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Comparing the Performance Rating Between Neutral Network and Autoregressive Integrated Moving Average Model for Vehicle Traffic Prediction Estimation

UDEJI, P. I.[1,*], OKHAIFOH, J. E.[2]

[1]*Department of Electrical and Electronics Engineering, Federal University of Petroleum Resources*

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ABSTRACT

Traffic congestion poses significant challenges worldwide, resulting in lost hours of travel time and increased fuel consumption. Accurate traffic prediction is crucial for mitigating these issues. Traditional traffic prediction approaches such as ARIMA are limited by their inability to handle large datasets, inaccurate predictions, and time constraints. This study explores the use of Feed Forward Back Propagation Artificial Neural Network (FFBPANN) in the determination of traffic prediction. Five different FFBPANN architectures were created to determine the optimal topology. The results show that the architecture with 20 hidden layer neurons achieved the best performance, with a mean square error of 0.19188 at 5 epochs. The implementation of FFBPANN can enhance traffic management systems, reduce congestion, and improve urban mobility, ultimately contributing to more efficient transportation networks.

1. INTRODUCTION

The transportation and logistics industry of Uvwie local government area is faced with several challenges in vehicle route optimization and this issue has persisted for a long period of time. Traditional route planning encounters obstacles related to inefficient travel time and escalating operational costs. Additionally, static route plans often fail to adapt to dynamic and unpredictable changes in traffic conditions, hindering last-mile delivery strategies. Fleet management poses challenges in optimizing resource utilization, and conventional methodologies struggle to accommodate evolving delivery schedules and time constraints. These issues collectively underscore the need for a comprehensive and adaptive solution that addresses the intricacies of modern transportation logistics.

An intelligent approach to vehicle traffic prediction is of great essence and key technology within the transportation industry in the state due to increase in traffic congestions and road accidents which have caused hindrance to movements of vehicle and loss of lives. Vehicular traffic prediction plays a role in finding the improved or most effective route for a vehicle to reach its end point minimizing congestion of traffic on its way. Transportation serves as a vital component that enhances and facilitates

*Corresponding author, e-mail: parlyonline@yahoo.com
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various social and economic endeavors. Whether we communicate via telephone, engage in grocery shopping, peruse letters, or embark on bus or air travel for business or leisure, we reap the advantages of systems that efficiently convey messages, goods, or individuals between different locations (Gülsün, 2018).

Research has showed that the problem associated with vehicle routing involves planning, optimal distribution and pickup routes for vehicles assigned to serve geographically dispersed centers from one or more location (Toth, 2002). It is given in the data set such that each city is passed through just once and the traveling salesman comes back to the initial city from where he started. The algorithms have looked at the problems by generating a fitness function genetic operators like selection, crossover, and mutation (Saji, Y., 2016). The problem cannot be solved without adopting machine learning because the job of artificial intelligence in actualizing this priority cannot be overemphasized. Machine Learning, which is an application of artificial intelligence is referred to as the science of programming computer algorithms that learn from different data patterns after being trained (Centiner, 2010). Artificial neural networks are artificial intelligence mode which has been used for vehicle route search, they are machine learning tools which are patterned after biological neural system, they learn by training from experience data (Kabari, L.G., 2012).

(Changxi, *et al*., 2024) tried to address the traffic flow in Beijing city of China by working on complex and low-quality data to achieve good results. However, it is hard for the researchers to look at the visual aids used in the work to predict the number of vehicles and time that the traffic occurs. (Yuan, *et al.,* 2025) attempts yielded good results that could only prove that their comparative approach works very well with tested performance indices. However, the optimal hidden layer neuron that would obtain the best prediction was not given a consideration.

BPANN will be the major tool used in this research study because of its advantages over other classifiers algorithms. The system architecture of (ANN) consists of three basic components which are: the knowledge base, the inference engine, and the user interface. This research explored these ANN components to develop an expert system capable of predicting vehicle routes in Uvwie local government area of Delta state. ANN offers the possibility to gain complex examples and connections from information, empowering more exact and solid forecasts of traffic streams. By tending to the impediments of existing expectation models, ANNs can possibly alter traffic board and metropolitan preparation, prompting more productive and feasible transportation frameworks. What makes the model so unique is its flexibility and simplicity in obtaining the optimal hidden layer neuron model for the prediction.

2. MATERIALS AND METHOD

This research was conducted in Uvwie which is the economic nerve center of Delta state, Nigeria, with the following coordinates 5°31’2.5’’N latitude and 5°45.004’E longitude. The area is the most populated area in Delta state located at the southern end of Delta state with about 826 square kilometers while Delta state covers a land mass of 17,689 square kilometers with a total of 60% being land. The Figure 1 below shows the map of Uvwie metropolis.

Figure 1: Map of Uvwie local government area (Google Maps, 2023)

Sampling locations considered in this study are shown in Table 1. Sampling locations were selected to cover area of vehicular traffic to have representative coverage of the study area

Table 1: Study Locations and Coordinates

Location Name	Latitude	Longitude
P.T.I Junction	N05°34'.386"	E005°47.996
Effurun Roundabout	N05°34'.167"	E005°47'.058"
Jakpa Junction	N05°33'.357"	E005°47.082
D.S.C Roundabout Junction	N05°34'.258"	E005°48.562
Enerhen Junction	N05°31'.684"	E005°46'.410

2.1 Model Formulation of Autoregressive Integrated Moving Average (ARIMA)

The concept of autoregressive processes assumes that the time series Y(t) is explored linearly in terms of the past values.

$$Y(t) = f(y(t-1), y(t-2), y(t-3), y(t-4) \ldots y(t-m)) \quad (1)$$

$$Y(t) = M + \emptyset_1 y(t-1) + \emptyset_2 y(t-2) + \ldots + \emptyset_p y(t-p) + u(t,k) \quad (2)$$

But $M = \mu_y \left(1 - \sum_{i=1}^{p} \Phi_i\right)$

where $\emptyset_i$ is the autoregressive parameter and u(t) is a random shock with zero mean and a variance (white noise)

If, the current value of the time series y(t) is expressed using the current and previous values of white noise u(t), then we have moving average model as follow:

*Corresponding author, e-mail: parlyonline@yahoo.com
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$$Y(t) = M - u(t) - \emptyset_1 u(t-1) + \ldots + \emptyset_n * u(t-q) \quad (3)$$

Or

$$Y(t) = \Upsilon(B)^* u(t) \quad (4)$$

But $\Upsilon(B) = 1- \Theta_1 B - \Theta_2 B^2 - \ldots - \Theta_n B^n$ (5)

Combining eqn.(2) and eqn.(3) changes to autoregressive moving average in the following form:

$$Y(t)- \emptyset_1 y(t-1)+\ldots+ \emptyset_q u(t-q) \quad (6)$$

But M is a constant formed by the mean of y(t) that is μ_y and the AR coefficient as shown

$$M = \mu_y \left(1-\sum_{i=1}^{p} \Phi_i\right)$$

To simplify eqn.(6), a back shift operator B is given as

$$By(t) = y(t-1) \quad (7)$$

In general form eqn.(7) becomes

$$B^m y(t) = y(t-m) \quad (8)$$

Eqn.(8) allows the expression of any ARMA model in a backshift form. For instance, an ARIMA (1,1,1), p=1,d=1, and q = 1, can be in this form:

$$(1-\emptyset_1 B)(1-B)\, y(t) = C + (1-\Theta_1 B)\, u(t) \quad (9)$$

The ARMA model can be expressed as

$$\emptyset(B) y(t) = M + \Upsilon(B)\, u(t) \quad (10)$$

Where $\Upsilon_q(B)$ and $\emptyset_p(B)$ are polynomials in B of order q and p

$$\emptyset(B) = 1- \emptyset_1 B- \ldots - \emptyset_m B^p \quad (11)$$

$$\Upsilon(B) = 1- \emptyset_1 B- \ldots - \emptyset_n B^q \quad (12)$$

A time series y (t) can be stationary or non-stationary. A stationary process is the one whose mean, variance and auto-correlation function are constant throughout time.

$$\omega(t) = \omega^*(t)- \omega^*(t-1) = (y(t)-y(t-1)-(y(t-1)-y(t-2)) \quad (13)$$

For ARIMA (0, 1, 1) with B=1, P=0 and q=1. The ARIMA term is given as

$$\omega(t) = M - \emptyset_1 u(t-1)+ u(t) \quad (14)$$

Eqn.(13) and eqn .(14) yields:

$$Y(t) = y(t-1)+ M- \Theta_1 u(t-1)+ u(t) \quad (15)$$

Combining eqns. (10) and (15) yields the ARIMA model as

$$\emptyset(B)\nabla^{d}y(t) = M + \Upsilon(B)\,u(t) \qquad (16)$$

Where $\nabla^{d} = (1 - B)^{d}$

$$\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \ldots - \emptyset_P B^P \qquad (17)$$

$$\Upsilon(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \ldots - \emptyset_q B^q \qquad (18)$$

2.2. Development of Network Topology of Artificial Neural Network

Figure 1 represents the developed topologies of FFBPANN. The two inputs to the neuralnetwork are time and number of vehicles. The hidden layer comprises the bais, the weight, the summer and the tansigmoid transfer function. The difference between the hidden layer and the output layer is the linear (purelin) transfer function. In the thinkig of the authors, an optimal hidden layer neuron would be obtain if there are various ranges of the neurons. Thus, the neurons were chosen from 10 to 50 hidden layer neurons in order to obtain an optimal one.

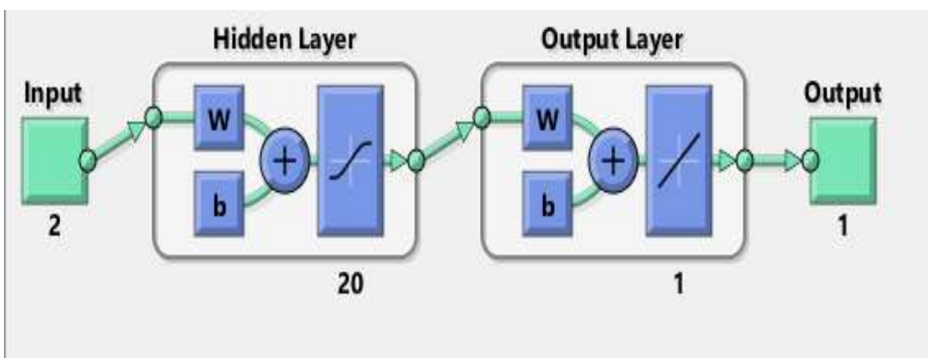

Figure 2: 20-Hidden layer topology of FFBPANN

3. RESULTS AND DISCUSSION

3.1 Performance Evaluation

Figures 3 to 8 comprises training, testing and validation. The overall regression value gives "All". For the five topologies created, it was found that the best performce is the 20 hidden layer neuron . Neuron 20 has the least mean square error and the highest correlation coeficient. The higher the value of the regression coeficient the better is the prediction. From the models and the results of the simulation as can be seen in Figures 3 has 20-topology based hidden layer neuron with the best performance of 0.90919. The model is therefore used for the prediction. Performance evaluation of the model using mean square error gives 0.19188 at 5 epoch.

The performance of five neural network topologies was evaluated through training, testing, and validation. The 20-hidden-layer-neuron topology demonstrated the best performance. The regression value is 0.90919, indicating strong predictive capability. The Mean square error (MSE) is 0.19188 at 5 epochs, demonstrating low error rates. It can be inferred that the 20-hidden-layer-neuron model as can be seen in Figure 3 outperformed other topologies, showcasing its potential for accurate predictions. Its high regression value and low MSE make it suitable for further application.

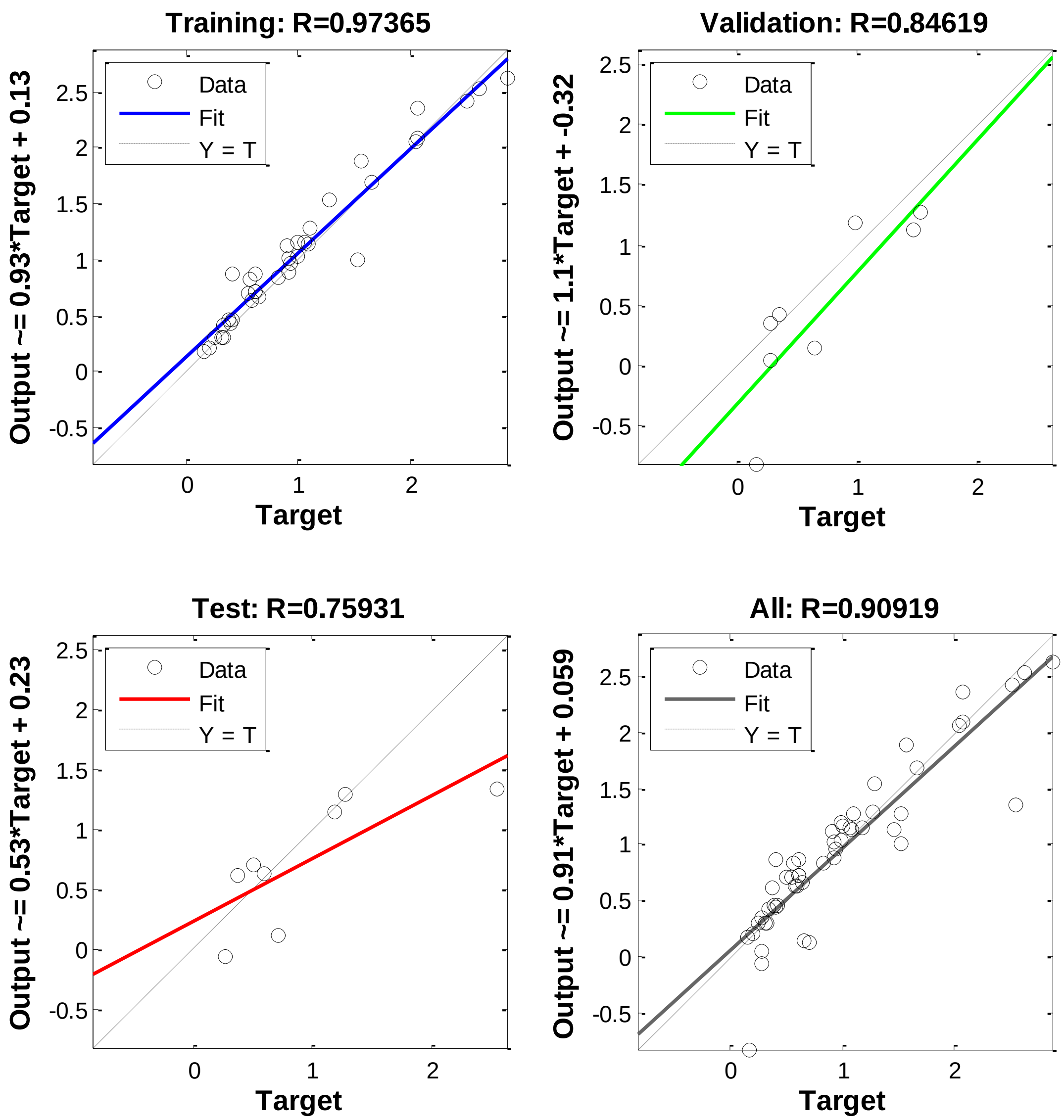

Figure 3: Performance evaluation using Mean square Error for 20-hidden layer neuron topology

Vehicular traffic prediction using conventional approach and feed forward back propagation artificial neural network (AI). In the Figures 4 to 8, a conventional approach known as time series model (TSM) approach were compared with artificial neural network known as feed forward backpropagation artificial neural network (FFBPANN). The results show that by far, FFBPANN out performs the TSM in vehicular traffic prediction. This can be attributed to data preprocessing associated with AI approaches. The data preprocessing ensures that there is no overfitting underfitting. The inputs to the FFBPANN are the number of vehicles that comprises number of vehicles plying the roads and the time. The target is the flow of vehicles along those roads. The data was collected from 6am to 10pm. The variation in the number of vehicles passing various junctions can be seen in the Figures 4 to 9 at a given time. More importantly, the FFBPANN proves to be better than TSM by the overlapping of the plots.

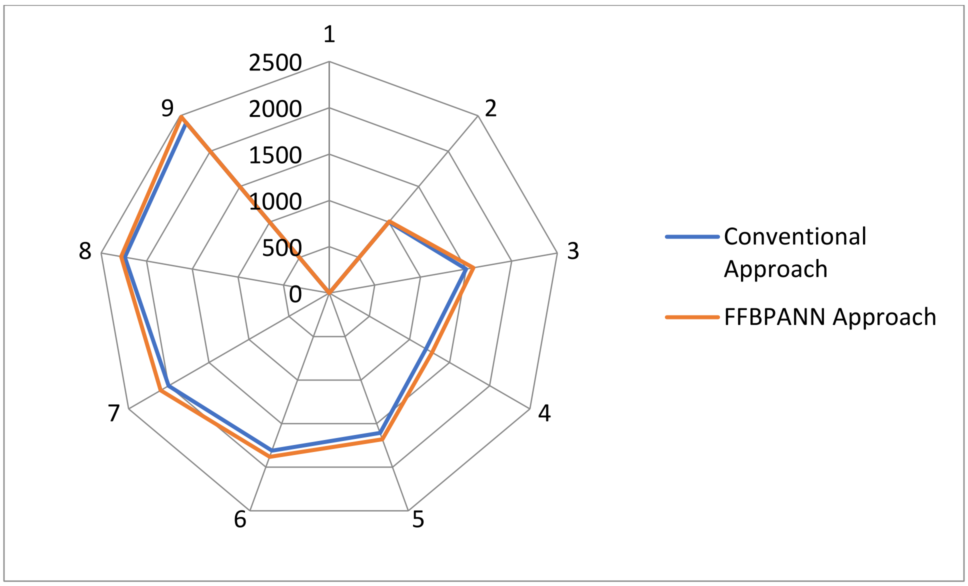

Figure 4: Vehicular traffic prediction at DSC round about

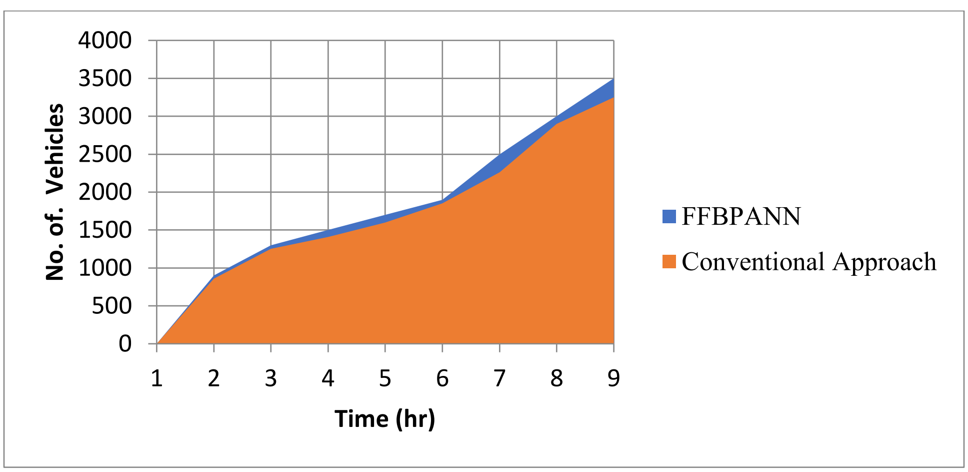

Figure 5: Vehicular traffic predictions at Enerhen Junction

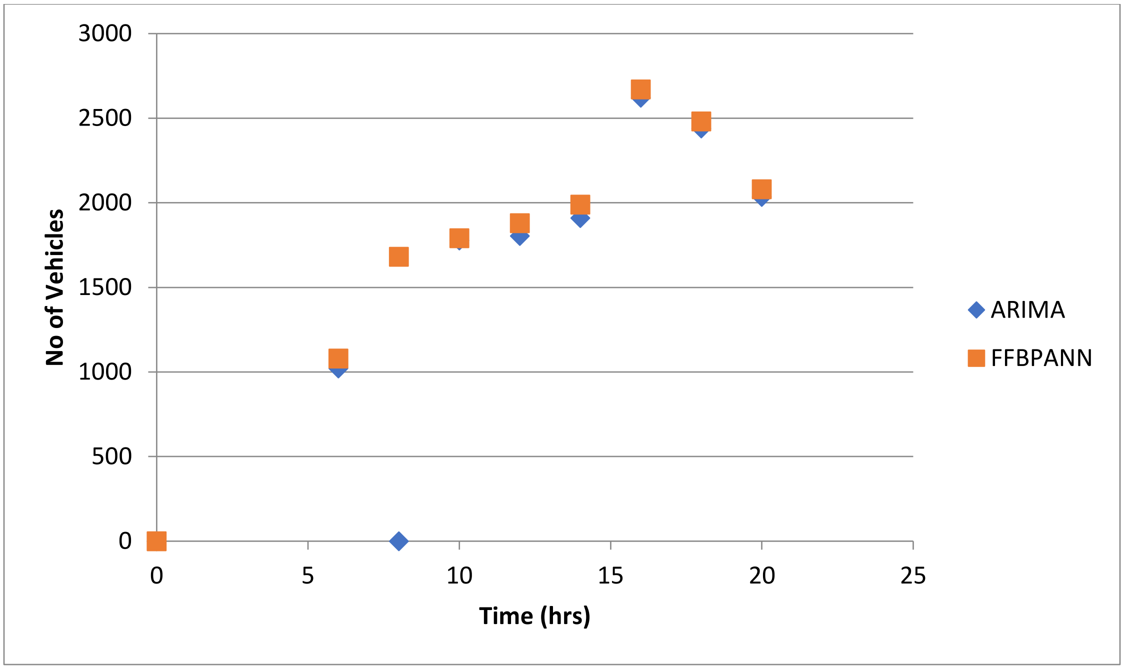

Figure 6: Vehicular traffic predictions at Effurun Round about

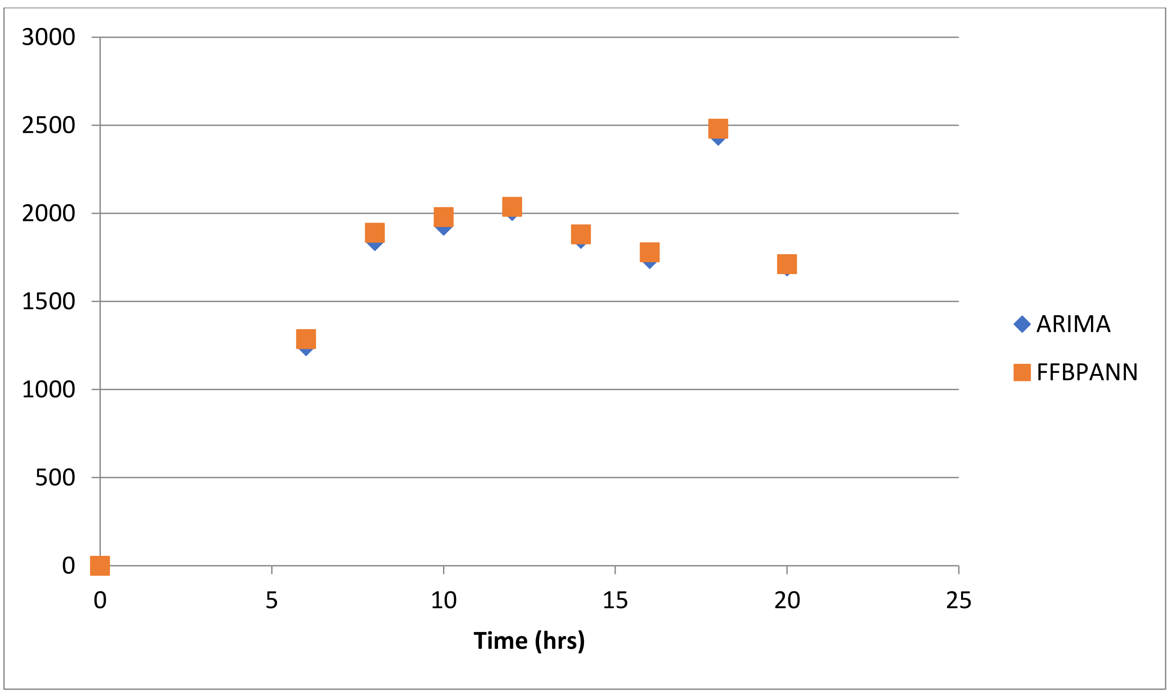

Figure 7: Vehicular traffic prediction at PTI junction

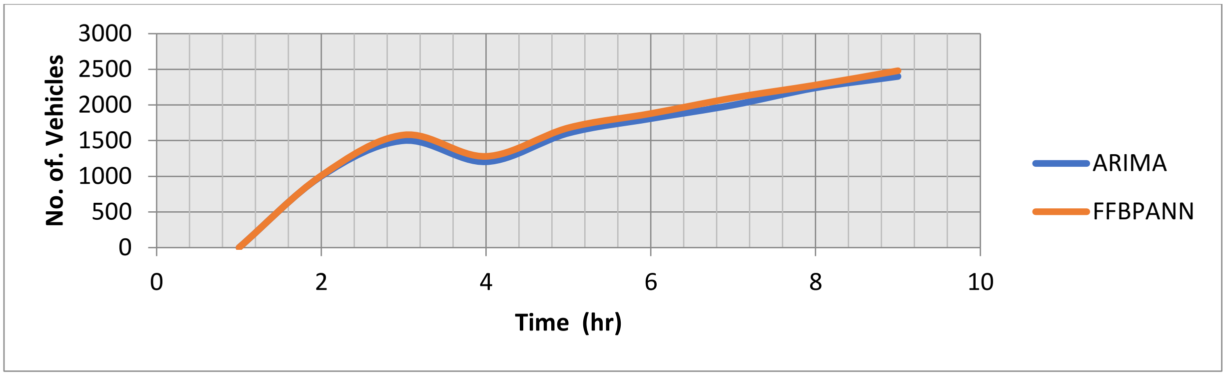

Figure 8: Vehicular traffic predictions at Jakpa Junction

4. CONCLUSIONS

This study demonstrated the effectiveness of Artificial Neural Networks (ANNs) in predicting vehicular traffic, outperforming traditional ARIMA models. The Feed Forward Back Propagation ANN (FFBPANN) achieved a regression value of 0.90919 and a mean square error of 0.19188, showcasing its ability to learn complex traffic patterns. While the study had limitations, including manual data collection and a limited dataset, the findings suggest that ANN is a suitable tool for predicting vehicular flow in urban areas. This implies that the predictive capability of ANN can significantly aid transportation planning, reduce congestion, and improve traffic management. By leveraging ANN's strengths, transportation systems can become more efficient, reducing travel time and enhancing urban mobility. The future direction aims at addressing the study's limitations by expanding the dataset, incorporating diverse variables, and exploring more network topologies that can further enhance the model's performance and applicability. With its potential to transform traffic systems, ANN-based traffic prediction warrants continued research and development.

REFERENCES

Abdullahi, I. M., Alaro, O. T., Alogun, A. O., and Ibrahim, A. (2015). The effect of image resolution on the performance of automatic classification of diabetic retinopathy and storage memory. *International Journal of Research in Engineering and Technology*, 3(3): 29-36.

Alizadeha, S. (2014). Prediction of vehicle traffic accidents using Bayesian networks. *Scientific Journal of Pure and Applied Science*, 3(6): 356-362.

Atif, Y. K., and Kumar, A. (2020). Internet of things data analytics for parking availability prediction and guidance. *Transactions on Emerging Telecommunications Technologies*, 31(5):10-21.

Bharti, S. S. K., Tiwari, P., Yadav, P., and Nezhurina, M. I. (2018). ANN-based short-term traffic flow forecasting in undivided two-lane highway. *Journal of Big Data*, 5(1): 1-16.

Centiner, B. G. (2010). A neural network-based traffic-flow prediction model. *Math Comput Appl*.6(3):12-23

Changxi, M., Bowen, Z., Shunkai, L., Youpeng, L., (2024). Urban rail transit passenger flow prediction with ResCNN-GRU based on self-attention mechanism. Physica A: Statistical Mechanics and its Applications (638):129619

Ferdiani, R., and Harahap, S. (2023). Study vehicle routing problem using nearest neighbor algorithm. *Journal of Physics: Conference Series*, 1-7.

Friedrich, C., and Ralph, E. (2021). Adaptive large neighborhood search for vehicle routing problems with transshipment facilities arising in city logistics. *Computers and Operations Research*, 137(4): 10-21.

Gülsün, P. M. (2018). Vehicle route planning for multiple targets in online map for a patient transport vehicle. *International Academic Research Conference* in Oslo, 161-169.

Hadka, D., and Pedro, R. (2013). An adaptive many-objective evolutionary computing framework. *Evolutionary Computation*, 21(2): 231-259.

Izquierdo, R., and Teddy, B. L. (2017). Vehicle trajectory and lane change prediction using ANN and SVM classifiers. *IEEE 20th International Conference on Intelligent Transportation Systems* (ITSC), 1141-1146.

Jadaan, K. S., and Martins, A. F. (2014). Prediction of road traffic accidents in Jordan using artificial neural network (ANN). *Journal of Traffic and Logistics Engineering*, 2(2): 92-103.

Kabari, L. G., and Nero, E. (2012). Neural networks and decision trees for eye diseases. *Creative Commons Attribution License*, 7(5): 90-102.

Lin, B., Ghaddar, B., and Nathwani, J. (2021). Electric vehicle routing with charging/discharging under time-variant electricity prices. *Transportation Research Part E: Emerging Technologies*, 130.

Mangai, J. A., Wangle, K., and Kumar, V. S. (2013). An improved K-nearest neighbor classifier using interestingness measure for medical image mining. *World Academy of Science, Engineering and Technology, International Journal of Medical, Health, Biomedical, Bioengineering and Pharmaceutical Engineering*, 3(4):35-40.

Meng, Y., and Zhang, S. (2022). Route planning for autonomous driving based on traffic information via multi-objective optimization. MDPI, 7(6): 1-12.

Moumen, I., and Jargua, A. (2023). Adaptive traffic lights based on traffic flow prediction using machine learning models. International Journal of Electrical and Computer Engineering, 13(5): 5813-5823.

Ogwueleka, F. N., and Martins, S. (2014). An artificial neural network model for road accident prediction: A case study of a developing country. Acta Polytechnica Hungarica, 11(5): 177-186.

Pan, Z. L. (2019). Urban prediction from spatio-temporal data using deep meta learning. Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1720–1730.

Saji, Y. (2016). A novel discrete bat algorithm for solving the traveling salesman problem. Neural Computing and Applications, 27(7): 1853-1866.

Sheeba, O., and Shun, A. (2009). Neural network in the diagnosis of diabetic retinopathy. International Conference on Modelling and Simulations, Goa India, 256-259.

Shaygana, M., Collin, M., Wanxin, L., Xiaoliang, G., and Mark, N. (2022). Traffic prediction using artificial intelligence: Review of recent advances and emerging opportunities. Transportation Research Part C: Emerging Technologies, (45): 40-45.

Yuan, G., Kaifeng, Y., Yibing, Y., and Yunfeng W. (2025). A vehicle trajectory prediction model that integrates spatial interaction and multiscale temporal features. A vehicle trajectory prediction model that integrates spatial. Scientific Reports (15): 8217. https://doi.org/10.1038/s41598-025-93071-9