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ENERGY CONSUMPTION REDUCTION IN 5G TELECOMMUNICATION NETWORK USING MACHINE LEARNING APPROACH

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Abstract - This paper introduces a machine learning-based fuzzy optimizer aimed at reducing energy consumption in 5G telecommunication networks. The methodology involved characterizing energy consumption patterns and developing a neuro-fuzzy model to regulate energy use while maintaining quality of service. The model was implemented in MATLAB and validated through comparative analysis. Results demonstrated significant energy savings: for Day 1, average power consumption decreased from 5,254.043 kW/day to 3,895.433 kW/day with machine learning, leading to a cost reduction of ₦81,542 and a 25.86% improvement. For Day 2, consumption dropped from 5,031.041 kW/day to 3,790.412 kW/day, resulting in savings of ₦74,617 and a 24.66% improvement. These findings highlight the effectiveness of machine learning in enhancing energy efficiency and reducing costs in telecommunication networks, paving the way for future sustainable network management solutions.

Keywords: Artificial Network, Machine Learning, Fuzzy Logic, 5G Network

1. Introduction

5G telecommunication networks offer improved connectivity, ultra-low latency, and faster data rates but come with the challenge of increased energy consumption, which impacts sustainability (Auer et al., 2011). Managing this energy footprint is critical as 5G expands globally, driven by IoT, smart cities, and advanced data-driven applications. Machine learning (ML) presents an effective solution by optimizing resource allocation, enhancing network management, and dynamically adjusting network parameters to reduce energy use (Li et al., 2018). The Radio Access Network (RAN) is responsible for most of the energy consumption in 5G, accounting for up to 80% (Hasan et al., 2011). ML strategies, such as sleep mode management, power scaling, and traffic prediction, significantly reduce energy usage during low-traffic periods (Sun et al., 2017). Techniques like reinforcement learning, deep learning, and supervised learning help optimize power control, manage traffic, and integrate renewable energy sources, leading to more energy-efficient 5G networks (Wang et al., 2020; Yu et al., 2019).

2. Review of literature

Zhang et al. (2021) examine machine learning algorithms like reinforcement and deep learning for optimizing energy use in 5G networks. While promising, these models face limitations in real-time deployment due to high computational demands. Liu et al. (2022) focus on deep learning-based traffic prediction models for adaptive power management in 5G, showing high accuracy but lacking integration with renewable energy sources. Sun et al. (2023) present a reinforcement learning method for resource allocation, effectively reducing idle times and adjusting base station power levels, though real-time implementation is hindered by long training times.

Wang et al. (2023) discussed AI-driven self-organizing networks (SON) for autonomously optimizing energy consumption, noting that current models remain limited to simulations with little real-world testing. Qiu et al. (2023) review energy-efficient 5G techniques, highlighting the gap in combining machine learning optimization with renewable energy sources for sustainable 5G networks.

3. Materials and Method

3.1. Materials

The hardware components, including the HP laptop, Fluke meter, and USB cable, were used to collect and manage current and voltage data from the 5G network infrastructure. This data was processed and analyzed using Excel and Fluke Connect software. Machine learning models were developed using the Neural Network Toolbox and MATLAB Classification Learner, all running on Windows 10. The results from the simulations helped optimize energy consumption in the 5G network without compromising service quality.

3.2. Methodology

The methodology for this work started with characterizing the energy consumption patterns in a 5G network infrastructure. A neuro-fuzzy model was then developed to regulate the energy consumption rate in the network while maintaining the quality of service. Fuzzy logic was employed to define the operational rules for the optimization process, while the neural network was trained to make the fuzzy inference system adaptive for controlling high energy usage. The model was implemented in MATLAB and tested through simulations, and the results were validated using comparative analysis.

4. System Design

Machine Learning and Fuzzy **(**MLF) are developed for managing energy consumption in the 5G telecommunication network. Here, the MLF is made of neural network and fuzzy logic. The neural network is designed as the backbone of the fuzzy inference engine and is used for energy management during the based station operation. The sequence diagram of fuzzy logic is presented in Figure 1.

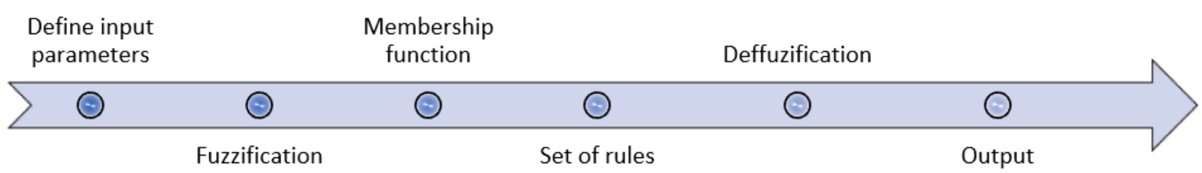


Figure 1: Sequence Diagram of the Fuzzy Operation

The fuzzy logic defines the input which is the power consumption level of the cell and also the quality of service considering the load factor to model congestion. These inputs were converted to fuzzified variables and membership functions, before programming the set of rules which are defuzzified as output. Table 1 presents the rule base.

Table 1 presents the rule base of the fuzzy logic. These inputs were defuzzied as output and then used to train the neural network. These outputs are statistical values which model the base station behaviour at diverse conditions and the energy consumed, then the algorithm shown in the sequence diagram in Figure 2 was used to train a neural network.

Table 1: Fuzzy Rule Base

Variables	Power	Congestion	Decision
1	High	High	Bad
2	Low	High	Bad
3	Partially high	High	Bad
4	Moderate	High	Bad
5	High	Low	Bad
6	Low	Low	Very good
7	Partially high	Low	Good
8	Moderate	Low	Good

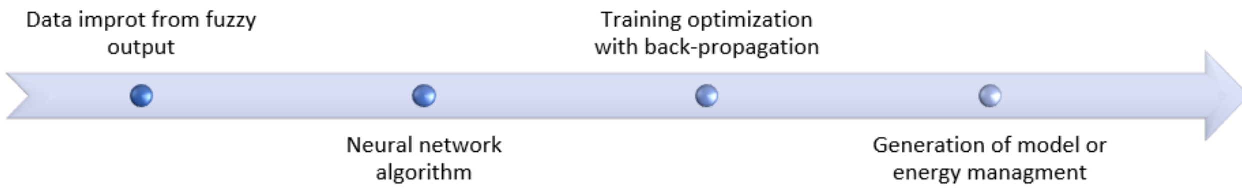


Figure 2: Sequence of the Neural Network

The input to the neural network is the fuzzed output and was fed to the algorithm for automatic configuration and splitting into training, test and validation sets, before the application of the back-propagation algorithm for the training optimization process, to generate the model for energy management.

4.1 The Energy Control Model

The energy control model for reducing energy consumption rates is based on a published characterization result (Okonko & Okafor, 2024). From the work, the minimum power consumed by the cell occurs on day 14, at 5230.24282 kW, while the maximum power consumption is observed on day 18, reaching 5368.46079 kW at 1.5 hours. These findings were utilized in the optimization process as follows:

Minimize

$P = X + 13.3Y$

Subject to:

$14X + 1.5Y \leq 5230.24282$

$18X + 1.5Y \leq 5368.46079$

Where:

P represents the minimum power consumed by the cell site,

X denotes the day of power consumption at the cell site, and

Y signifies the hour of power consumption at the cell site.

4.2. System Integration with MLF and Energy Optimization

The system block diagram in Figure 3 shows how the MLF and energy optimization algorithm were integrated to enhance the efficiency and performance of the network in energy consumption.

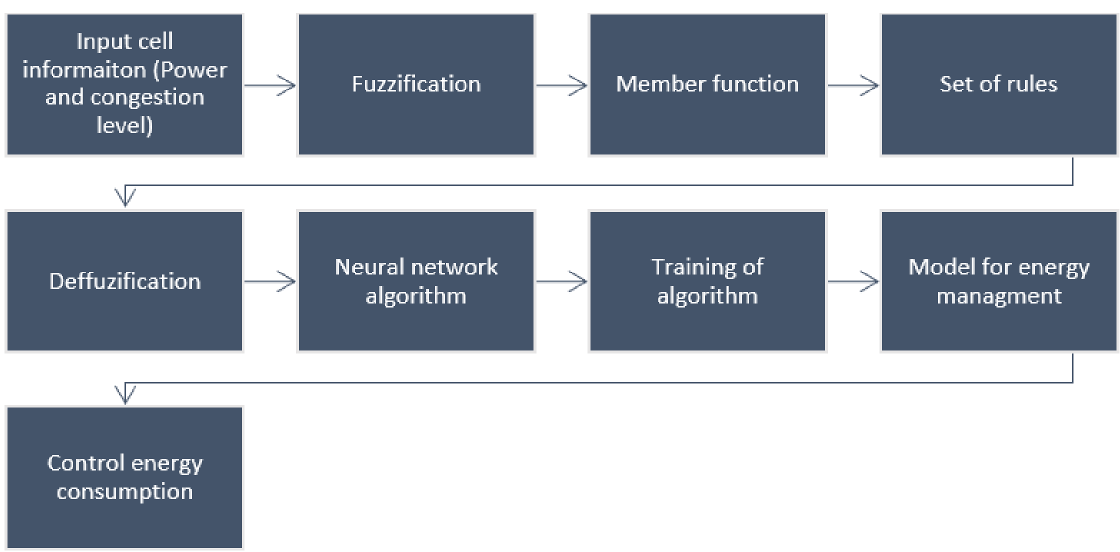


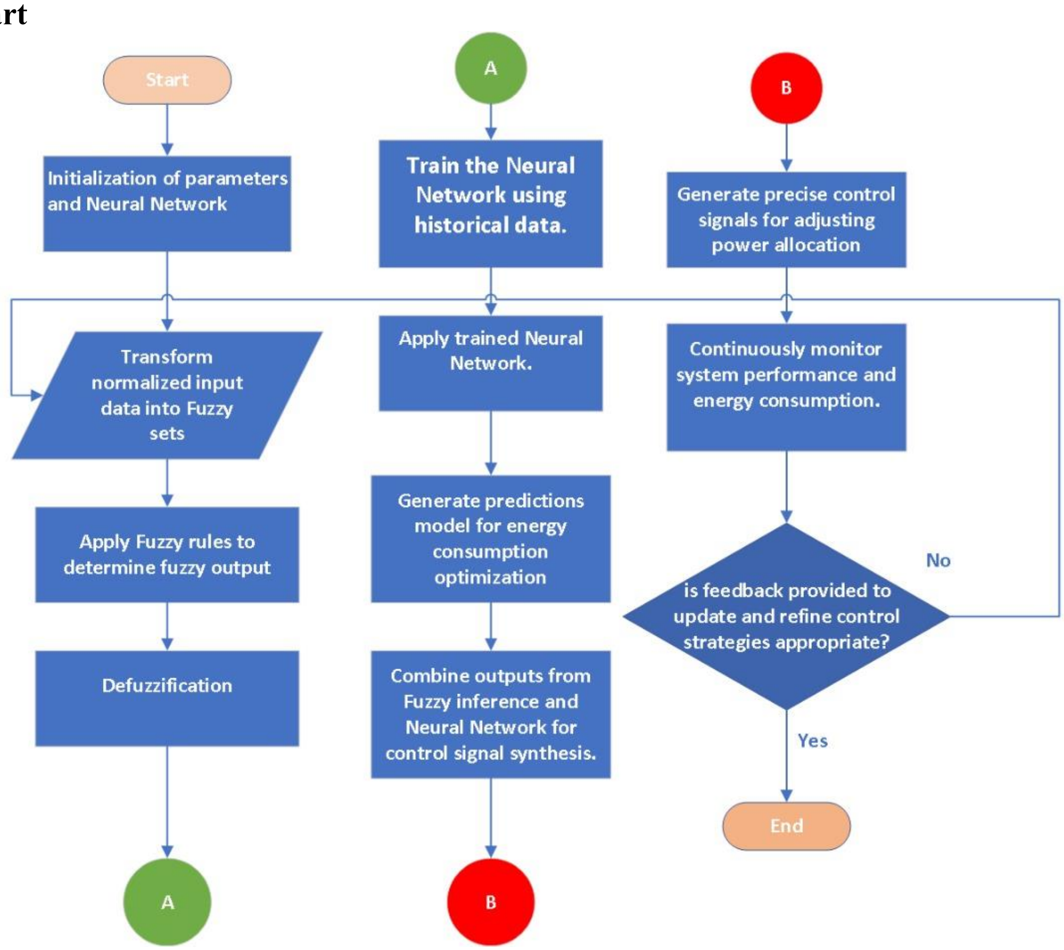
Figure 3: System Block Diagram of the MLF

Figure 3 illustrates the block diagram of the energy management and control system, centered around the MLF Controller that integrates neural networks and fuzzy logic. This controller processes input data, like power levels and congestion, through a fuzzy inference engine that generates fuzzy outputs for optimal energy management. Concurrently, historical and real-time data feed into the Neural Network Module, which uses advanced algorithms to identify patterns and refine its understanding of energy consumption dynamics. The outputs from both the Neuro-Fuzzy Controller and the Neural Network Module converge at the Energy Optimization Block, producing precise control signals for the Energy Management System. This system dynamically adjusts power allocation and transmission parameters in real time, optimizing energy consumption, and enhancing efficiency, reliability, and sustainability while meeting performance requirements.

Energy Management and Control Algorithm

1. Initialization of parameters and neural network
2. Transform normalized input data into fuzzy sets.
3. Apply fuzzy rules to determine fuzzy output.
4. Defuzzification
5. Train the neural network using historical data.
6. Apply trained neural network.
7. Generate predictions model for energy consumption optimization.
8. Combine outputs from fuzzy inference and neural network for control signal synthesis.
9. Generate precise control signals for adjusting power allocation
10. Continuously monitor system performance and energy consumption.
11. Provide feedback to update and refine control strategies.
12. Iterate through steps 2 to 11 to adapt to changing system conditions
13. Stop

Flowchart



5. System Implementation

Implementing the described system in MATLAB involves utilizing its extensive toolset for data manipulation, fuzzy logic, and neural network modelling. The first step is to import the necessary libraries and define variables that represent input data, such as power consumption and congestion levels. MATLAB offers efficient functions for data acquisition from various sources, including databases and real-time sensors, facilitating the collection of relevant information for analysis. After data acquisition, the Fuzzy Logic Toolbox in MATLAB allows for the creation of linguistic variables, membership functions, and rule bases essential for fuzzification and fuzzy inference. With user-friendly functions for defining membership functions and fuzzy rules, MATLAB simplifies the transformation of normalized input data into fuzzy sets and the determination of fuzzy outputs.

6. Result and Discussion

A simulation was carried out with MLF and the optimization algorithm to reduce the rate at which energy is consumed in a 5G network. During the simulation process, the power consumed by the network for three days was considered for 10 hours and the data each hour was collected. Figure 4 presents the results of the network energy consumption simulation for day 1 with machine learning and also without machine learning, while Figure 5 presents for day 2.

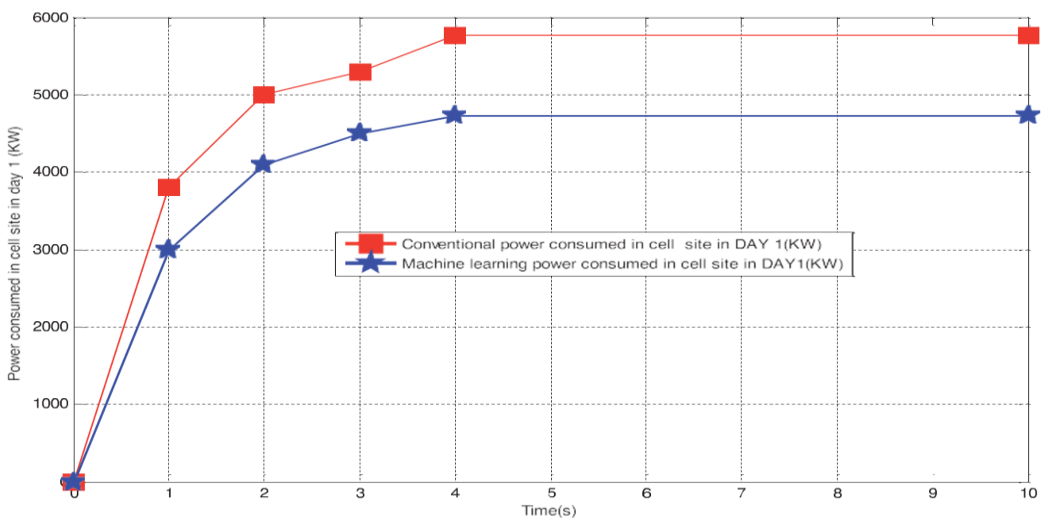


Figure 4: Result of Simulated Energy Consumption for Day 1

Figure 4 illustrates the simulated network power consumption for Day 1, comparing the machine learning-based fuzzy optimizer to a system without machine learning (ML). The results indicate that energy consumption was reduced with machine learning, whereas the system without ML exhibited higher energy usage. Specifically, the average power consumption without ML was 5,254.043 kW/day, while the average consumption with ML was 3,895.433 kW/day. The electricity cost without ML amounted to ₦315,242, compared to ₦233,700 with ML, resulting in a price difference of ₦81,542. The percentage improvement in energy consumption with machine learning (ML) for Day 1 is approximately 25.86%

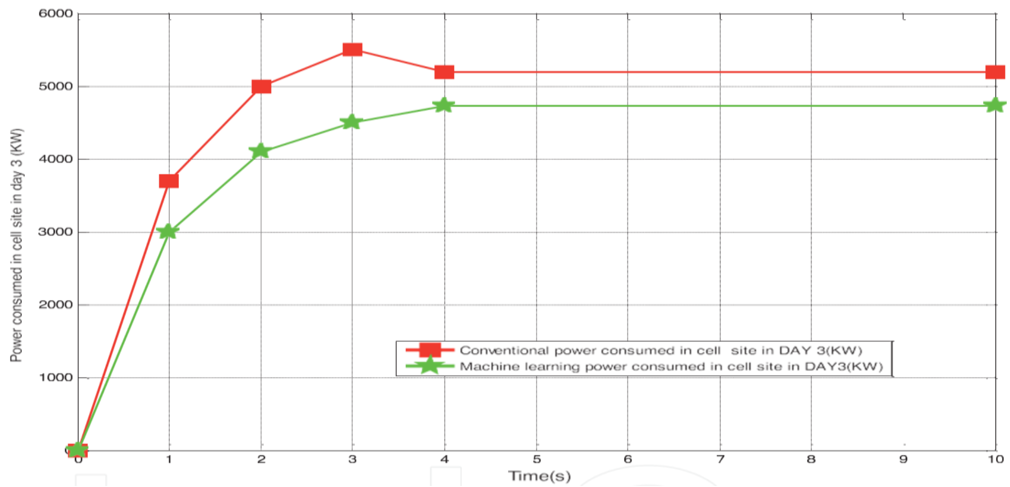


Figure 5: Result of Simulated Energy Consumption for Day 2

In Figure 5, which displays the simulated energy consumption for Day 2, it was observed that the average power consumption without machine learning (ML) was 5,031.041 kW/day, while the average consumption with ML was 3,790.412 kW/day. The cost of electricity without ML amounted to ₦302,042, compared to ₦227,424 with ML, resulting in a price difference of ₦74,617. The percentage improvement in energy consumption with machine learning (ML) is approximately 24.66%.

Conclusion

This study demonstrates that a machine learning-based fuzzy optimizer effectively reduces energy consumption in 5G telecommunication networks. For Day 1, average power consumption decreased from 5,254.043 kW/day without machine learning to 3,895.433 kW/day with it, resulting in a cost reduction of ₦81,542 and a 25.86% improvement in energy consumption. Similarly, Day 2 data showed a drop from 5,031.041 kW/day to 3,790.412 kW/day with machine learning, yielding cost savings of ₦74,617 and a 24.66% improvement. These findings highlight machine learning's potential to enhance energy efficiency, reduce operational costs, and support sustainability in telecommunications. Future research should focus on real-world applications and further optimizations to maximize energy savings while maintaining service quality.

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