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Short Term Traffic Prediction at Airport Road in Benin City using Artificial Neural Network

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ABSTRACT *: Short-term traffic speed prediction is an essential part of proactive traffic control in intelligent transportation systems. This study aimed to predict short-term traffic flow along airport road in Benin city, using artificial neural networks (ANN). Traffic studies were conducted along the road, from Oyaide junction to Irrhirrhi Junction. The time mean speed, flow rate, and flow density were determined for different classes of vehicles. The independent variables used were the different classes of vehicles and their respective time mean speeds and flow rates, while the dependent variable was the flow density on both roads. The ANN model was highly accurate in predicting traffic flow along both roads and had a strong ability to generalize unseen data, as shown by the low value of validation performance in both roads. The high goodness of fit suggests that the model captured a significant portion of the variability in the traffic flow data and provides a highly accurate representation of the pattern from both roads. The best model occurred when the hidden layer was 12 with an epoch of 301 iterations along the airport road.*

KEYWORDS: *Intelligent transport system, traffic congestion, traffic count, traffic prediction, spot speed*

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I. INTRODUCTION

The accelerating urbanization and population growth in cities have placed significant strain on urban traffic management. Over the past two decades, there has been a global surge in transportation demand, posing challenges for transportation engineers dealing with increased traffic congestion and safety concerns (Guo et al., 2019).

In developing nations, traffic is experiencing rapid growth, and this trend is expected to persist. By 2050, approximately 60% of the population is projected to reside in cities, leading to a surge in vehicles and critical situations monitored by intelligent transportation systems (Thondoo et al., 2020). Intelligent Transportation Systems (ITS) aim to enhance decision-making for transport network controllers and users, often in real time, thereby improving overall transportation system performance (Miles and Chen, 2004). Various ITS applications include Advanced Traffic Management Systems (ATMS), Advanced Traveller Information Systems (ATIS), Dynamic Route Guidance (DRG), and Urban Traffic Control (UTC) (Miles and Chen, 2004).

Short-term traffic prediction, spanning 5–30 minutes, relies on historical data to anticipate imminent traffic conditions. This brief timeframe is pivotal, as congestion may surge rapidly. Accurate predictions enable proactive measures, like redirecting traffic to alternative routes, if imminent high congestion is anticipated (Sharma et al., 2018).

Traffic flow, akin to water flow, encompasses various parameters. These parameters offer insights into traffic nature, aiding analysts in detecting flow variations (Sharma et al., 2018). To better represent traffic flow, relationships have been established between the three main characteristics; which include flow, density, and speed.

The intensity (or flow) is a local characteristic specified for a period T at a cross-section x by

$$q = \frac{N}{T} \ (Number\ of\ vehicles\ per\ unit\ Time) \qquad (1)$$

Density is quantifiable solely over a length. In instances of point measurements, it is derived from occupancy or speed and flow (TRB, 2016). Traffic density signifies the vehicles on a unit of road length at a specific moment, with units in veh/km or veh/m (Chakroborty and Das, 2010).

$$k = \frac{N}{L} \qquad (2)$$

Where, L = length of the roadway section under consideration, and

N = Number of vehicles present over the length at the given instant of time.

As per Chakroborty and Das (2010), the speed of a traffic stream is the mean speed of all its vehicles. The time mean speed is also referred to as the spot mean speed and is the average of the observed speeds, and this is given as:

$$\overline{u}_{TMS} = \overline{u}_{spot} = \frac{1}{N}\sum_{i=1}^{N} u_i \qquad (3)$$

Conversely, the space-mean of the characteristics α at some time t_1, (α L, t_1), is obtained from the observations taken at that time over a segment of length L. This is the space mean speed is represented by Equation 4:

$$\overline{u}_s = \frac{D}{t} = \frac{D}{\frac{1}{N}\sum_{i=1}^{N}\frac{D}{u_i}} = \frac{1}{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{u_i}} \qquad (4)$$

Benin City, the capital of Edo State, Nigeria, grapples with multifaceted traffic challenges, including mixed traffic flow, congestion due to irregular flow and weather, noise and air pollution, and traffic accidents (Nwankwo et al., 2019). The city's urban dynamics form a unique traffic ecosystem, marked by intricate interactions among road infrastructure, vehicle density, weather, and cultural events (Kubek et al., 2016). Traditional traffic prediction models, rooted in statistical methods, struggle with the complex non-linear relationships among these dynamic factors, resulting in suboptimal predictions that hinder effective traffic management (Sharma et al., 2018). The current traffic prediction system employs shallow approaches, which are inefficient in capturing the intricate dynamics of urban traffic (Abadi et al., 2015). Further research is essential to enhance the accuracy of traffic predictions and improve overall traffic management strategies.

A. Traffic flow Models

The qualities and requirements of fundamental relations are depicted in Fig. 1. According to de Castillo (2012) sound basic relation has the following properties:

i. Velocity ranges from zero to a maximum value u_{max};

ii. Density ranges from zero to a maximum value k_{jam};

iii. Velocities at the extreme density values are $u(0) =$ u_{max} and $u(k_{max}) = 0$;

iv. Flows at the extreme density values are $q(0) = q(k_{jam}) = 0$;

v. Maximum velocity and congestion wave speed are the slopes of the fundamental relation at the extreme density values: $u_{max} = \frac{dq}{dk} = 0$ and $= \frac{dq}{dk(k_{jam})}$.

vi. The fundamental relation is strictly concave: $\frac{d^2q}{dk^2}$ for almost all $k \in \{0, k_{jam}\}$.

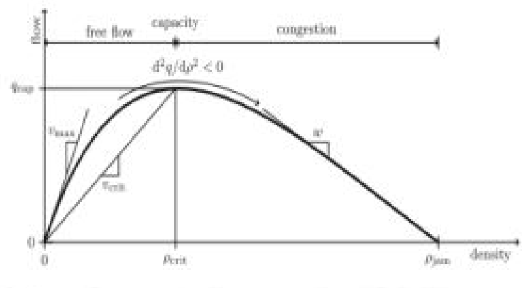

Fig. 1: A sound fundamental relation and its properties (del Castillo, 2012)

At extremely low densities, traffic moves at some finite speed referred to as the free speed u_f, and the speed is zero or very close to zero when the density of the stream reaches an upper limit referred to as jam or congestion density k_{jam}.

B. Traffic Flow Regime

Traffic flow measurement primarily uses the fundamental diagram, depicted in Fig. 1, illustrating traffic flow (q) in vehicles per hour as a function of density (k) in vehicles per km. The flow reaches its maximum value (q_{max}) at density (k_{max}.), with regimes distinguished as "free-flow" at low densities and "congested" at high densities, separated by a gap (Nagel et al., 2003).

Slimani et al. (2019) applied ANN for traffic forecasting in Morocco, utilizing data recorded hourly from 2015 to 2018, segmented by vehicle classification. The study showcased neural networks' ability to learn from the past and predict the future, with Multi-Layer Perceptron architecture providing the best forecasts.

Odesanya and Odesanya (2020) assessed traffic congestion performance using selected neural network training algorithms in Akure, Nigeria. Corridors like Oba Adesida Road, Oyemekun Road, and Oke Ijebu Road were studied, with Bayesian Regularization emerging as the superior training algorithm based on Mean Square Error (MSE) and Coefficient of Regression (R).

This study focuses on applying Artificial Neural Networks (ANN) to predict short-term traffic in Benin City, with a specific focus on Airport Road.

II. MATERIALS AND METHOD

A. Description of the Study Area

Benin City, the capital of Edo State in Nigeria, boasts a rich cultural heritage and a burgeoning population, contributing to the evolution of its transportation infrastructure. At the heart of the city is the pivotal Airport Road, a vital 10-kilometre transportation artery connecting the city centre to the airport. Renowned for its diverse traffic, the dual carriageway navigates through various neighbourhoods and commercial hubs. While serving as a crucial route for commuters and cargo, the road encounters unpredictable traffic patterns, especially during peak hours, reflecting the city's vibrant dynamics and developmental strides. Fig.2 shows the map of Benin City.

Fig. 2: Map of Benin-city showing Study Section

The study involved the collection of data along Airport Road in Benin City, specifically from Oyaide Junction to Irrhirrhi Junction, covering an 850-metre section. Over five days, a comprehensive traffic count was performed from 7:00 a.m. to 5:00 p.m., with 15-minute intervals. The vehicles considered included passenger cars, light goods vehicles, and heavy goods vehicles with 2 or 3 or more axles. Simultaneously, a speed study was conducted for each vehicle class, with 40 datasets obtained daily, resulting in a total of 199 datasets over the study period. The time taken for each vehicle class to traverse the designated length was meticulously measured using a stopwatch with 0.01s precision, capturing entry (T_1) and exit (T_2) times. Utilising the time difference (T_2-T_1) and trap length, vehicle speeds were computed, and the data were comprehensively analysed using MS Excel, as outlined in Table 1.

Table 1: Summary of Traffic Study along Airport Road

	LGV	PC	HGV2	HGV3	PCS	LGVS	HGV2S	HGV3S	k	Q
N	199	199	199	199	199	199	199	199	199	199
Mean	20.51	42.3	16.73	13.83	59.59	54.97	50.12	47.92	109.84	373.47
Std. Dev	3.85	5.47	3.43	3.90	5.04	5.71	7.17	7.91	18.47	62.80
Min	10	30	7	0	50.21	43.87	38.43	35.81	55	188
Max	33	64	26	24	72.31	67.33	69.34	67.75	171	584
Skewness	0.42	0.63	0.19	-0.52	0.02	0.18	0.66	0.54	0.24	0.24
Kurtosis	0.89	0.71	0.66	1.64	-0.71	-1.17	-0.42	-0.64	0.88	0.88
Pvalue	0.001	0.002	0.067	0.000	0.005	0.000	0.000	0.000	0.042	0.042

III. RESULTS AND DISCUSSION

The prediction of traffic flow on Airport Road in Benin City utilised a multilayer perceptron (MLP) network. The dataset comprised 199 entries, each with ten variables, encompassing vehicle classes (passenger cars, light goods vehicles, heavy goods vehicles with 2 axles, and heavy goods vehicles with 3 or more axles), average speeds for each vehicle class, traffic density, and traffic flow. To standardize the dataset, min-max scaling normalized the values between 0 and 1. The dataset was further partitioned into training (60%), cross-validation (25%), and testing (15%) subsets, resulting in 139, 20, and 40 entries, respectively. Table 2 outlines the architecture of the MLP network and its application to the Airport Road dataset, illustrating the division of data and training specifics.

Table 2: Summary of ANN Networks Architecture for Traffic Volume Prediction along Airport Road

Model	M1	M2	M3	M4
Algorithm	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt
Hidden layer	1	1	1	1
Hidden Neurons	6	8	10	12
Transfer Function	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Number of Epoch	210	210	427	301
Training MSE	$8.8568 x 10^{-10}$	$6.5535 x 10^{-11}$	$6.9668 x 10^{-11}$	$2.6264 x 10^{-11}$
Validation MSE	$1.2154 x 10^{-8}$	$1.2915 x 10^{-7}$	$1.2590 x 10^{-8}$	$1.8282 x 10^{-10}$
Testing MSE	$6.5275 x 10^{-9}$	$1.3965 x 10^{-9}$	$3.6938 x 10^{-7}$	$5.6675 x 10^{-9}$
R(%)	99.99	99.99	99.99	99.99

From the table, four distinct ANN models were created to train the Airport Road dataset. Notably, model M4 demonstrated superior predictive capabilities, featuring 12 hidden layers, 9 input variables, and 1 output variable. With a coefficient of determination of 99.99%, this model displayed a remarkably high degree of fit between testing and training data. Model 4 also exhibited the lowest validation mean square error across all testing scenarios, establishing its superior validation performance. Performance, gradient function, and regression plots are depicted in Figs.3, 4 and 5 respectively.

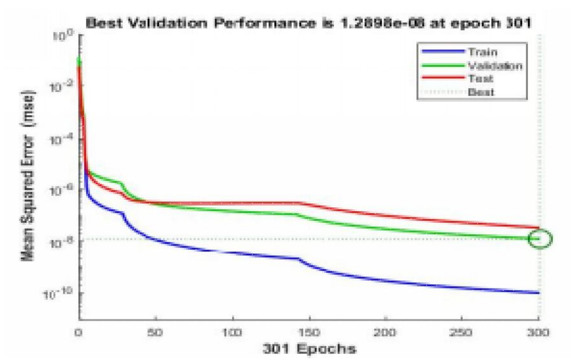

Fig. 3: Performance Plot of the Analysis Performed on the Data from Airport Road

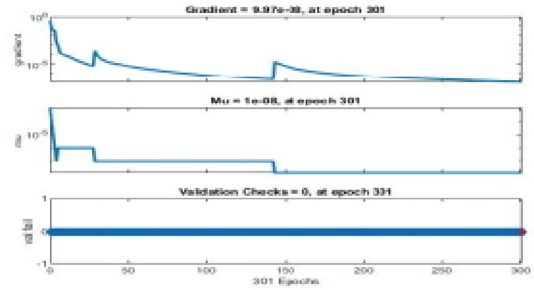

Fig. 4: Gradient Function Plot of the Analysis Performed on the Data from Airport Road

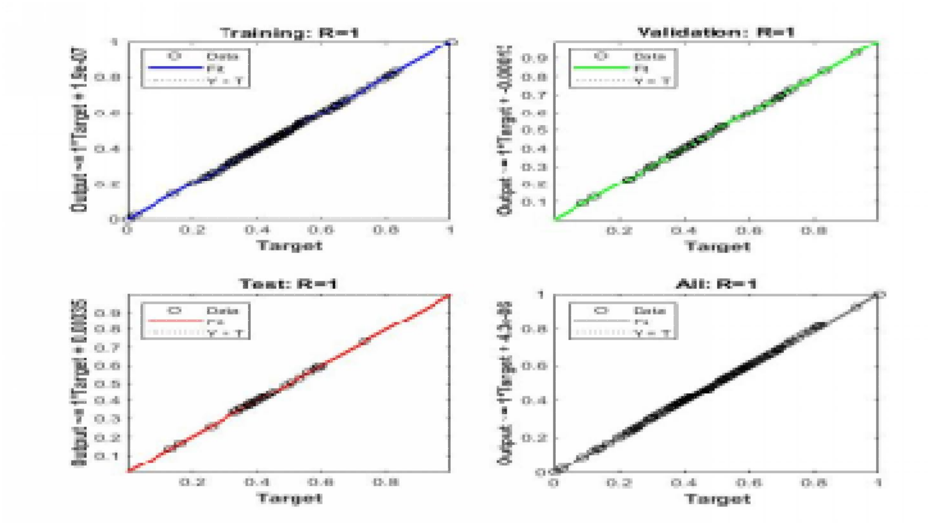

Fig. 5: Regression Plot of Neural Network Analysis Performed on the Data from Airport Road

V. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

From this study, the following conclusions can be drawn:

(i) The primary vehicles utilising these facilities include passenger cars, light goods vehicles, 2-axle heavy goods vehicles, and heavy goods vehicles with 3 or more axles. The prevalence of passenger cars is attributed to the high residential occupancy in the area.

(ii) The study focused on key traffic characteristics: speed, volume, and density. Traffic volume was assessed by manually counting various vehicle classes every 15 minutes, and the time mean speed method was employed to determine flow speed. This facilitated the calculation of hourly flow rates, density, and speed for each vehicle class.

(iii) Utilising MATLAB with an integrated artificial neural network, predictions were conducted for both road sections. Input parameters encompassed passenger cars (PC), light goods vehicles (LGV), heavy goods vehicles with 2 axles (HGV2), and heavy goods vehicles with 3 or more axles (HGV3), along with corresponding speeds and flow density. The output focused on flow rate (q).

(iv) The optimal model was identified with a 12-hidden-layer configuration after 301 iterations (epochs). The best validation performance, gauged by a mean square error of 1 $1.8282\ x\ 10^{-10}$, exhibited a 99.99%

goodness of fit. This indicates a near-perfect alignment between testing and training data for the study.

(v) The deduction is that the ANN model demonstrates high accuracy in predicting traffic flow on the road and exhibits a strong capacity to generalize unseen data, evident from the low validation performance values. The substantial goodness of fit indicates that the model effectively captures a significant portion of variability in traffic flow data, offering a highly accurate representation of patterns on both roads.

B. Recommendations

The use of space mean speed should be applied in determining the speed of flow, and the use of automatic counters should also be applied in future studies. Longer duration of traffic study should be performed so as to get more data for carrying out the analysis. Given the exceptional validation performance and high goodness of fit achieved by the artificial neural network, government should prioritize the integration and enhancement of advanced traffic management systems that leverage predictive models.

References

Abadi, A., Rajabioun, T. and Ioannou, P. A. (2015) Traffic Flow Prediction for Road Transportation Networks with Limited Traffic Data, IEEE Transport Intelligent Transport System, 16(2): 653 – 662.

Chakroborty, P. and Das, A. (2010) Principles of Transportation Engineering, PHI Learning Private Limited, New Delhi, Eastern Economy Edition.

Daganzo, C. F. (1997) Fundamentals of Transportation and Traffic Operations, Emerald Publishing, First edition.

del Castillo, J. (2012) Three New Models for the Flow–Density Relationship: Derivation and Testing for Freeway and Urban data. Transportmetrica, 8(6): 443 – 465.

Guo, J. and Williams, B. M. (2010) Real-Time Short-Term Traffic Speed Level Forecasting and Uncertainty Quantification Using Layered Kalman Filters, Transportation Research Record, 1(2175): 28 – 37.

Kubek, D., Więcek, P. and Chwastek, K. (2016) The Impact of Short-Term Traffic Forecasting on The Effectiveness of Vehicles Routes Planning in Urban Areas, Transportation Research Procedia, 18: 172 – 179.

Miles, J. C. and Chen, K. (2004) ITS Handbook: Recommendations from the World Road Association (PIARC) Artech House, 2nd Edition.

Nwankwo, W., Olayinka, A. S. and Ukhurebor, K. E. (2019) The Urban Traffic Congestion Problem in Benin City and The Search for An ICT Improved Solution, International Journal of Scientific and Technology Research, 8(12): 65 – 72.

Odesanya, I. and Odesanya, J. F. (2020) Performance Analysis of Traffic Congestion Using Designated Neural Network Training Algorithms, International Journal of Engineering and Technologies, 20: 23 – 33.

Rogers, M. (2003) Highway Engineering, Blackwell Science.

Sharma, B., Kumar, S., Tiwari, P., Yadav, P. and Nezhurima, M. I. (2018) ANN Based Short-Term Traffic Flow Forecasting in Undivided Two-Lane Highway, Journal of Big Data, 5(48): 1 – 17.

Slimani, N., Slimani, I., Sbiti, N. and Amghar, M. (2019) Traffic Forecasting in Morocco using Artificial Neural Networks, Procedia Computer Science, 151: 471 – 476.

Thondoo, M., Marquet, O., Marquez, S. and Nieuwenhuijsen, M. J. (2020) Small cities, big needs: Urban transport planning in cities of developing countries. Journal of Transport and Health. Vol;ume 19, pp. 1 – 14.

Transportation Research Board (2016) Highway Capacity Manual: A Guide for Multimodal Mobility Analysis, Sixth Edition, Volume 1.

Zhang, S. and Lin, K. P. (2020) Short-Term Traffic Flow Forecasting Based on Data-Driven Model, Mathematics, 8(152): 1 – 17.

