiency. In order to improve power efficiency and reduce strength consumption, as in the case of the Telecommunication Base Transceiver Station (BTS) Site, computer learning is being used in the project.

In order to reduce electricity consumption and unburned hydrocarbon pollution, research has been done on methods for improving strength effectiveness [13]. The energy fed on by cell stations (user terminals), whose more than 50% of electricity consumption is immediately attributed to the base station (BTS) equipment, accounts for more than 50% of the total power consumption of mobile communications networks as of today[14]. However, from the perspectives of your budget (cost reduction), the environment (reduced CO_2 emissions), and efficiency, a reduction in the electricity consumption of cellular networks is of remarkable importance. Therefore, each decrease in energy use and CO_2 emissions is a key factor in the development of the ICT sector[15]. In the most recent report from the International Telecommunications Union (ITU) and Alliance for Telecommunications Industry Solutions (ATIS), a number of energy-efficient practices and strategies have been outlined for consideration by organisations looking to improve the efficiency of their wireless networks. Although there is active research being done on energy use, reduction, and efficiency in wireless access networks, issues pertaining to the implementation of desktop learning methods have not been extensively and explicitly addressed. The power consumption of base transceivers stations (BTS) is examined in this paper, along with possible reduction strategies, as well as the possibility of managing energy Optimization without sacrificing

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community first-class of the carrier (QoS). The research also looks into the impact of using optimization techniques on power efficiency[16].

We are aware that a base transceiver station (BTS) is a transceiver that serves as a connection point for mobile stations to networks. Depending on the geography and provider demand in an area, a BTS will have 1 to 16 Transceivers (TRX). TRX stands for one ARFCN (Absolute radio frequency channel number). However, a BTS can also host up to two, three, or six sectors, or a cell may be serviced using multiple BTSs with redundant sector coverage, depending on geography, carrier demand, and the operator's network method and architecture. A quarter antenna, which is a directional antenna, shields each area. The typical macro BTS that we found today is shown in Figure 1. Numerous noteworthy records of interconnected research methodologies and philosophies have been mentioned in great detail. Sadly, there are few studies that compare and integrate data from different sources. The research and application of computer mastering and sensible agents were discussed frequently in this article. This paper focuses on using contemporary mathematical techniques to successfully reduce energy consumption to maximize profit[17],than discussing in-depth electricity efficacy technologies. The framework enclosing the literature on AI and ML research is discussed only in terms of energy-efficient methods. Instead, it makes an effort to offer a starting point for integrating knowledge across this field of study and suggests directions for future research. It examines research in several cutting-edge fields, including pollution of the environment, medicine, upkeep, manufacturing, etc. It is hoped that additional research will extend the current knowledge boundary for computer learning and optimization approaches. To maximize the advantages of this approach, incorporating machine learning disciplines into the current AI frameworks should shed more light. This paper offers insightful ideas and viewpoints for those conducting AI and ML research. Understanding a decrease in electricity consumption using power efficiency techniques was the final goal. The research provides a foundation for the application of intelligent agents and machine learning techniques in the future to reduce power consumption, which will ultimately result in cost savings[18].

This research also looks at the power consumption of commercially available equipment such as routers and DSL modems [19]. More specifically, what concerns the core network, is the capacity of the existing diesel generator[20]. The cost-saving implications of running a hybrid renewable power source to augment the present means of generating are considered [21]. In some cases, the estimate is based on the global total switching capacity required to support a given access rate, and with a predefined share of add/drop and bypass traffic in each node[22]. The power consumption in the core network is then a function of the oversubscription rate, connected homes and peak access rate[23]. In another paper [24], the core network is modeled as a function of the

Materials and Methods

Following the stated objectives in order and adhering to the procedure are required if we are to get the desired outcomes and fulfil our purpose. Characterize and ascertain the power consumption of the modules of the cell site under investigation. To do this, the base station (BS), configuration model, transceiver, and power models of the cell site were examined. The cell site, also known as a base station or base transceiver station (BTS), is a microcell run by IHS Towers West Africa Limited. It is located at Mount Street by Idaw River Layout in Awkunanaw, Enugu, and houses base station

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equipment from MTN Nig Ltd and Airtel Nig Ltd. Within its coverage area, the site controls (hops) about thirty (30) additional MTN/Airtel base stations (terminal and fibre sites), and it manages voice, data, and streaming service transmission and reception (TX and RX).The measurements were monitored and performed over the course of 27 days. The days consist of the peak morning hours, off-peak afternoon hours, and nighttime hours (main Peak). The readings are displayed in Appendix Tables C1 through C27.

Obtaining the data from the company under study and determining the power consumption of the cell modules to be optimized.

A time series method of measurement was used to collect data for twenty-seven (27) days at the study cell site. Measurements were taken eight (8) times over the course of each day, every two (2) hours at intervals of fifteen (15) minutes. In the end, an average for all of the equipment's eight (8) intervals was calculated for each day. For instance, on day 1, the 2G BTS Airtel had current readings of the following on average at eight (8) intervals every fifteen minutes over the course of two hours: 25.4A; 24.6A; 25.8A; 24.3A; 25.6A; 24.4A; 24.7A; and 25.4A for the intervals. The average is;

$$Average = \frac{25.4 + 24.6 + 25.8 + 24.3 + 25.6 + 24.4 + 24.7 + 25.4}{8}$$

= 25.03Amps ≅ 25Amps

In Table C1 of Appendix C, a sample of the 2G BTS Airtel measurement process is displayed. The transmitter and receiver modules, which form the foundation of the cell site, are housed in the BTS equipment booth, where the measurement was first carried out. For broadcasting and hopping operations with other cell sites connected to the tower via RF and microwave antennas, BTS is also connected to equipment on the tower. A 27-day summary was computed after the measurements were completed.

To determine the module to go on sleep mode and its power requirement

Power consumed = $P_{Con} = V_{Aver} \times I_T$ (Watt) (3.2)

Where P_{Con} is the power consumed in (Watt)

V_{Aver} is the average voltage calculated from each day measurement (Volt).

I_T is the average total current consumed by the equipment in the cell site (Amps).

Day 1 at 13:30HRS – 15:30HRS on 3rd September 2019.

Total current = I_T = 109.8 Amps

Average Voltage = V_{Aver} = 52.5 Volts

Power consumed = $P_{Con} = I_T \times V_{Aver}$ = 109.8 x 52.5

= 5764.50 Watts

Day 2 at 11:00HRS – 13:00HRS on 4thSeptember 2019.

Total current = I_T = 102.4 Amps

Average Voltage = V_{Aver} = 50.7 Volts

Power consumed = $P_{Con} = I_T \times V_{Aver}$ = 102.4 x 50.7

= 5191.68 Watts

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Day 3 at 15:00HRS – 17:00HRS on 5th September 2019

Total current = I_T = 110.8 Amps

Average Voltage = V_{Aver} = 52 Volts

Power consumed = $P_{Con} = I_T \, x V_{Aver} = 110.8 \text{ x } 52$

$= 5761.60$ Watts

Day 4 at 10:00HRS – 12:00HRS on 6th September 2019

Total current = I_T = 94.9 Amps

Average Voltage = V_{Aver} = 52.8 Volts

Power consumed = $P_{Con} = I_T \, x V_{Aver} = 94.9 \text{ x } 52.8$

$= 5010.72$ Watts

Day 5 at 14:00HRS – 16:00HRS on 9th September 2019

Total current = I_T = 105.6 Amps

Average Voltage = V_{Aver} = 51.3 Volts

Power consumed = $P_{Con} = I_T \, x V_{Aver} = 105.6 \text{ x } 51.3$

$= 5417.28$ Watts

Day 6 at 10:30HRS – 12:30HRS on 11th September 2019

Total current = I_T = 98.5 Amps

Average Voltage = V_{Aver} = 52.3 Volts

Power consumed = $P_{Con} = I_T \, x V_{Aver} = 98.5 \text{ x } 52.3$

$= 5151.55$ Watts

Day 7 at 16:00HRS – 18:00HRS on 12th September 2019

Total current = I_T = 107.9 Amps

Average Voltage = V_{Aver} = 52.9 Volts

Power consumed = $P_{Con} = I_T \, x V_{Aver} = 107.9 \text{ x } 52.9$

$= 5707.91$ Watts

Day 8 at 12:00HRS – 14:00HRS on 15th September 2019.

Total current = I_T = 97.5 Amps

Average Voltage = V_{Aver} = 52.7 Volts

Power consumed = $P_{Con} = I_T \, x V_{Aver} = 97.5 \text{ x } 52.7$

$= 5138.25$ Watts

Day 9 at 15:30HRS – 17:30HRS on 17th September 2019

Total current = I_T = 108.3 Amps

Average Voltage = V_{Aver} = 52.4 Volts

Power consumed = $P_{Con} = I_T \, x V_{Aver} = 108.3 \text{ x } 52.4$

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= 5674.92 Watts

Day 10 at 14:30HRS – 16:30HRS on 19th September2019

Total current = I_T = 106.9 Amps

Average Voltage = V_{Aver} = 53.2 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 106.9 x 53.2

= 5687.08 Watts

Day 11 at 13:00HRS – 15:00HRS on 20th September 2019.

Total current = I_T = 104.7 Amps

Average Voltage = V_{Aver} = 52.7 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 104.7 x 52.7

= 5517.69 Watts

Day 12 at 19:00HRS – 21:00HRS on 23rd September 2019.

Total current = I_T = 160.8 Amps

Average Voltage = V_{Aver} = 53.7 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 160.8 x 53.7

= 8634.96 Watts

Day 13 at 18:00HRS – 20:00HRS on 26th September 2019

Total current = I_T = 151.1 Amps

Average Voltage = V_{Aver} = 53.7 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 151.1 x 53.7

= 8114.07 Watts

Day 14 at 20:00HRS – 22:00HRS on 27th September 2019.

Total current = I_T = 144.3 Amps

Average Voltage = V_{Aver} = 52.4 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 141.3 x 52.4

= 7404.12 Watts

Day 15 at 18:30HRS – 20:30HRS on 28thSeptember 2019

Total current = I_T = 151.7 Amps

Average Voltage = V_{Aver} = 53.3 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 151.7 x 53.3

= 8085.61 Watts

Day 16 at 19:30HRS – 21:30HRS on 2nd October,2019

Total current = I_T = 153 Amps

Average Voltage = V_{Aver} = 53.4 Volts

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Power consumed = $P_{Con} = I_T \; xV_{Aver} = 153 \text{ x } 53.4$

$= 8170.20$ Watts

Day 17 at 06:30HRS – 08:30HRS on 3rd October,2019

Total current = $I_T = 131.4$ Amps

Average Voltage = $V_{Aver} = 52.8$ Volts

Power consumed = $P_{Con} = I_T \; xV_{Aver} = 131.4 \text{ x } 52.8$

$= 6937.92$ Watts

Day 18 at 07:00HRS – 09:00HRS on 6th October,2019

Total current = $I_T = 125$ Amps

Average Voltage = $V_{Aver} = 53.3$ Volts

Power consumed = $P_{Con} = I_T \; xV_{Aver} = 125 \text{ x } 53.3$

$= 6662.50$ Watts

Day 19 at 08:00HRS – 10:00HRS on 7th October,2019

Total current = $I_T = 121.2$ Amps

Average Voltage = $V_{Aver} = 52.4$ Volts

Power consumed = $P_{Con} = I_T \; xV_{Aver} = 121.2 \text{ x } 52.4$

$= 6350.88$ Watts

$= 5138.25$ Watts

Day 9 at 15:30HRS – 17:30HRS on 17th October,2019.

Total current = $I_T = 108.3$ Amps

Average Voltage = $V_{Aver} = 52.4$ Volts

Power consumed = $P_{Con} = I_T \; xV_{Aver} = 108.3 \text{ x } 52.4$

$= 5674.92$ Watts

Day 10 at 14:30HRS – 16:30HRS on 19th October 2019.

Total current = $I_T = 106.9$ Amps

Average Voltage = $V_{Aver} = 53.2$ Volts

Power consumed = $P_{Con} = I_T \; xV_{Aver} = 106.9 \text{ x } 53.2$

$= 5687.08$ Watts

Day 11 at 13:00HRS – 15:00HRS on 20th October 2019.

Total current = $I_T = 104.7$ Amps

Average Voltage = $V_{Aver} = 52.7$ Volts

Power consumed = $P_{Con} = I_T \; xV_{Aver} = 104.7 \text{ x } 52.7$

$= 5517.69$ Watts

Day 12 at 19:00HRS – 21:00HRS on 23rd October 2019.

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Total current = I_T = 160.8 Amps

Average Voltage = V_{Aver} = 53.7 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 160.8 x 53.7

= 8634.96 Watts

Day 13 at 18:00HRS – 20:00HRS on 26th October 2019.

Total current = I_T = 151.1 Amps

Average Voltage = V_{Aver} = 53.7 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 151.1 x 53.7

= 8114.07 Watts

Day 14 at 20:00HRS – 22:00HRS on 27th October 2019.

Total current = I_T = 144.3 Amps

Average Voltage = V_{Aver} = 52.4 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 141.3 x 52.4

= 7404.12 Watts

Day 15 at 18:30HRS – 20:30HRS on 28th October 2019.

Total current = I_T = 151.7 Amps

Average Voltage = V_{Aver} = 53.3 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 151.7 x 53.3

= 8085.61 Watts

Day 16 at 19:30HRS – 21:30HRS on 2nd November 2019.

Total current = I_T = 153 Amps

Average Voltage = V_{Aver} = 53.4 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 153 x 53.4

= 8170.20 Watts

Day 17 at 06:30HRS – 08:30HRS on 3rd November 2019.

Total current = I_T = 131.4 Amps

Average Voltage = V_{Aver} = 52.8 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 131.4 x 52.8

= 6937.92 Watts

Day 18 at 07:00HRS – 09:00HRS on 6th November 2019.

Total current = I_T = 125 Amps

Average Voltage = V_{Aver} = 53.3 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 125 x 53.3

= 6662.50 Watts

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Day 19 at 08:00HRS – 10:00HRS on 7th November 2019.

Total current = I_T = 121.2 Amps

Average Voltage = V_{Aver} = 52.4 Volts

Power consumed = $P_{Con} = I_T \ x V_{Aver} =$ 121.2 x 52.4

= 6350.88 Watts

Day 20 at 07:30HRS – 07:30HRS on 9th November 2019.

Total current = I_T = 124 Amps

Average Voltage = V_{Aver} = 53.6 Volts

Power consumed = $P_{Con} = I_T \ x V_{Aver} =$ 124 x 53.6

= 6646.40 Watts

Day 21 at 06:45HRS – 08:45HRS on 16th November 2019.

Total current = I_T = 122.3 Amps

Average Voltage = V_{Aver} = 52.2 Volts

Power consumed = $P_{Con} = I_T \ x V_{Aver} =$ 122.3 x 52.2

= 6384.06 Watts

Day 22 at 06:00HRS – 08:00HRS on 17th November 2019.

Total current = I_T = 127.8 Amps

Average Voltage = V_{Aver} = 53.4 Volts

Power consumed = $P_{Con} = I_T \ x V_{Aver} =$ 127.8 x 53.4

= 6824.52 Watts

Day 23 at 07:45HRS – 09:45HRS on 20th November 2019.

Total current = I_T = 120.7 Amps

Average Voltage = V_{Aver} = 52.7 Volts

Power consumed = $P_{Con} = I_T \ x V_{Aver} =$ 120.7 x 52.7

= 6360.89 Watts

Day 24 at 08:15HRS – 10:15HRS on 22nd November 2019.

Total current = I_T = 117.5 Amps

Average Voltage = V_{Aver} = 52.7 Volts

Power consumed = $P_{Con} = I_T \ x V_{Aver} =$ 117.5 x 52.7

= 6192.25 Watts

Day 25 at 08:15HRS – 10:15HRS on 26th November 2019.

Total current = I_T = 128.8 Amps

Average Voltage = V_{Aver} = 53.3 Volts

Power consumed = $P_{Con} = I_T \ x V_{Aver} =$ 128.8 x 53.3

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= 6865.04 Watts

Day 26 at 08:30HRS – 10:30HRS on 27th November 2019.

Total current = I_T = 122.1 Amps

Average Voltage = V_{Aver} = 53.1 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 122.1 x 53.1

= 6483.51 Watts

Day 27 at 06:15HRS – 08:15HRS on 28th November 2019.

Total current = I_T = 125.4 Amps

Average Voltage = V_{Aver} = 53.1 Volts

Power consumed = P_{Con}= I_T xV_{Aver}= 128.8 x 53.3

= 6658.74 Watts

Total = 170098.78watts =170.09878kw = 170.1kw (approximation)

Number of hours for 27days = 27 x 2 = 54hours

KWH = 170.1 x 54 =9185.4KWH

#60 = 1KWH

9185.4KWH = # 9185.4 x 60 = #551124

Optimization of the established high power consumed by the modules of the cell site to a minimum value

Table 1: Power consumed from the characterized cell site under study

Days	Time	Power consumption Watts
1	13:30HRS	5764.50
2	11:00HRS	5191.68
3	15:00HRS	5761.60
4	10:00HRS	5010.72
5	14:00HRS	5417.28
6	10:30HRS	5151.55
7	16:00HRS	5707.91
8	12:00HRS	5138.25
9	15:30HRS	5674.92
10	14:30HRS	5687.08

Minimize

$P = X + 13.3Y$

Subject To

$X + 13.3Y \leq 5764.50$

$7X + 16Y \leq 5707.91$

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Where

P is the minimum power consumed by the cell site

X is the day the power is consumed in the cell site

Y is the hour the power is consumed in the cell site

```
>> % Optimizing Energy Efficiency through Reduction of Power Consumption in a Telecommunication Base Transceiver Station (BTS) Site Using Machine Learning %
    % Minimize  P = X + 13.3Y
        %        Subject to
        %       X + 13.3Y ≤ 5764.50
        %      10X + 14. 3Y≤ 5687.08
        %
        %     Where
        % P is the minimum power consumed by the cell site
        %X is the day the power is consumed in the cell site
        %Yis the hour the power is consumed in the cell site
          f=[-1;-13.3];
          A=[1 13.3;7 16];
          b=[5764.50;5707.91];
        Aeq=[0 0];
        beq=[0];
          LB=[0 0];
          UB=[infinf];
          [X,FVAL,EXITFLAG]=linprog(f,A,b,Aeq,beq,LB,UB)
        Optimization terminated.
        X =
          0.0000
          356.7444
        FVAL =
        -4.7447e+003
        EXITFLAG =    1
        >>
```

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Designing a machine learning rule base that will monitor the power consumed on the modules and minimize it if high

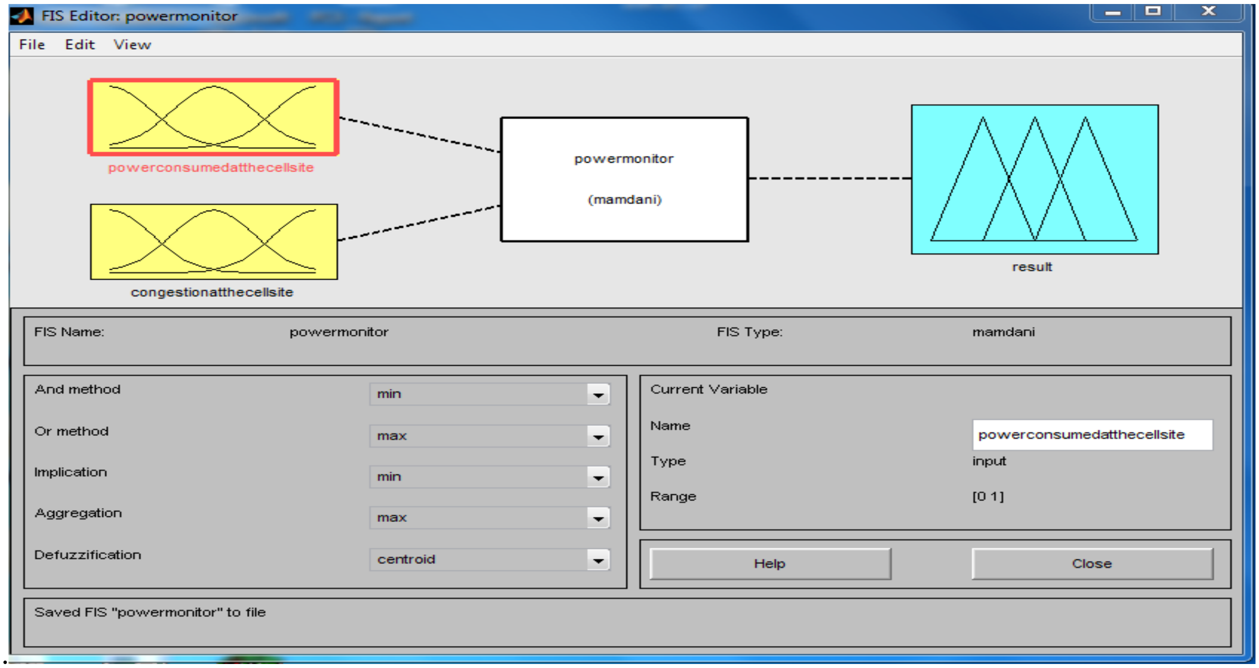

Figure 1: Designed machine learning fuzzy inference system that will monitor the power consumed on the modules and minimize it if high.

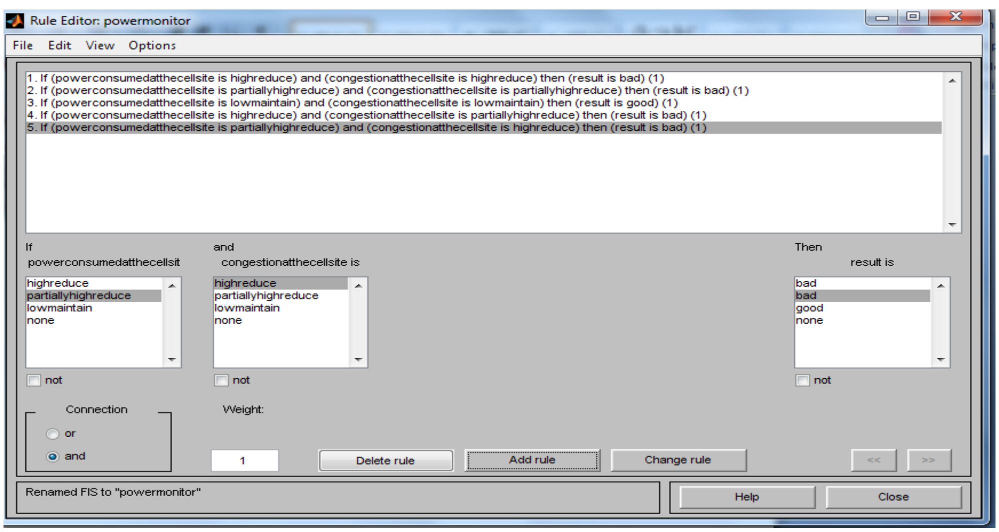

Figure 2: Designed machine learning rule base that will monitor the power consumed on the modules and minimize it if high

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Table 2:Details of designed machine learning rule base that will monitor the power consumed on the modules and minimize it if high

1	If power consumed at the cell site is high reduce	And congestion at the cell site is high reduce	Then, result is bad
2	If power consumed at the cell site is partially high reduce	And congestion at the cell site is partially high reduce	Then, result is bad
3	If power consumed at the cell site is low maintain	And congestion at the cell site is low maintain	Then, result is good
4	If power consumed at the cell site is high reduce	And congestion at the cell site is partially high reduce	Then, result is bad
5	If power consumed at the cell site is partially high reduce	And congestion at the cell site is high reduce	Then, result is bad

Training ANN in the designed machine learning rules for reduced power consumption in the cell site thereby enhancing its network performance.

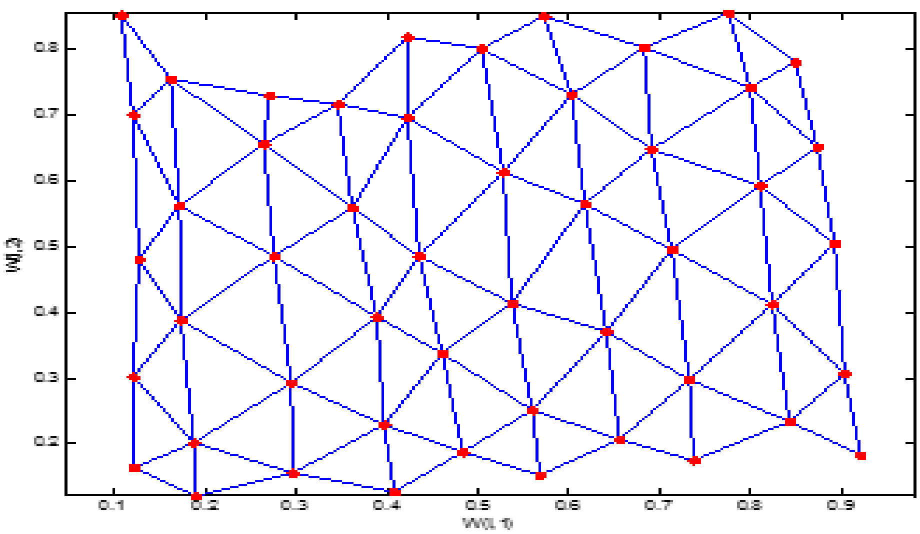

Figure 3: Trained ANN in the designed machine learning rules for reduced power consumption in the cell site thereby enhancing its network performance.

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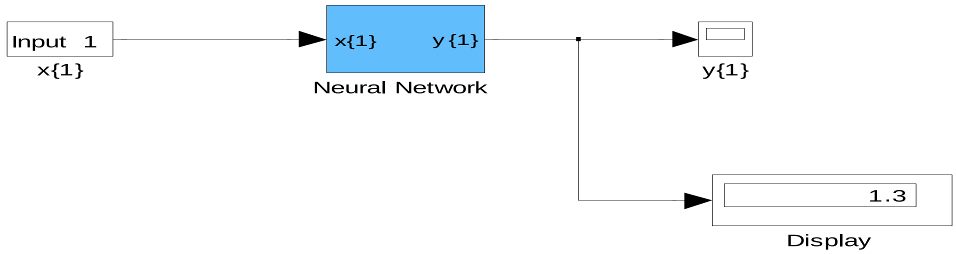

Figure 4: Model that resulted in the training

The Figure above will be implemented in the machine learning to enhance its proper functioning to minimize the power consumption in the cell site to save costs.

Developing an algorithm that will implement 4, 5 and 6

1. Identify the much power consumed by the module of cell site.
2. Optimize the identified much power consumed by the module of the cell site to a minimal.
3. Apply designed machine learning rule base that will monitor the power consumed on the modules and minimize it if high.
4. Apply the trained ANN in 3 to retain minimal power consumption in the module of the cell site.
5. Does the power consumption at the module of the cell site minimized after the application of 4?
6. No go to 4
7. Yes go to 9
8. Minimized power consumption by the module of the cell site.
9. Stop.
10. End
11. To develop a power consumption model for the network under study based on results obtained

Developing power consumption model for the network under study based on results obtained. The power consumption model is shown in figure 5 below reflecting all the simulations obtained as depicted in figures 6, 7, 8 and 9.

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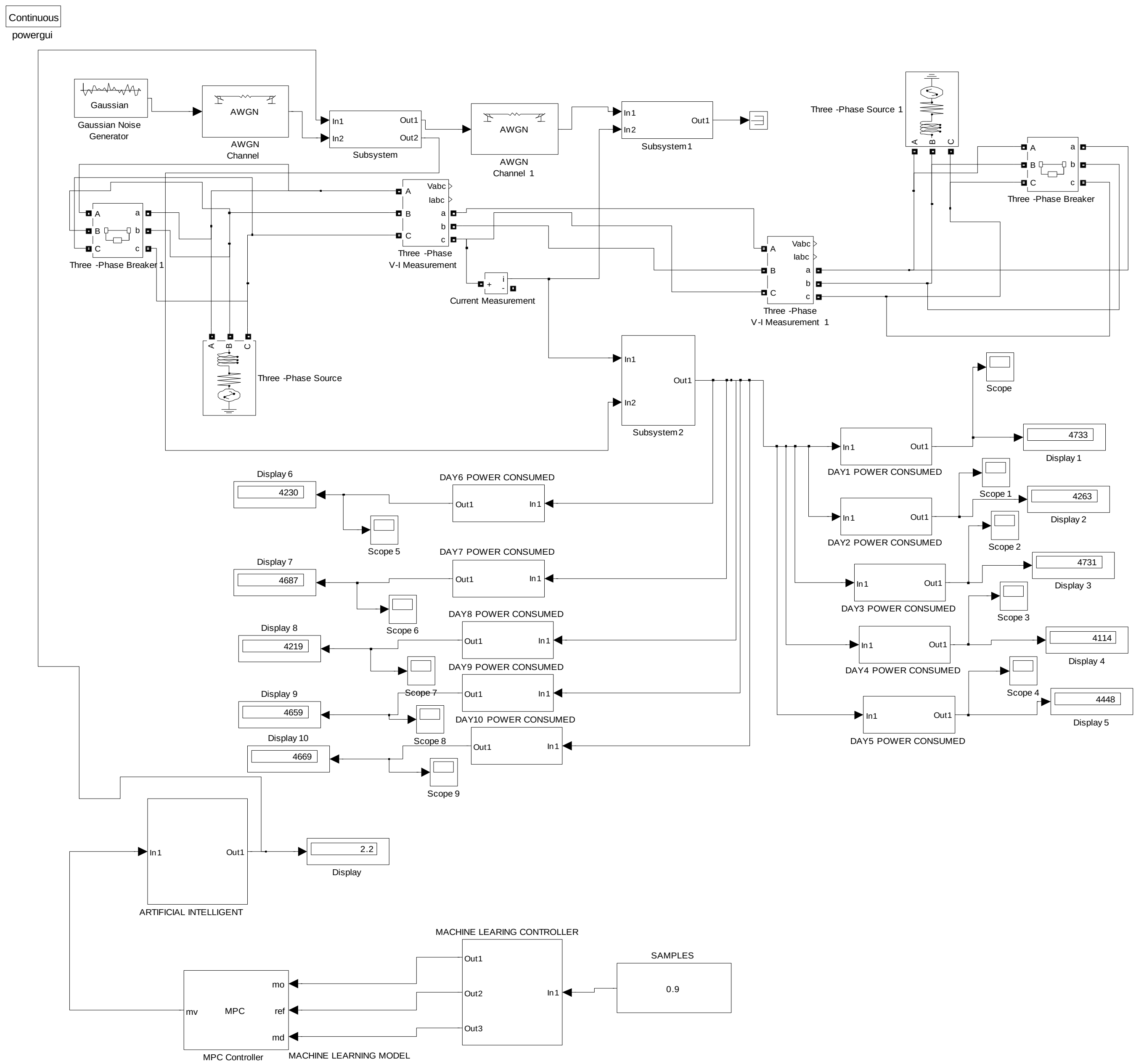

Figure 5: Developed power consumption model for the network under study based on results obtained. The results obtained after simulation are as shown in figures 6, 7, 8 and 9Table 3:

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Table 3: Comparison between conventional and machine learning power consumed in cell site in day 1

Time (s)	Conventional power consumed in cell site in DAY 1(KW)	Machine learning power consumed in cell site in DAY1(KW)
0	0	0
1	3800	3000
2	5000	4100
3	5300	4500
4	5764	4733
10	5764	4733

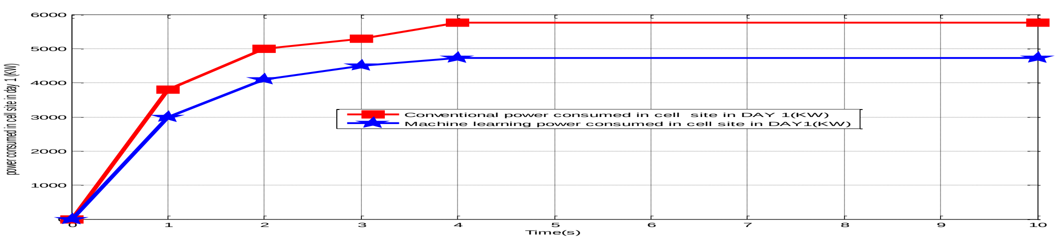

Figure 6: Comparing conventional and machine learning power consumed in cell site in day

Table 4:Comparison between conventional and machine learning power consumed in cell site in day

Time (s)	Conventional power consumed in cell site in DAY 3(KW)	Machine learning power consumed in cell site in DAY3(KW)
0	0	0
1	3700	3000
2	5000	4100
3	5500	4500
4	5191	4731
10	5191	4731

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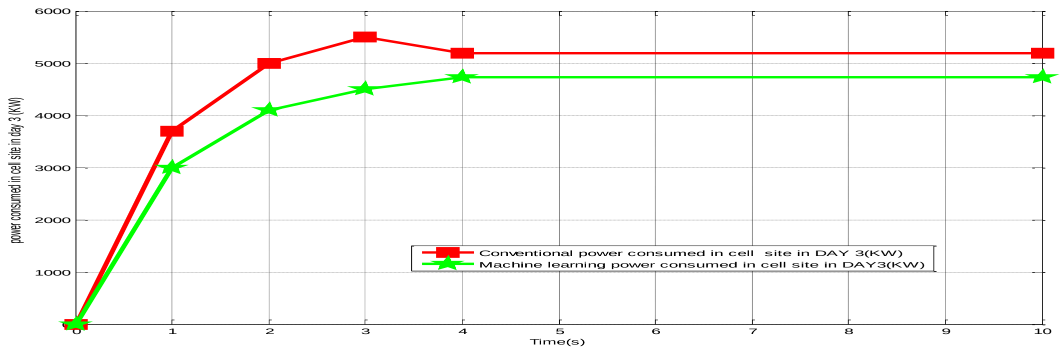

Figure 7: Comparing conventional and machine learning power consumed in cell site in day 3

Table 5: Comparison between conventional and machine learning power consumed in cell site in day 5

Time (s)	Conventional power consumed in cell site in DAY 5 (KW)	Machine learning power consumed in cell site in DAY 5 (KW)
0	0	0
1	3200	2700
2	4700	3800
3	5200	4900
4	5417	4448
10	5417	4448

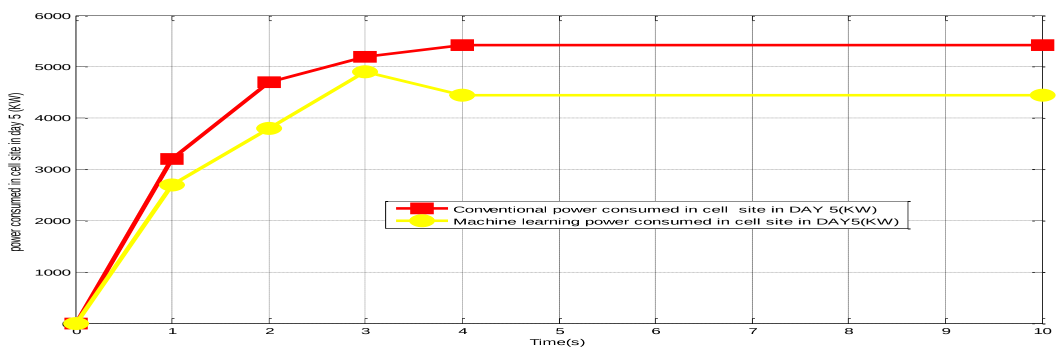

Figure 8: Comparing conventional and machine learning power consumed in cell site in day 5

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Table 6: Comparison between conventional and machine learning power consumption in day 7

Time (s)	Conventional power consumed in cell site in DAY 7 (KW)	Machine learning power consumed in cell site in DAY 7 (KW)
0	0	0
1	3400	3000
2	5000	4000
3	5500	4500
4	5708	4687
10	5708	4687

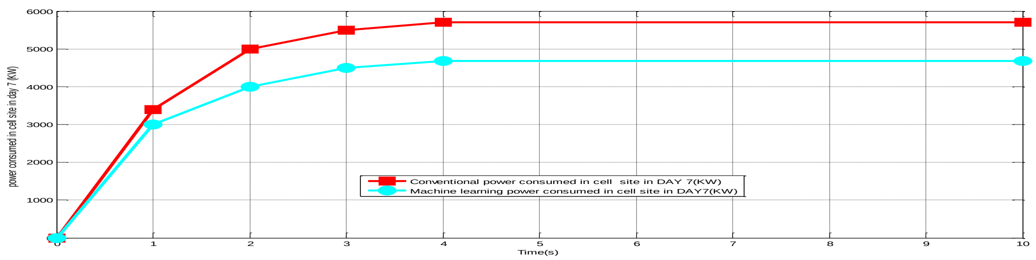

Figure 9: Comparing conventional and machine learning power consumed in cell site in day 7

Results and Discussion

The outcomes of minimizing power consumption with machine learning are presented and discussed. Congestion and power used at the cell site are two inputs in Figure 1. Additionally, it produces results.

Figure 2 shows a machine learning rule base that is designed to monitor the power used by the modules and reduce it if necessary. It tracks the amount of power used by the cell site's modulus and reduces it when a high level is found. The details of the machine learning rule base that is designed to monitor the power consumed on the modules and minimize it if high are tabulated in Table 2, which provides a thorough analysis of the rules. In Figure 3, an artificial neural network (ANN) was trained ten times using machine learning's five rules to produce fifty neurons that resemble the human brain. These neurons act in accordance with instructions and mimic human intelligence.

Figure 4 is incorporated into machine learning to increase its effectiveness in terms of lowering the amount of power consumed in the cell site, improving the site's financial situation. Based on the results, a power consumption model for the network under study is shown in Figure 5 below. The simulation's outcomes are depicted in figures 6, 7, 8, and 9. Figure 6 compares the amount of traditional and machine learning power used at the cell site on day 1. In Figure 6, the cell site uses the most conventional power at 5764kW, while the system uses 4733kW when machine learning is used. These findings indicate that when machine learning is incorporated into the system on day one, the improvement in the percentage reduction of power consumed in the cell site is 17.9%.

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Figure 7 demonstrates that on Day 3 of the cell site, the highest conventional power consumption was 5191KW, while 4731KW was used when machine learning was incorporated into the system.

This clearly demonstrated that when machine learning technique is incorporated into the system on day 3, the percentage improvement in power consumption reduction in the cell site is 8.9%.

Figure 8 makes it clear that the cell site's highest conventional power consumption is 5417 KW. On the other hand, when machine learning is incorporated into the system, it drastically reduced to 4448KW, or 17.9% of the power consumed by the reduction in cell sites. Figure 9 shows that when machine learning is implemented into the system, the highest conventional power consumed by the cell site is 4687KW rather than 5708KW, which is 17.9% better than the conventional approach in terms of power consumption reduction in the cell.

Conclusion

Some of these cell sites no longer have as much financial stability as they once did due to their sustained high power consumption. By using machine learning to optimise energy efficiency, the ugly situation of high cell site power consumption is alleviated at communication base station (BTS) sites. increase. To successfully accomplish this, in this process, the relevant work is examined to identify any weaknesses and the examined cell site module's power consumption is characterised, established, and examined. The developed and optimised SIMULINK model is specified. An artificial intelligence rule base that monitors the power used by the cell site module and reduces it when it is using a lot of power. To reduce power consumption, create ANNs and train them with designed machine learning rules. Enhance base station network performance. We will then create an algorithm to put it into practise. We developed a power consumption model for the network under investigation and increased energy efficiency at the cell site with and without machine learning based on the outcomes of the algorithm's network integration. Justify and validate the rate. According to the results of in-depth simulation, the cell site's conventional maximum power consumption is 5746 kW, while the system's maximum machine learning power consumption is 4733 kW. According to these findings, integrating machine learning into the system reduces cell site power consumption by 17.9% on the first day, whereas conventional cell sites consume the most power after three days of machine learning. Its 5191kW rating is visible to the naked eye. Learning Learning is a 4731kW integrated part of the system. These results show that, compared to the cell site's typical maximum power consumption of 5417 kW, the machine learning technology's integration into the system on the third day results in an 8.9% improvement rate in the cell site's power consumption reduction. I comprehend. While the conventional maximum power consumption of cell sites is 5708 KW, when machine learning is integrated into the system, the reduction of cell sites significantly reduces the power consumption to 4448 KW, which is 17.9% of the power consumption. In terms of reducing the power used by cell sites, the learning capacity of the system is 4687 kW, which is 17.9 more effective than the conventional method.

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