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Evaluation of Urban Traffic Flow with Neural Network Algorithms in Intelligent Traffic Control Systems

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Abstract

Traffic congestion in road transportation presents a significant issue for both developed and developing nations. This research leverages artificial intelligence (AI) to assess, retime, and analyze pre-timed traffic signals in the Oredo local government area of Edo State, where vehicle volume has recently surged. Traffic data, including vehicle flow, composition, and movement, was manually recorded at 15-minute intervals. Machine learning techniques, particularly an Artificial Neural Network (ANN) combined with SUMO (Simulation of Urban Mobility), were applied to optimize signal timing and reduce intersection control delay. The analysis demonstrated a 15% reduction in average control delay, from 44.4 seconds to 36.6 seconds, and improved the level of service (LOS) from 'D' to 'C' during peak hours. The ANN model achieved a low root mean squared error (RMSE) of 2.26 × 10^-13, indicating high accuracy. The optimal model, which featured four hidden layers with 64 neurons each and was trained for 250 epochs, achieved the best validation performance of 0.01748667. These results demonstrate the effectiveness of AI-based models in improving traffic signal performance and mitigating congestion at intersections.

Keywords: *Traffic Congestion, Artificial Neural Network, Traffic Signal Optimization, Intersection Control Delay*

1. Introduction

Transportation plays a critical role in national development by facilitating the movement of knowledge, goods, and people across societies (Oyesiku, 2002). In urban areas, effective transportation systems are essential for sustaining economic activities and social interactions (Mehndiratta and Quiros, 2017). However, the rapid production and sale of approximately 253 million vehicles annually (Hippolitus et al., 2017) have intensified traffic congestion, a persistent global issue requiring innovative solutions. Extensive research efforts are focused on alleviating these challenges, particularly through the application of Artificial Intelligence (AI) (Voženílek, 2009). AI, which emulates human-like reasoning and decision-making, offers powerful tools such as expert systems and heuristic algorithms (Zuylen, 2009). The paper explores convolutional neural networks for intelligent traffic signal control, offering insights into real-time system optimization. (Chen et al., 2021). A hybrid neural network model is developed to optimize traffic control strategies, demonstrating substantial delay reductions (Jiang et al., 2022).

Further advancements in technology, such as Virtual Reality Geographical Information Systems (VRGIS), enable detailed visual analyses and enhanced data management, providing crucial support for transportation planning (Li et al., 2019). Despite these innovations, traffic congestion remains a pressing problem, especially in urban centers like Edo State, where fixed pre-timed traffic signals are commonly used. These systems, unable to adapt to fluctuating traffic conditions, contribute to delays, increased fuel consumption, accidents, and pollution (ITE, 2005). Studies from developed regions, including the United States and Europe, have demonstrated that signal retiming—updating the timing settings, phasing sequences, and control strategies of traffic signals—offer a cost-effective approach to improving traffic flow and reducing congestion (Paulson, 2002). The effectiveness of such interventions is typically measured using metrics like the average intersection control delay, a key indicator of performance (Camp, 2010; Hadiuz et al., 2014). However, as populations grow, vehicle numbers increase, and land-use patterns diversify, intersections face mounting pressure. This is particularly evident at the Iyaro intersection on Urubi-Lagos Road in Benin City, where inadequate traffic management exacerbates congestion (ITE, 2005). This research seeks to address these challenges by systematically analyzing and improving the pre-timed traffic signals at intersections in Oredo Local Government Area of Edo State. The study begins by determining the existing signal specifications for the intersections. Traffic volume counts and saturation flow headway surveys are then conducted to capture comprehensive data on traffic patterns. A retiming analysis of the signal timing parameters is performed using neural network models, which are also employed to evaluate the effectiveness of the retimed signal design. Finally, the study compares the performance of the neural network models to the existing signal designs by analyzing the average intersection control delay and level of service as defined by the Highway Capacity model. Through these efforts, this research aims to optimize traffic flow, reduce delays, and improve the operational efficiency of signalized intersections, ultimately enhancing commuter experiences, reducing accidents and emissions, and promoting sustainable urban transportation management.

2.0 RESEARCH METHODOLOGY

2.1 Description of the Study Area

The study took place specifically at Iyaro Intersection, located along Urubi-Lagos Road in the Oredo Local Government Area of Benin City, Edo State, Nigeria. This four-way intersection connects two major Federal Government roads: Dawson-Urubi-Uselu Road on the East-West axis and Lawani-Evbiemwen on the North-South axis. The intersection is set on a dual carriageway with relatively flat terrain. The location is precisely defined by the geographical coordinates: latitude 06°21' 6".38 to 06°21' 7".80N and longitude 05°37'43".22 to 05°37'44".80E.Figure 1 shows the intersection contains both Federal Government roads, the Dawson-Urubi-Uselu roadon the East-West axis and the Lawani-Evbiemwen road on the North-South axis.

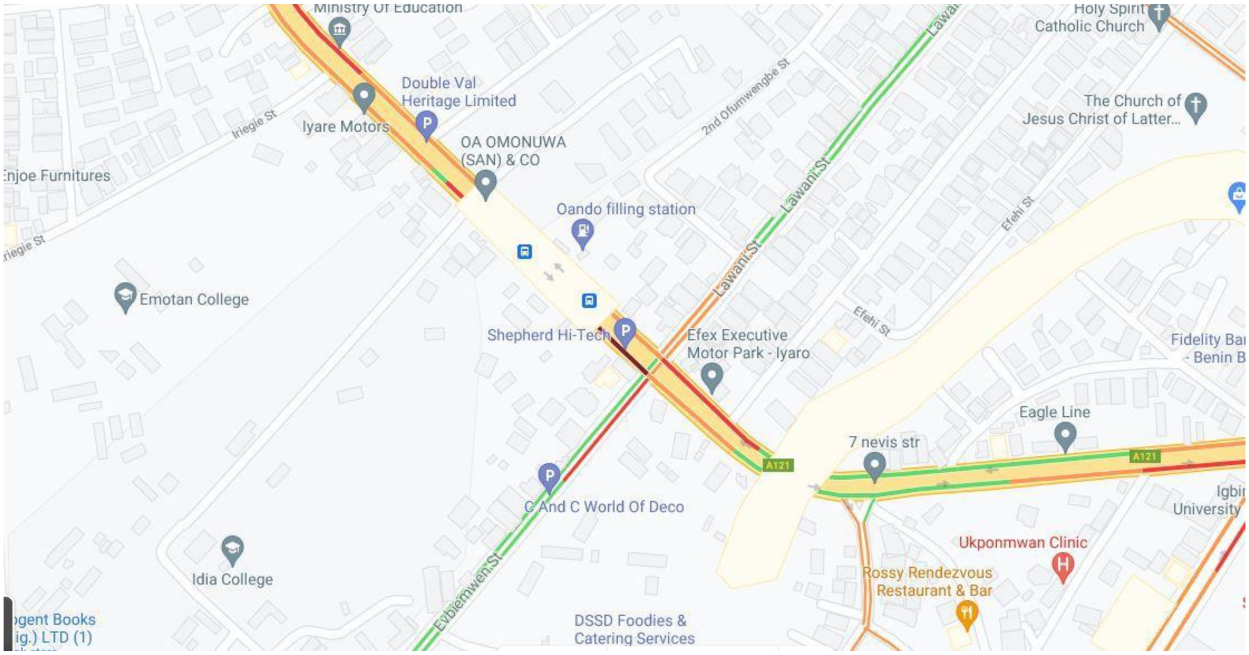

Figure1: Real-time traffic conditions, Iyaro Intersection (Source: Google Earth, 2021)

2.2 Traffic Volume Acquisition and Prediction

The traffic data consisting of the Total Traffic Volume for each road, Day, Time/Class, Weather Condition and Green Times for each road for this study were collected through on-site observations using tools like a notepad, measuring tape, and video camera. The neural network model was designed by defining key variables and factor ranges that aligns with the study objective. Input variables included Total Traffic Volume for each road, as well as Day, Time/Class, and Weather Condition, while the output variable was Green Time (seconds) for each road in the study. The influence of these independent variables was analyzed and categorized into various levels, forming the basis for a neural network model developed in Python using Anaconda and Jupyter. The range and levels of the experimental variables used for the statistical design of the experiment are shown in Table 1 below.

Table 1: Input/output variables of the feed Forward Back Propagation Neural Network System

Sr. No	Input/Output Variable Name
Input 1	Total Traffic Volume for each road
Input 2	Day
Input 3	Time/Class
Input 4	Weather Condition
Output 1	Green Time(s) for each road

Using the variables presented in Table 1, feed forward back propagation method using Tensor Flow was done. Neural network design was done with the aid of python programming language using Anaconda Jupyter. Through basic Calculus and with the help of Anaconda Jupyter, all the values of effective green time were determined and added to the table for every corresponding movement.

The basic vehicular and pedestrian timing requirements for an intersection can be obtained by analyzing the intersection layout, including lane configurations, pedestrian crossings, and traffic volumes. Field studies are conducted to measure vehicular flow rates, pedestrian counts, and peak traffic periods. These data are then used to calculate minimum green times, clearance intervals, and pedestrian walk intervals according to traffic engineering standards. The timing plans are validated through simulation or on-site testing to ensure they meet both efficiency and safety requirements.(Zhou et al., 2024).

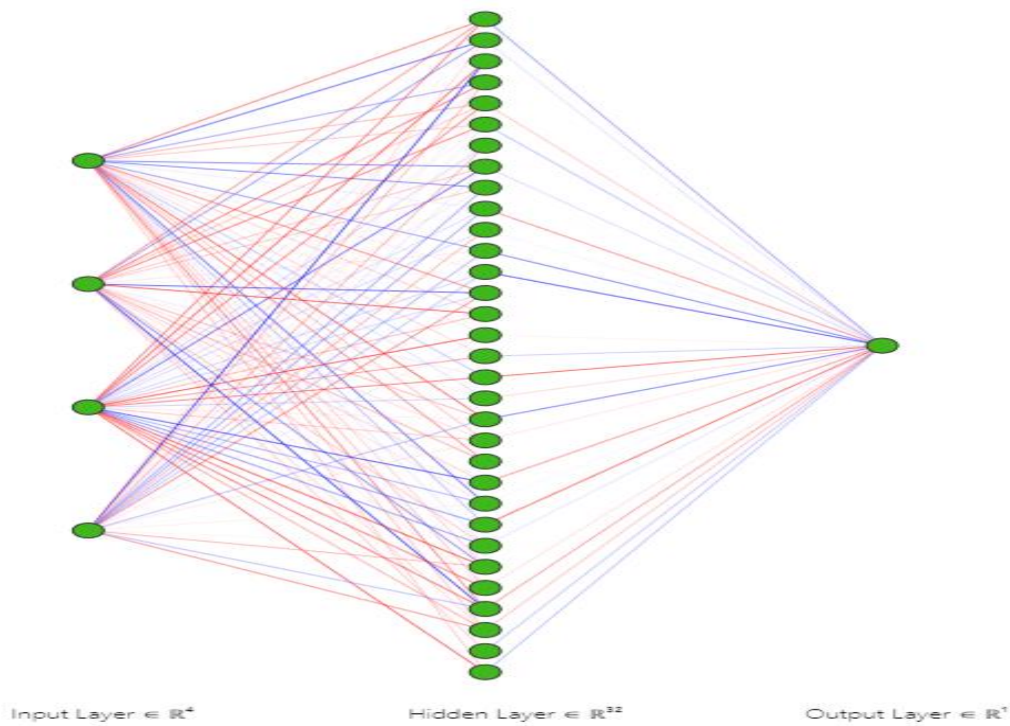

Figure 2: Feed Forward Neural Network Model Architecture

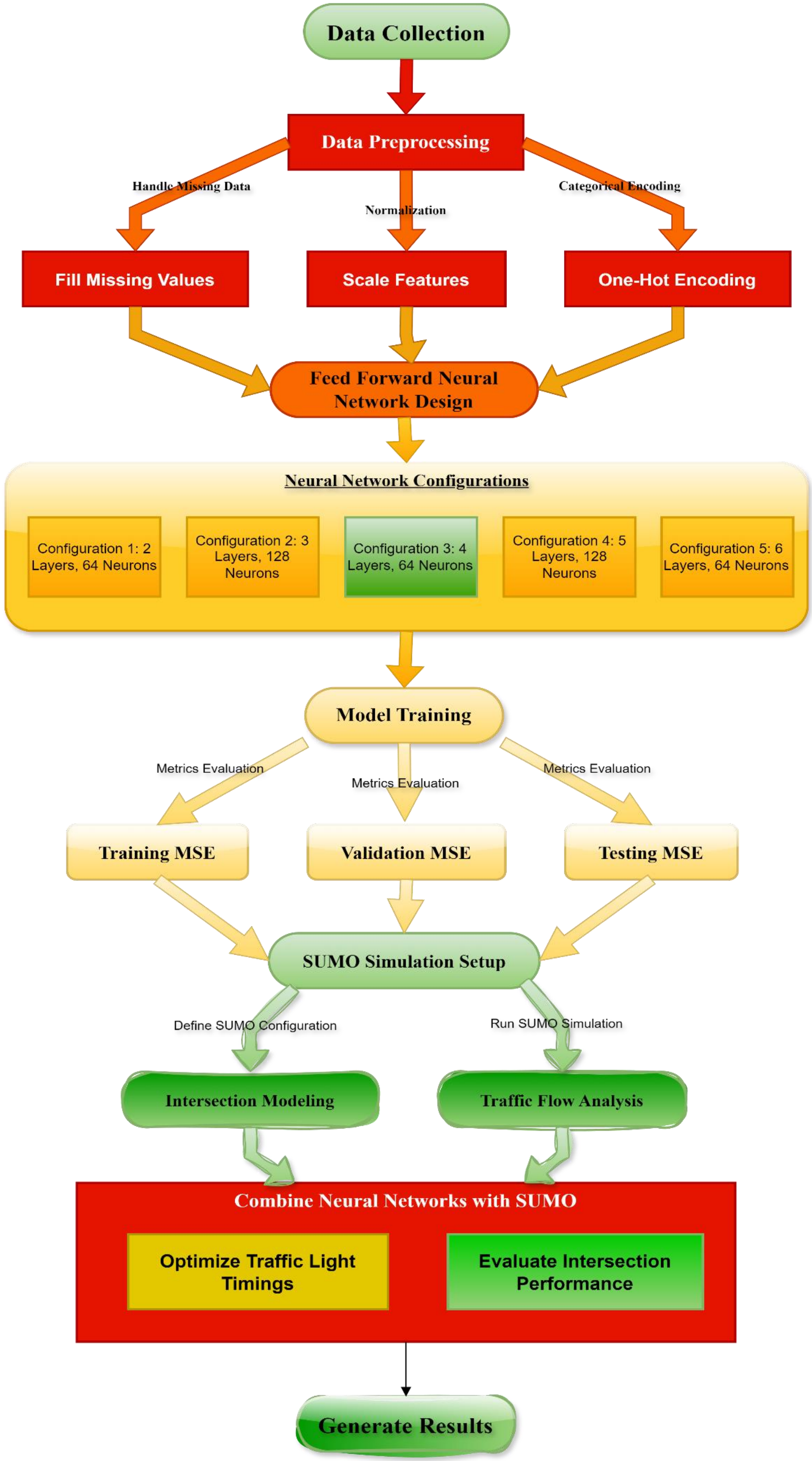
Data Collection
Data Preprocessing
Handle Missing Data
Normalization
Categorical Encoding
Fill Missing Values
Scale Features
One-Hot Encoding
Feed Forward Neural Network Design
Neural Network Configurations
Configuration 1: 2 Layers, 64 Neurons
Configuration 2: 3 Layers, 128 Neurons
Configuration 3: 4 Layers, 64 Neurons
Configuration 4: 5 Layers, 128 Neurons
Configuration 5: 6 Layers, 64 Neurons
Model Training
Metrics Evaluation
Metrics Evaluation
Metrics Evaluation
Training MSE
Validation MSE
Testing MSE
SUMO Simulation Setup
Define SUMO Configuration
Run SUMO Simulation
Intersection Modeling
Traffic Flow Analysis
Combine Neural Networks with SUMO
Optimize Traffic Light Timings
Evaluate Intersection Performance
Generate Results

Figure 3: A flowchart of the Algorithm used for the python programming project

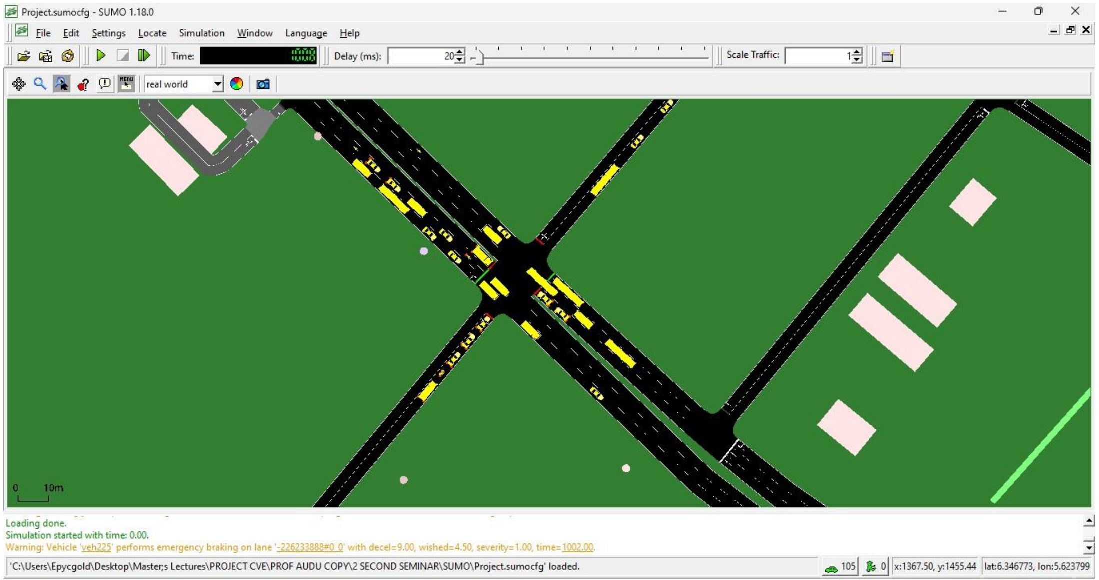

Figure 4: A Four-Way Intersection Simulation on SUMO.

Figure 2 shows the Feed Forward Neural Network Model Architecture with the input, hidden and output layers and neurons connected. Figure 3 shows the flowchart of the Algorithm used for the study and Figure 4 shows a Four-Way Intersection Simulation generated on a SUMO interface. However, the study of this phenomenon is beyond the scope of this research.

3.0 RESULTS AND DISCUSSION

3.1 Traffic Volume of the Study Area

The results of this study comprise of both field data and the values gotten from processed information using appropriate, python programming language (Anaconda Jupyter) and Microsoft Excel.The optimal equation which shows the individual effects, and the combine interactions of the selected input variables, namely; Total Traffic Volume for each road, Day, Time/Class and Weather Condition against the measured output variable, namelyGreen Time(s) for each road is presented based on actual factors. Table 2 shows traffic volumes in Passenger Car Units per hour (PCU/hr) for various vehicle categories across four roads: Dawson Road, Urubi Road, Lawani Street, and Evbiemwen Street.

Table 2: Traffic volume at Iyaro intersection for all approaches in pcu/hr

Vehicle Category	Dawson Road	Urubi Road	Lawani Street	Evbiemwen Street
3 Wheelers	188.8	696.8	396	1388.8
Passenger cars	23752	54023	4987	5420.1
Small buses	16888	41352	1294	819.7
Medium Buses	16484	49900	432	388
Light Goods vehicles	8818.5	24354	210.75	411
Heavy Goods Vehicles	8394.8	29912.8	112	318.5
Total PCU/hr	74526	200238.6	7431.8	8746.1

The average saturation flow rate for each lane, derived from the saturation flow headway survey and presented in Table 2, highlighted notably reduced rates for directional movements from minor roads Lawani and Evbiemwen. This reduction was linked to the poor pavement conditions, which increased the approach time for vehicles and decreased the saturation flow rate, thereby intensifying congestion and leaving many vehicles queued through subsequent green signal periods.Figure5 shows the 15 minutes' variation of the volume of passenger cars unit making use this intersection obtained from Table 2.

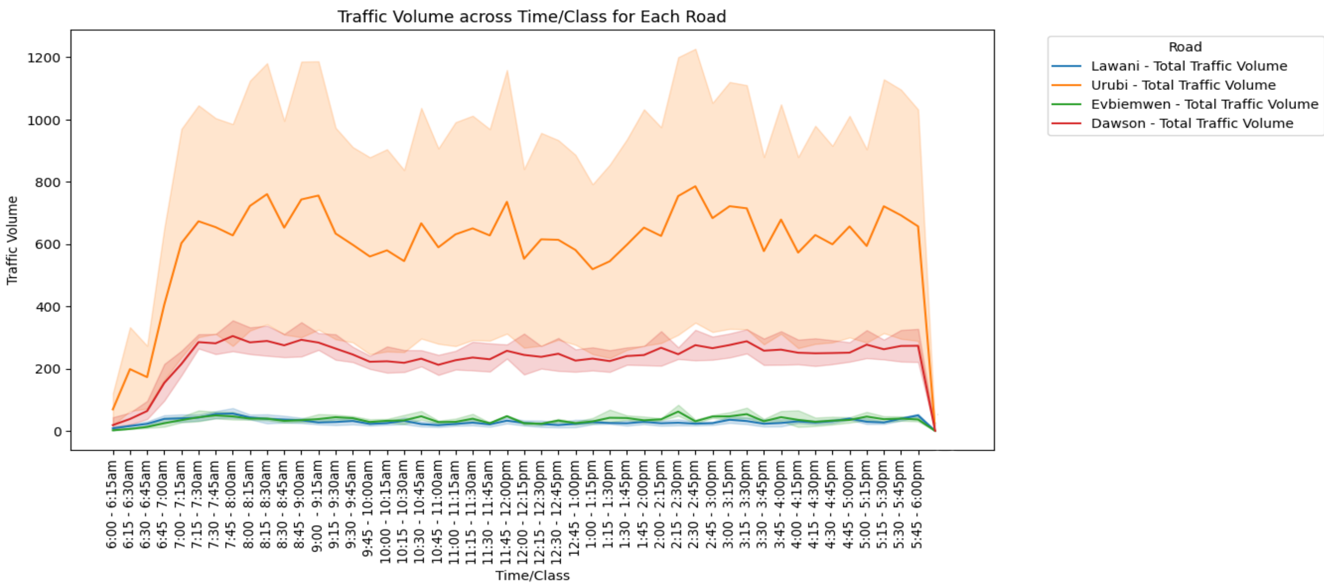

Figure5: Total Traffic Volumes at Iyaro intersection at 15 minutes interval

Figure6 shows the current phase diagram for the intersection based on Highway Capacity model for creating protected left turns. It shows the allowed movements during the phases based on the examination of the arrival flows and allowable movements.

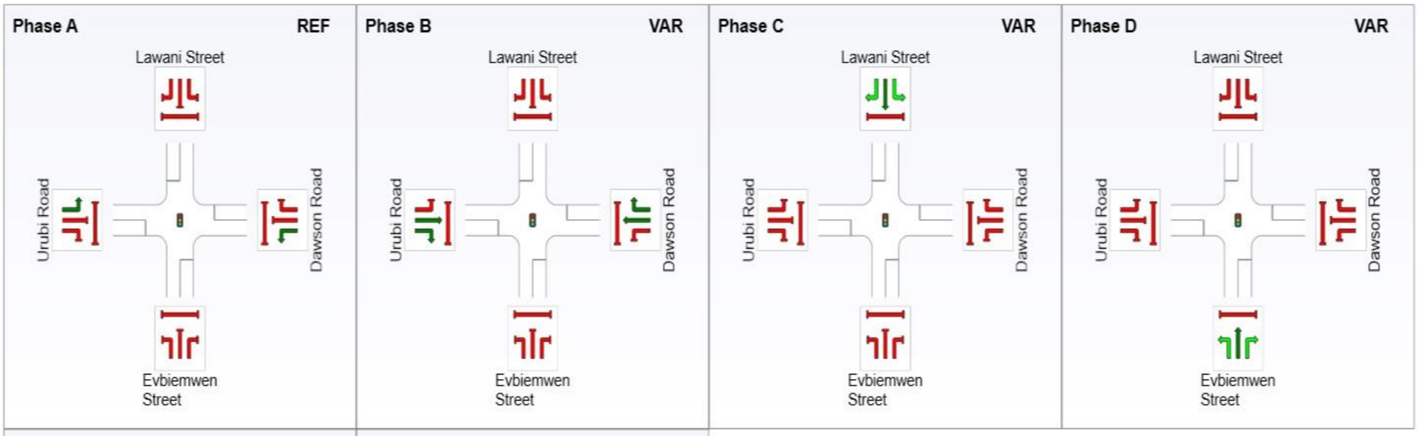

Figure6: Four Phase Cycle Configurations showing the allowed movements

A retiming analysis of the signal parameters, using Neural Network Models, was conducted to optimize the intersection's efficiency. The four-phase cycle design for the intersection, shown in Figure 3, outlines the permitted vehicle movements for each phase. Observations revealed extended waiting times even when no vehicles were utilizing the intersection, pointing to inefficiencies. By implementing a neural network model, waiting times during green intervals were reduced, enhancing vehicular safety by enabling paired movements that minimize the risk of collisions.

The basic timing requirements for each approach lane, outlined in Table 3, specify a 3-second amber light, based on an approach speed of 54 km/hr to align with local standards. This timing provides attentive drivers with sufficient time to stop safely. An all-red phase of 2 seconds, where all lights show red, was also established. The ITE report (ITE, 2005) and practiced in Canada recommend a minimum of 1 second for straight-through movements. Additionally, a 6-second inter-green period was implemented to stagger conflicting movements across phases, while a lost time of 5 seconds per phase was allocated to account for any halted traffic movements.

Table 3:Basic Vehicular Timing Requirements

Approach lane	Phase	Amber interval (s)	All-red period (s)	Intergreen period (s)	Lost time (s)
U-L(LT)	A	2	2	6	6
D-E(LT)	A	2	2	6	6
U-D(TH & RT)	B	0	2	6	6
D-U(TH & RT)	B	0	2	6	6
L-E (RT, TH&LT)	C	1	2	6	6
E-L (RT, TH&LT)	D	1	2	6	6

U - Urubi Road TH - STRAIGHT
D - Dawson Road LT - LEFT
L - Lawson Street RT - RIGHT
E - Evbiemwen Street

3.2 Feature Description on the Neural Network Model

The main features considered for the Neural Network Model include the total traffic volume from the four main roads: Lawani, Urubi, Evbiemwen, and Dawson, along with the day of the week and specific time classes. Table 4 shows total traffic volume statistics for four roads: Lawani, Urubi, Evbiemwen, and Dawson. Each road has 247 data points. Urubi Road has the highest average traffic volume (592.13 PCU) and the greatest variation (std: 446.01).

Table 4: Feature Description of Retimed Signal Timing Parameters

Statistical parameters	Total Traffic Volume			
	Lawani	Urubi -	Evbiemwen	Dawson
Count	247	247	247	247
Mean	29.953	592.131	35.49939107	233.350
Std	19.488	446.0125	21.496	82.114
Min	0	0	0	0
25%	19	278.5	25.5	202.5
50%	27	320	33	244
75%	39.5	1079.5	43.5	282
max	233.350	1457	233.350	406

Investigation of the performance of various neural network configurations for predicting traffic patterns at Iyaro intersection were performed. The study has shown that different architectural choices impact the model's ability to learn complex relationships within the traffic data while avoiding overfitting.

Table 5 shows performance metrics for five neural network models (C-1 to C-5) using a Feed Forward Back Propagation algorithm. Each model varies in the number of hidden layers (ranging from 2 to 6) and hidden neurons (either 32 or 64), with the ReLU transfer function applied across different epochs (150 to 300). Training and validation Mean Squared Error (MSE) values are provided, showing similar trends across models, while testing MSE indicates varying performance.

Table 5: Summary of Feed Forward Neural Networks Architecture for Traffic Volume Prediction at the Intersection

Model	C-1	C-2	C-3	C-4	C-5
Neural Network Algorithm	FFBP	FFBP	FFBP	FFBPon	FFBP
Hidden layer	2	3	4	5	6
Hidden Neurons	32	64	64	32	64
Transfer Function	ReLU	ReLU	ReLU	ReLU	ReLU
Number of Epoch	150	200	250	200	300
Training MSE	0.03909774	0.01993858	0.01748667	0.0220057	0.0175215
Validation MSE	0.03909774	0.01993858	0.01748667	0.0220057	0.0175215
Testing MSE	0.03462691	0.04886178	0.09942784	0.09901242	0.10394439

Where FFBP - Feed Forward Back Propagation

Figure7 shows the performance plots of various neural network configurations used to predict traffic patterns at the Iyaro intersection. The chart compares five configurations, each differing in the number of hidden layers, neurons per layer, and training epochs. Key metrics such as Training Mean Squared Error (MSE), Validation MSE, and Testing MSE are plotted for each configuration

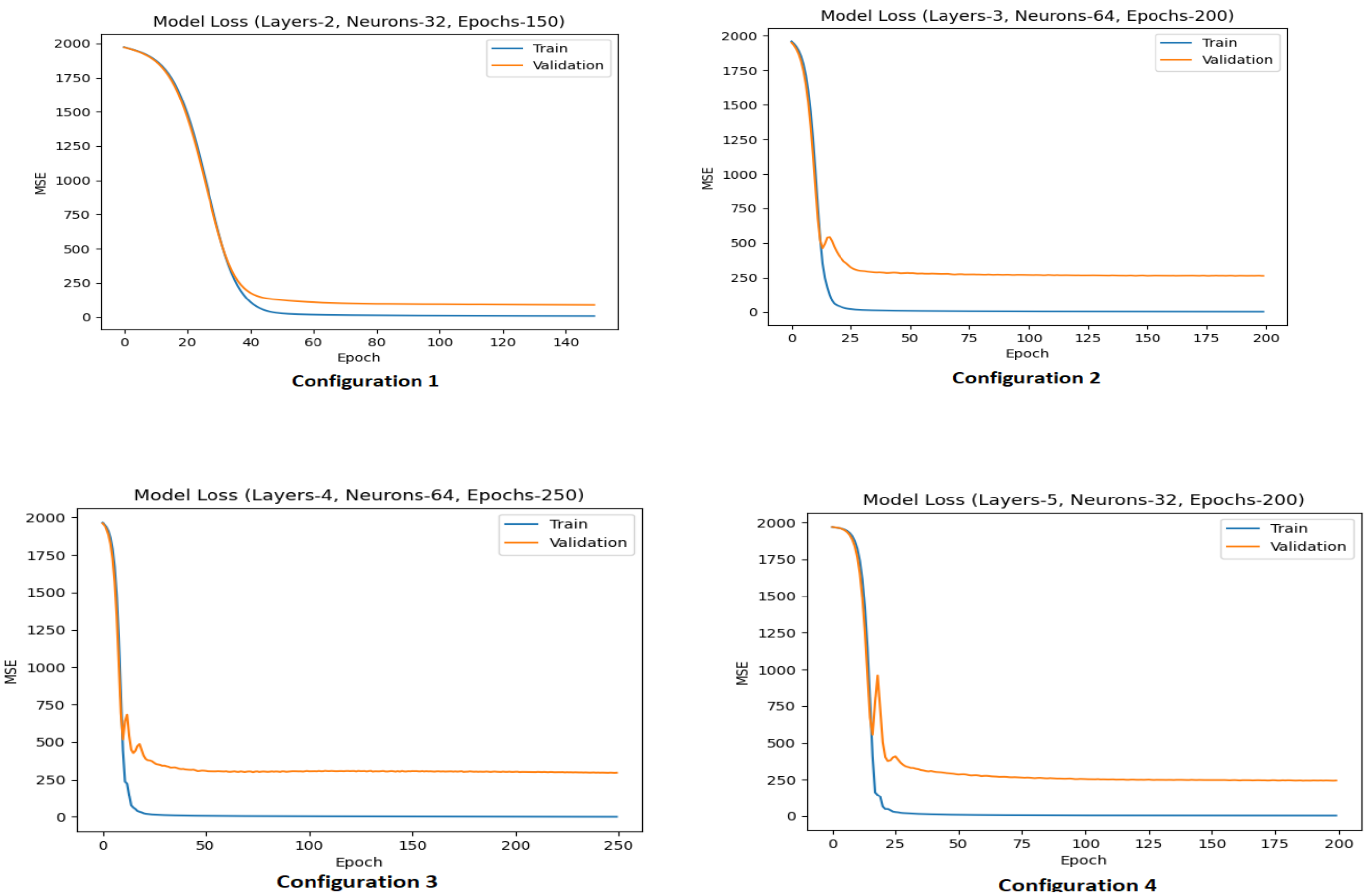

Figure 7: Performance Plots of the Analysis Performed on the Data from Iyaro Intersection

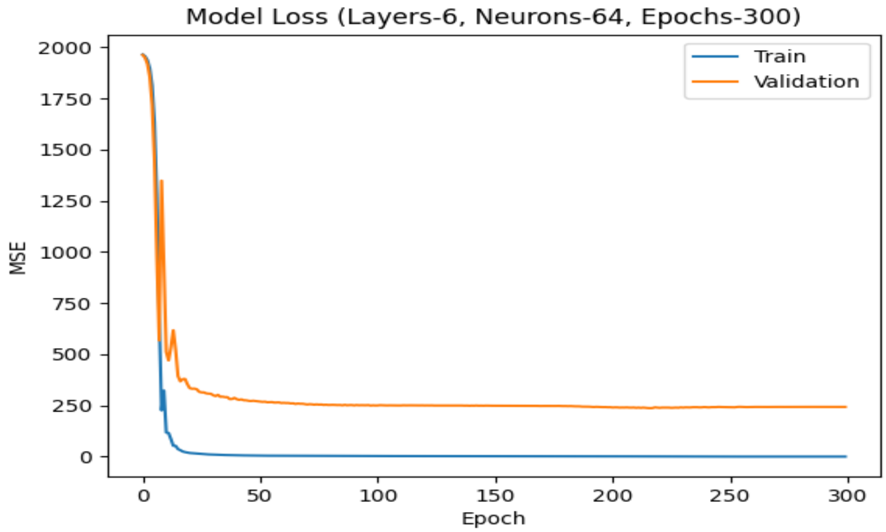

Figure7: Performance Plots of the Analysis Performed on the Data from Iyaro Intersection (continue)

3.2 Neural Network Performance

The neural network was trained to predict the green light timings based on the input features. A sample of its predictions is shown in Table 6. Table 6 shows the green time (in seconds) for four individuals: Urubi, Lawani, Dawson, and Evbiemwen. Each row represents a different observation. Urubi's green times range from 43 to 59 seconds, Lawani's from 24 to 33 seconds, Dawson's from 40 to 54 seconds, and Evbiemwen's from 24 to 32 seconds.

Table 6: Predicted Description of Neural Network Retimed Signal Timing Parameters (Green Time)

Road Green Time			
Urubi	**Lawani**	**Dawson**	**Evbiemwen**
52	28	48	30
44	24	40	25
45	25	43	26
48	27	46	27
46	26	44	26
44	25	41	25
59	33	54	32
43	24	40	24
43	24	40	24

For benchmarking purposes, a baseline model, which used the mean signal timings, was also implemented. A snapshot of the predictions from this linear regression model is:Table 7 shows consistent green times (in seconds) for four individuals: Urubi, Lawani, Dawson, and Evbiemwen. Each row reflects identical values, with Urubi, Dawson, and Evbiemwen consistently at 59 seconds and

Lawani at 24 seconds. This suggests a uniform pattern in their respective green times across multiple observations.

Table 7: Predictions from this Linear Regression Model

Road Green Time(s)			
Urubi	**Lawani**	**Dawson**	**Evbiemwen**
59	24	57	23.63
59	24	57	23.63
59	24	57	23.63
59	24	57	23.63
59	24	57	23.63
59	24	57	23.63
59	24	57	23.63
59	24	57	23.63
59	24	57	23.63

3.3 Performance Metrics Comparison

With the newly proposed signal timings, the average intersection control delay which was 44 seconds, reduced by approximately 15%, bringing it down to around 36 seconds.These improvements, while seemingly modest, can significantly enhance the overall efficiency of the intersection. Reduced delays mean less idle time for vehicles, leading to lower emissions and fuel consumption.

3.3.1 Categories of Level of Service (LOS)

1. **LOS A (Free Flow):** Minimal delays, free-flow speeds, negligible queues.
2. **LOS B (Stable Flow):** Slight delays, easy manoeuvrability, short queues.
3. **LOS C (Satisfactory Flow):** Moderate delays (15–25 seconds/vehicle), stable flow with manageable queues, reduced waiting times.
4. **LOS D (Approaching Unstable Flow):** Longer delays (25–35 seconds/vehicle), restricted maneuvers, longer queues.
5. **LOS E (Unstable Flow):** Significant delays (>35 seconds/vehicle), nearing capacity, risk of gridlock.
6. **LOS F (Failure):** Breakdown conditions, extensive delays (>50 seconds/vehicle), long queues, and gridlocks. (**HCM**, 2021)

An improved LOS enhances driver satisfaction and reduces the risk of intersection-related accidents.Figure8shows that the level of service improved from ‘D’ to 'C' during peak hours. This indicates a smoother flow of traffic, reduced vehicle queues, and shorter waiting times.

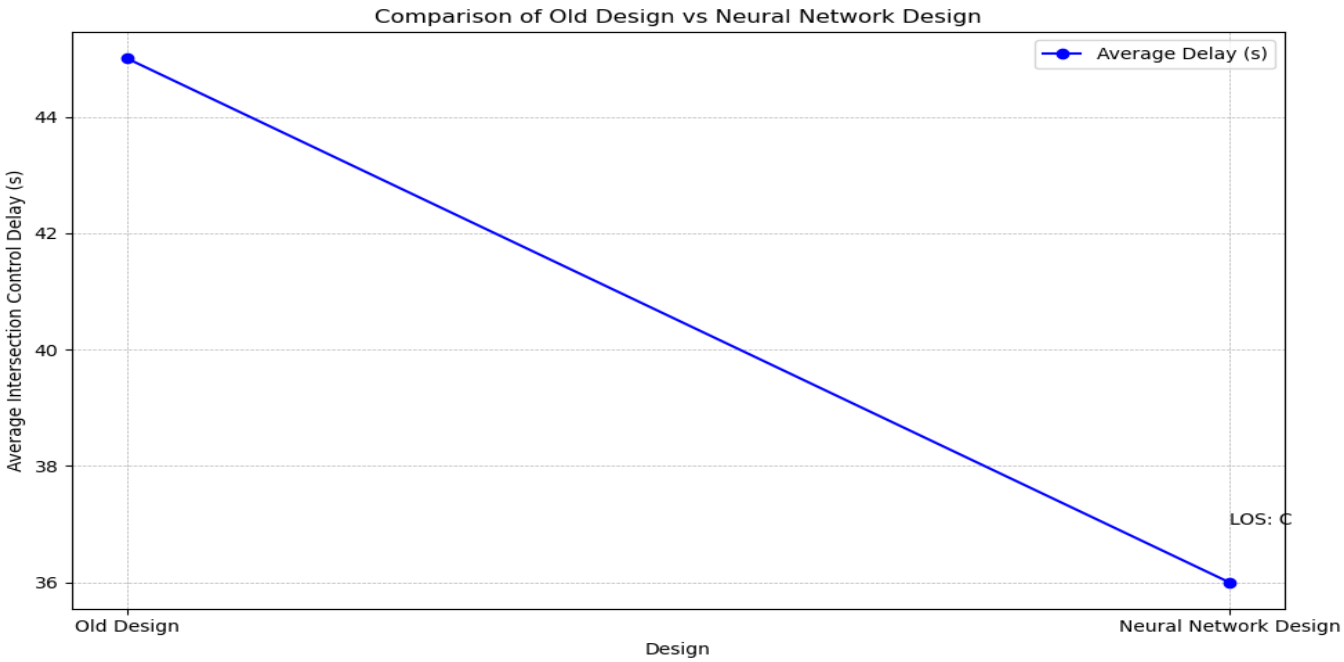

Figure 8: Comparison of old design and Neural Network Design

4.0 CONCLUSION AND RECOMMENDATIONS

The study has shown the application of Feed-Forward Neural Networks to predict traffic volume at isolated intersections and optimize traffic signal timing parameters. Through the development and implementation of a neural network model, a significant reduction was achieved in control delay to 36.6 seconds per passenger car unit (pcu), improving the service level from grade D to C, and decreasing the cycle length by 30 seconds. These findings demonstrate the potential of neural network-based traffic control systems to alleviate traffic congestion and improve overall traffic efficiency in urban areas like Oredo Local Government Area in Benin City. The adaptive learning capabilities of neural networks further enhance their suitability for real-world applications, making them a promising solution for addressing the challenges associated with traditional traffic signal control systems.

To further optimize traffic flow and efficiency at intersections within Oredo Local Government Area, several strategies are recommended. Maintaining pavement surfaces on all approach lanes is essential to ensure optimal driving conditions and maximize saturation flow rates. Effective intersection access control measures, such as restricting left turns or prohibiting U-turns, should be implemented to minimize conflicts and streamline traffic movement. Parking management, including strict enforcement of parking regulations and exploring alternative parking solutions, can also help reduce congestion and improve circulation.

Additionally, leveraging advanced traffic signal control systems, such as adaptive signal control, can optimize signal timings in response to real-time traffic conditions. Regular collection and analysis of traffic data are crucial for identifying trends, anticipating future needs, and informing traffic management decisions. These data-driven approaches enable more precise and effective strategies for addressing urban traffic challenges.By incorporating these strategies, the traffic network within the Oredo Local Government Area can achieve significant improvements. Reduced congestion, shorter travel times, and enhanced overall traffic efficiency are achievable goals, demonstrating the value and practicality of modern neural network-based traffic control systems in urban environments.

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