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MODELING AND CONTROL OF VEHICULAR TRAFFIC SYSTEMS USING ARTIFICIAL INTELLIGENT NETWORK

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Abstract

Artificial intelligence (AI) has emerged as a transformative tool in addressing complex urban challenges, including traffic congestion in densely populated metropolitan areas. This study explores the application of AI-based models for optimizing traffic systems in Nigeria, with specific reference to the Abule Egba and Ikeja areas of Lagos State. Field data on traffic light timing and vehicle queue distances were collected and used to determine time delays within the traffic network. These measurements served as inputs to two AI models: Artificial Neural Network (ANN) and Fuzzy Inference System (FIS). The ANN model was structured with two input neurons, one output neuron, and five hidden neurons utilizing a log-sigmoid activation function. The dataset was split into 70% for training, and 15% each for testing and validation using MATLAB's ANN toolbox. The FIS model employed four triangular membership functions for each input and 150 constant membership functions for output representation. Both AI models were integrated into a traffic management simulation in SIMULINK and evaluated using R-squared values to assess performance. Results indicated that while both AI approaches achieved prediction accuracies above 99%, the ANN model demonstrated superior performance, achieving 99.953% for Abule Egba and 100% accuracy for Ikeja. These findings underscore the potential of AI-driven models in enhancing traffic control efficiency in urban environments.

Keywords: Models, Simulink, Neurons, Simulation, Artificial Intelligent.

1. INTRODUCTION

Traffic congestion remains one of the most pressing urban challenges, particularly in rapidly growing metropolitan areas. The problem is amplified by increasing population density, inadequate infrastructure, poor traffic management systems, and a general lack of adherence to traffic regulations. In Nigeria, for instance, thousands of car accidents are recorded annually, with major cities like Lagos being especially prone to severe congestion and associated risks. Despite the creation of regulatory bodies such as the Federal Road Safety Corps (FRSC), the impact of such institutions has been minimal in curbing road mishaps and improving traffic flow. The core causes of these traffic-related challenges in Nigeria and similar developing countries stem from several factors. These include widespread noncompliance with traffic rules, especially by influential groups such as military and government officials during emergencies and a general disregard for speed limits and safety protocols. Moreover, environmental factors, natural disasters, and political instability also contribute to road congestion and accidents. Traditional efforts to expand road networks or optimize existing systems have proven insufficient due to the exponential growth in vehicle numbers.

In light of these challenges, this study focuses on an innovative approach: the application of Artificial Intelligence (AI) in managing and controlling vehicular traffic. AI-based traffic management, which is already being explored in some developed countries, offers a promising solution to reduce congestion and improve safety. These systems utilize real-time data and intelligent algorithms to make dynamic decisions on traffic signal timings and vehicle flow management. By modeling traffic behavior using AI, particularly Artificial Neural Networks (ANN) and Fuzzy Logic Controllers, it is possible to enhance the responsiveness and efficiency of traffic systems.

The research utilized simulated data from traffic intersections in Lagos State, Nigeria. Key inputs for modeling included the distance of vehicles in four directions, queue durations, and time delays, measured in 15-second intervals. These variables were used to develop AI models capable of dynamically adjusting traffic signal timings based on actual congestion levels rather than fixed time schedules. The goal was to eliminate the conventional system where equal signal times are given to all directions regardless of traffic volume, which often leads to prolonged congestion and increased crash risks.

Specifically, the objectives of the study were to gather relevant traffic data, develop intelligent traffic control models, implement these models in a simulated environment, evaluate their performance, and compare the effectiveness of different AI techniques. The AI models were tested using Simulink software, allowing for simulation-based evaluation of their performance in managing traffic more effectively. However, the study had some limitations. Notably, the data used for modeling was derived from observed relationships rather than directly measured in real-time field conditions. Additionally, the intelligent system was not deployed or tested in actual traffic scenarios, limiting its immediate practical application.

Despite these limitations, the study is significant in laying the groundwork for future applications of AI in traffic management. It demonstrates the potential of intelligent systems to reduce congestion, improve traffic flow, and enhance road safety. The findings can serve as a valuable reference for traffic planners, city administrators, and researchers exploring modern solutions for urban mobility issues.

1.1 Network Intelligent Control and Traffic Optimization Based on SDN and Artificial Intelligence

In order to achieve network intelligent control, Guo and Yuan (2021) used experimental verification network control mechanism and SDN-based network traffic algorithm optimization. They also devised traffic optimization solutions based on artificial intelligence and SDN. The author examined the network needs of operators, including the IP backbone network, multi-protocol label switching virtual private network optimization, cloudification of services, and the provision of 5G mobile network service. Next, using SDN and artificial intelligence, the author suggested an intelligent network control architecture. Three modules make up the suggested architecture: an SDN controller module, an AI intelligent analysis module, and a network status collection/perception module. Figure1.0 depicts the traffic structure that was in use.

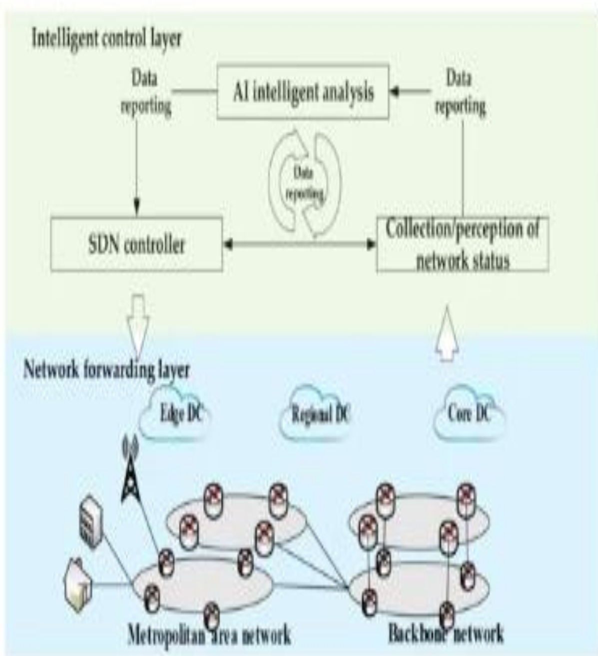

Figure1.0: Structure of the traffic model utilized (Guo and Yuan, 2021).

2. Modelling Smart Road Traffic Congestion Control System Using Machine Learning Techniques

With the use of Artificial Neural Networks (ANNs), Ata et al., (2019) want to develop a system to forecast traffic congestion, which would manage or limit the obstruction and lead to the smoothing of road traffic. The use of artificial back propagation neural networks (MSR2C-ABPNN) in the proposed modeling of smart road traffic congestion control for road traffic is expected to improve the availability, efficiency, and transparency of services provided to citizens. By training the neural network with the back-propagation method, the congestion prediction was made practical. The goal of the proposed system was to provide travelers more confidence to make wiser and better transportation decisions, and finding traffic circumstances using a neural network is a tenable strategy. When comparing the proposed MSR2C-ABPNN with Time series to the fitting technique, the MSE results are quite appealing.

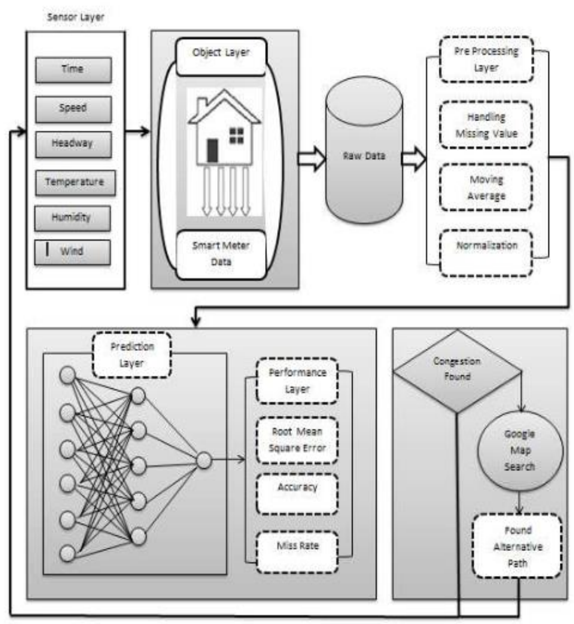

Figure1.1: Proposed MSR2C-ABPNN algorithm

2.1 Network Traffic Prediction Model Considering Road Traffic Parameters Using Artificial Intelligence Methods in VANET

In order to estimate network traffic, Sepasgozar and Pierre (2022) took into account the variables that may cause traffic on the roads. In order to estimate network traffic flow based on traffic in both the network and the road at the same time, the suggested model incorporates the Random Forest-Gated Recurrent Unit-Network Traffic Prediction algorithm (RF-GRU-NTP). The network traffic prediction based on V2R communication, road traffic prediction based on V2V communication, and network traffic prediction taking into account road traffic occurring based on V2V and V2R communication are the three phases of this model.

The hybrid proposed model, which is implemented in the third phase, uses the Random Forest (RF) Machine Learning algorithm to select the key features from the combined dataset (including V2V and V2R communications). Deep learning algorithms are then applied to predict network traffic flow, with the Gated Recurrent Unit (GRU) algorithm demonstrating the best performance. According to the simulation results, compared to previous algorithms utilized for network traffic, the suggested RF-GRU-NTP model performs better in terms of execution time and prediction errors.

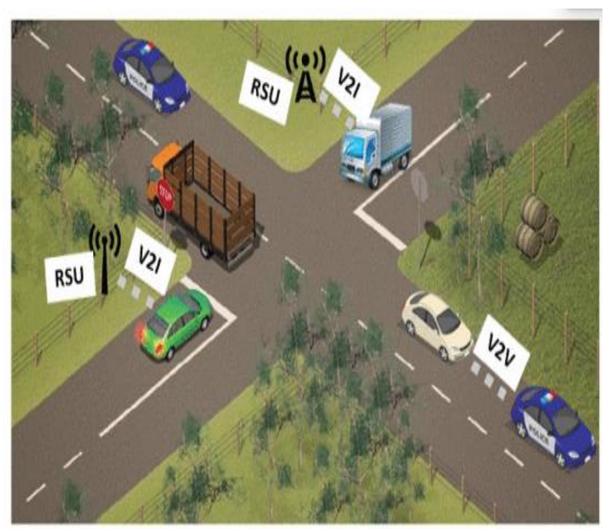

Figure1.2: Structure of VANET (Sepasgozar and Pierre, 2022).

3. MATERIALS AND METHODS

The materials utilized in this research are outlined in this section;

i. Traffic management data from two highly concentrated traffic in Lagos State, Nigeria.
ii. MATLAB application for data utilization in the ANN and FIS modeling.

iii. Microsoft excel and Microsoft office word for the arrangement of data.

3.1 Methods

The methods in this research include modeling of the traffic system network and the modeling and implementation of the traffic systems with MATLAB and Simulink for analyzing the performance of Artificial Neural Network (ANN)

3.2 Research Procedure

It was found that the existing traffic system in Nigeria was modelled by consuming the red and green light operate 90 seconds per direction totaling 360 seconds in all four directions. However, despite the placement of the traffic systems, long queues were seen on the concentrated congestion directions with one direction having no single vehicle for 5 seconds with the green light on. Hence, this study obtained information on site on the timing of the traffic systems, the distance covered by the vehicles before and after the green light systems with the average obtained. The average vehicle distance queue and the time of the traffic system for a period 6 hours were used as the input variable to the entire artificial intelligent model obtained and the time delay of vehicles in the traffic systems were utilized as the target to the artificial intelligent models utilized. The traffic systems were modeled in Simulink with the configured artificial intelligent models inserted in the traffic model to analyze the performance of both models to obtain the best model that would be utilized for intelligent traffic management systems. The summary of the research procedure is presented in the flow diagram below.

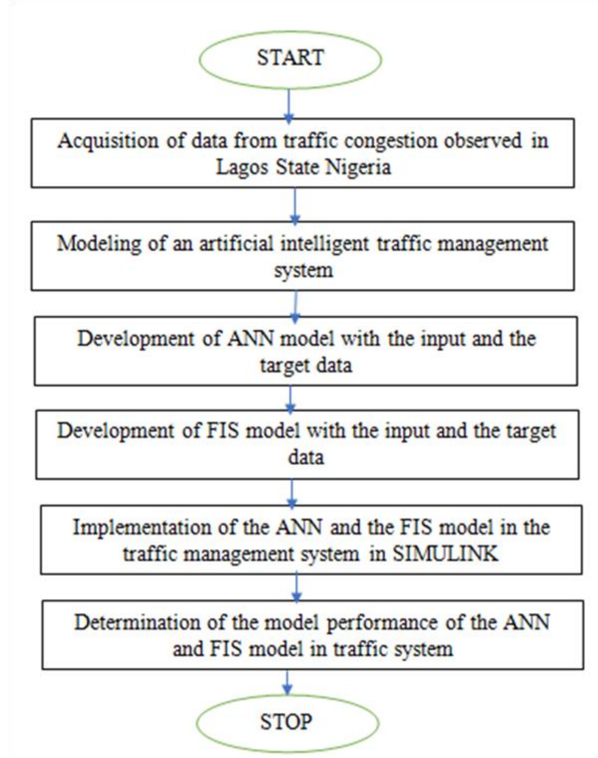

Figure1.3: Flow diagram of the research procedure

Source: The Researcher (2024)

3.2.1 Data Acquisition

The data was obtained from two traffic points; in Ikeja and Agege axis covering Abule Egba, route from mile 2 to Abeokuta. The snapshot of the first traffic junction captured in Abule Egba is shown in Figure1.4.

Figure1.4: Traffic junction at Abule Egba

The image in Figure1.2 has a four-direction traffic with the south and western directions being highly congested. It was found from observation that a vehicle from the south and western direction stayed up to 30 minutes due to long queues and the traffic timing were the same for each direction. The northern and eastern directions of the traffic system have a free flow of traffic and devoid of any form of traffic congestion. The distance of cars for every 90 seconds (time after the green traffic light) and 300 seconds (time before the green light traffic system) were obtained for each direction. The snapshot for the traffic system along Awolowo way in Ikeja is obtained and shown in Figure1.5.

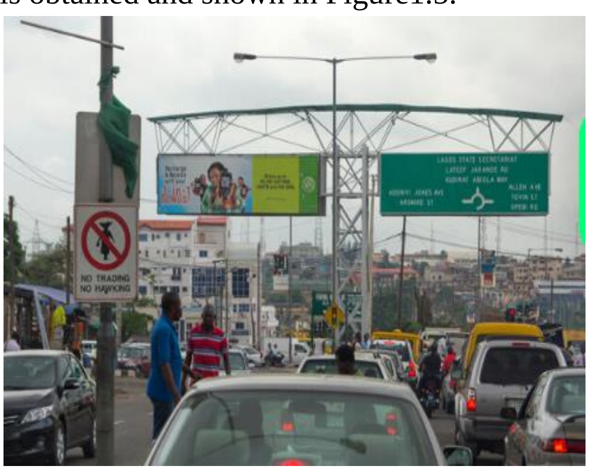

Figure1.5: Traffic system for Awolowo Way in Ikeja, Lagos State

The traffic light system as shown in Figure1.3 also operates in 40 seconds (for the green lights). The eastern and northern directions of the traffic were observed to be highly congested especially within the 6 hours it was monitored (6am to 12 noon) with the western and southern part of the traffic having quite a free flow of traffic. The time of the traffic systems were the same for all directions which was a source for concern. The data of the car queue distance every 90 seconds (after the green lights for each direction and 135 seconds (for before the green direction was obtained). The distance of vehicles per cycle (135 seconds) and after green light (40 seconds) were obtained with the time.

3.2.2 Modeling of the traffic system

The major essence of the traffic system model was to determine the delay time of the traffic with respect to increasing vehicular distance queue (D_{vq}) primarily using the green light timing (T_{gl}), combination of red-light timing and yellow light timing referred to as one full cycle (T_{RY}) and other factors mentioned at the course of the modeling.

The occurrence of queue overflow (Q_o) is expressed in Equation 3.1.

$$Q_o = n_o + n_1 D_{vo}^2 + n_2 \left(\frac{T_{gl}}{T_{RY}}\right) \quad \text{Equation 3.1}$$

where n_o to n_2 are to be determined through least square method in MATLAB

The delay time for one cycle (t_d) is shown in Equation 3.2.

$$t_d = dQ_o + \frac{2d(T_{gl})}{T_{RY}} \quad \text{Equation 3.2}$$

Hence, the total number of cycles for the total time the system was monitored (T_{cc}) is expressed in Equation 3.3.

$$T_{cc} = \frac{6 X 60 X 60}{T_{gl}+T_{RY}} \quad \text{Equation 3.3}$$

Hence the total time delay t_{Td} of the traffic is expressed in Equation 3.4.

$$t_{Td} = \int_0^{T_{cc}} \frac{t_d}{(T_{gl}+T_{RY})^{0.5}} T_{cc} \qquad \text{Equation 3.4}$$

The values from time delay for each cycle time was used as the target data for the targets to the artificial intelligent model.

4. RESULTS AND DISCUSSION

4.1 Results

The results of the models carried out are presented in this section.

4.1.1 Results for Abule Egba Traffic

The distance of the queue measured is shown in Figure 4.1;

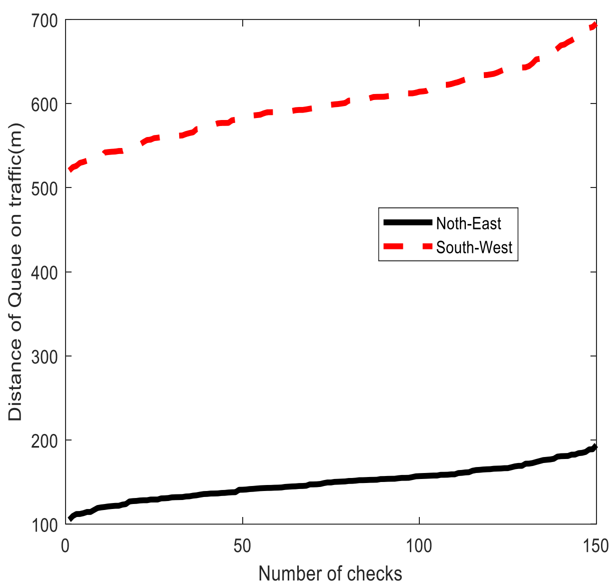

Figure 4.1: Distance of the queue measured form the Abule Egba traffic

The outcome in Figure 4.1 showed that the distance of the queue was longer in the south direction and the Western direction of the traffic while it was seen to be shorter in the Northern direction and the Eastern direction. This was found due to equal time assigned to the traffic light at all directions which increases the distance of both queues at every cycle. The actual time delay is shown in Figure 4.2.

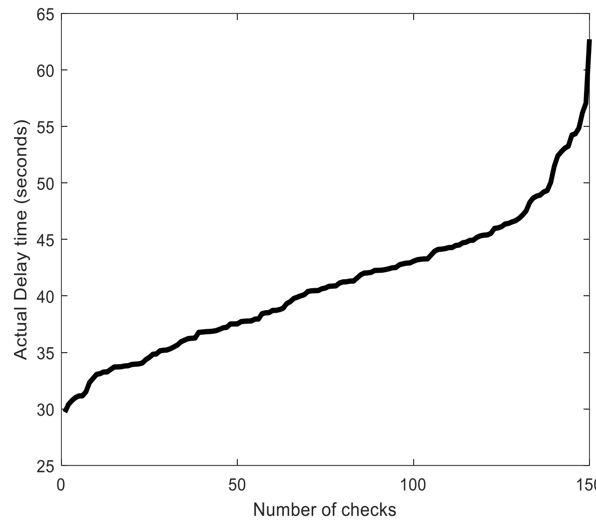

Figure 4.2: Actual time delay for the traffic system in Abule Egba

The time delay of the traffic system in Abule Egba in Figure 4.2 simply showed how the time should be implemented in Abule Egba showed that the time delay must be increased especially for the highly concentrated areas and as the cycle checks increases, the delay checks increases which implies that more vehicles emanates from the highly concentrated areas and the time must be automatically implemented the South and western areas to ensure less congestion.

The Mean Square Error (MSE) validation performance of the performance of ANN for traffic in Abule Egba had the best performance at 108th iteration (epoch) with the MSE value at that point approximately zero (0.000033291). This outcome implies that the outcome with ANN had an accept table performance. The R-values of the ANN model is shown in Figure 4.5.

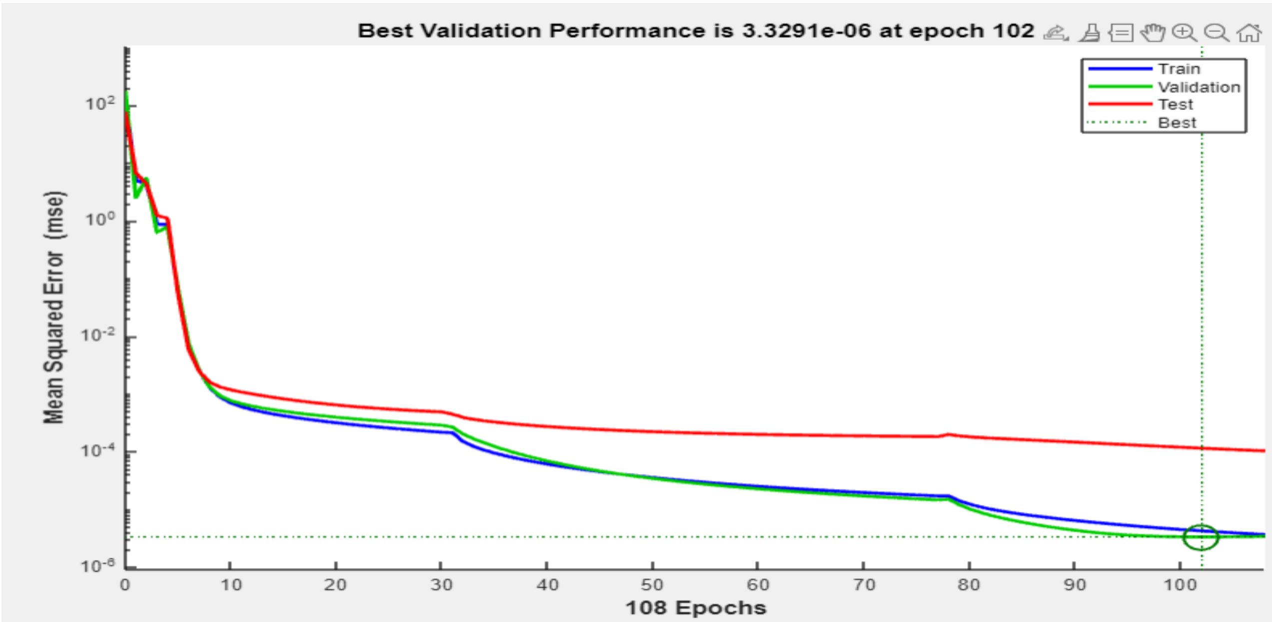

Figure 4.4: Model performance of the ANN model utilized for the validation of MSE

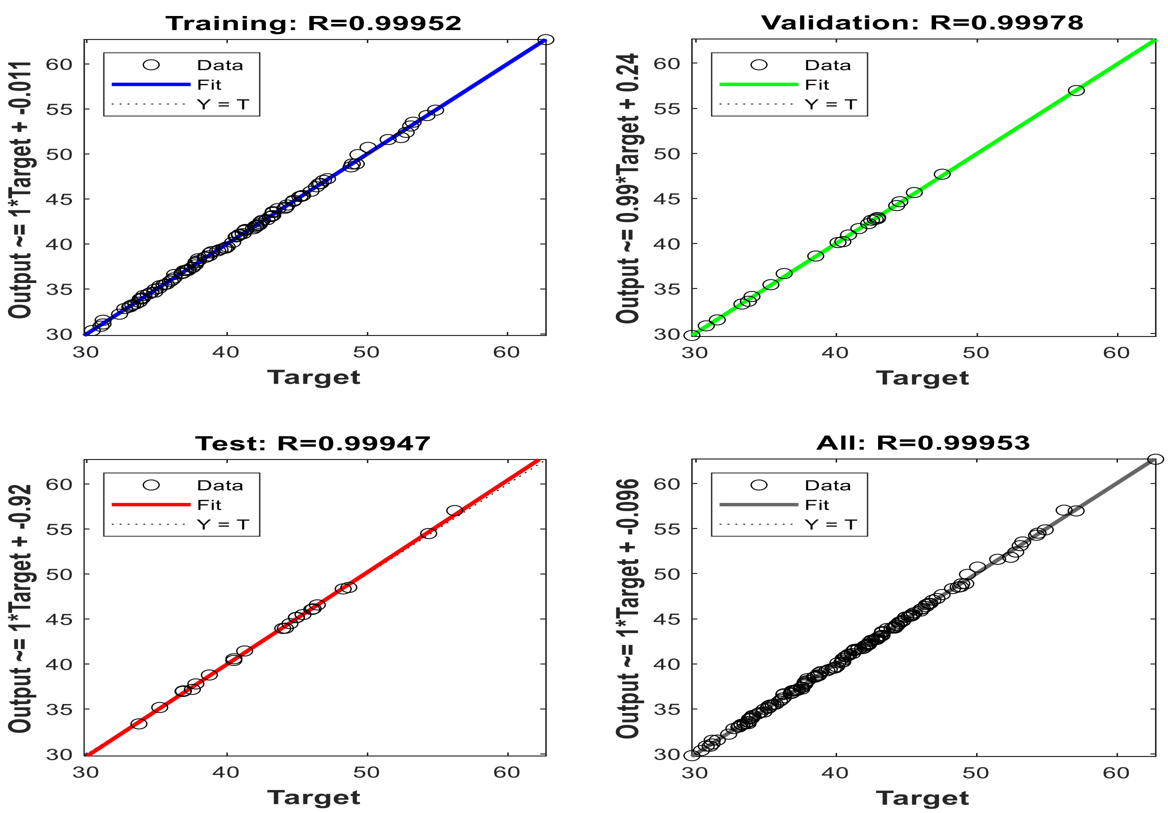

Figure 4.5: R-values of the ANN performance

The R-values shown in Figure 4.5 imply that the ANN model had a perfect performance. However, its level of performance was compared to the outcome from the fuzzy inference system.

The comparative plot between the actual time delay and the ANN predicted time delay is shown in Figure 4.6.

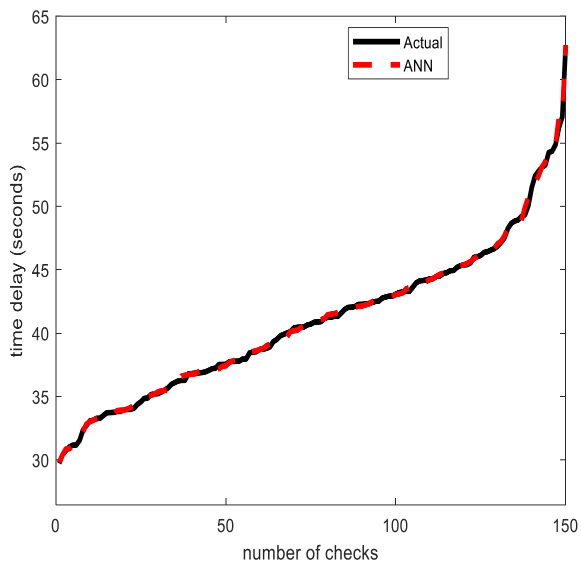

Figure 4.6: Comparative plot of the actual and ANN predicted time delay

It can be seen in Figure 4.6 that ANN perfectly tracked the actual time delay suggests that ANN should be implemented as a sensor to the traffic network at Abule Egba for appropriate control of the traffic system to minimize congestions in the area.

4.2 Discussion

The results for the traffic timing and the distance of the vehicles from the traffic system (congestion queue) were shown in Figure 4.1 and Figure 4.10 for Abule Egba traffic and Ikeja traffic respectively. While the congestion for the AgbuleEgba occurred at the South and the western direction, the lesser traffic was in north and the eastern directions. The reverse was the case for the traffic system in Ikeja. The actual time delay obtained for the traffic system in Ikeja and Abule Egba as shown in Figure 4.11 and Figure 4.2 show that the delay of the traffic system increases as the distance of the queues increases.

Hence, the time delay must be applied in the traffic signaling of the congested directions in both locations. The MSE validation performance in Figures 4.4 and Figure 4.12 for Abule Egba and Ikeja respectively showed that the error values were low with the ANN performance being its best at 102 iterations for Abule Egba and 1000 iterations for Ikeja axis. This implies that the ANN model comfortably predicted the time delay of the traffic system. This was confirmed by the R-values in Figure 4.5 (for Abule Egba with accuracy of 99.953%) and Figure 4.13 (for Ikeja with accuracy of 100%).

The comparative plots in Figure 4.6 (for Abule Egba) and Figure 4.14 (Ikeja) showed that ANN model comfortably tracked the time delay of which when implemented would effectively optimize the control of the traffic system by increasing the time delay where the congestions are high and lowering the timing where the directions are the same. This can also be said for the implementation of FIS in Figure 4.7 and Figure 4.8 (for Abule) and Figures 4.15 and Figure 4.16 (for Ikeja) which showed that the predicted time delay with FIS satisfactorily tracked the actual time delay data. However, the comparative analysis performed in Figure 4.9 and Table 4.1 (for Abule Egba) and Figure 4.17 and Table 4.2 (for Ikeja) stated that ANN model had a better performance than FIS model system though both models can be utilized due to high prediction performance accuracy.

5. Conclusion

The results of this study demonstrated the effectiveness of artificial intelligence in optimizing urban traffic management systems. The Artificial Neural Network (ANN) model, trained using real-time traffic data from Abule Egba and Ikeja in Lagos State, Nigeria, achieved remarkable prediction accuracies of 99.953% and 100% respectively. This high level of performance highlights the capability of AI, particularly neural networks, to accurately model and predict traffic time delays based on observed conditions. The successful integration of the ANN model into the simulated traffic control system underscores its potential as a robust tool for enhancing traffic flow and reducing congestion in metropolitan areas. It is therefore recommended that AI-driven models like ANN be adopted for real-time traffic management and control in urban centers to improve transportation efficiency and safety.

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