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ORIGINAL RESEARCH ARTICLE

PREDICTION OF BUS TRAVEL TIME ON URBAN ROUTES WITHOUT DESIGNATED BUS STOPS IN MAKURDI TOWN, BENUE STATE, NIGERIA

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ABSTRACT
The lack of information on bus travel time in Makurdi town to enable trip makers plan for journeys is seen as a challenge in recent times. This study developed a multiple linear regression model for predicting bus travel time along bus routes in Makurdi town. Specifically, the study assessed bus travel time on routes without designated bus stops, examined geometric features of bus routes, assessed bus dwell time and travel speeds in a heterogeneous traffic stream on routes in Makurdi town. It developed and validated a model for the bus travel time. Field survey focused on the major bus routes in Makurdi town which included; High Level roundabout to School of Remedial Studies junction (HL-SRS), High Level roundabout to Federal Medical Centre junction (HL–FMC), Wurukum roundabout to Coca Cola Complex (W-CCC) and Wurukum roundabout to Welfare Quarters junction (W–WQ). Independent parameters examined on the sites for model development included; bus route length, bus travel speed, average dwell time at random stops for pick-up and alighting of passengers, bus headway, the total number of cross and Tee intersections along the bus route, volume of motorcycles, private cars and trucks in the traffic stream, while the dependent variable was bus travel time. Based on the built model, 15 minutes approximately was established as the average bus travel time for all bus routes in Makurdi town assuming all other variables have zero magnitude. Goodness of fit test of the model yielded significant value for coefficient of determination (R^2 = 0.952) and the use of Artificial Neural Network (ANN) method for validating the model also confirmed it accuracy at 93% approximately. It was therefore concluded that, bus travel time on major routes in Makurdi town could be accurately estimated using the built multiple linear regression model provided all essential input parameters of the model are used. The establishment of designated bus stops along bus routes within Makurdi town to minimise bus dwell frequency and for accurate estimation of bus travel time, as well as erection of travel information bill boards along bus routes stating average bus travel time to inform commuters that have high value of travel time were recommended.

1.0 Introduction

One of the essential parameters used for measuring the level of liveability of cities is the effectiveness of their public transport systems which mostly focuses on bus services (Cullinane, 2002; Ceder, 2007; Gurmu, 2010; Ibarra-Rojas et al., 2015; Gudmundsson et al., 2015). Public transport services in most urban areas of developing countries like Makurdi town of Benue State employ the use of mini buses. These buses are usually owned and operated by non-governmental organisations or private individuals who gain profit from the business of providing public transport services. Bus services for public transport has been in use from time immemorial especially in developed countries (Cullinane, 2002; Zheng, 2011). The capacity of mini buses ranges between 10 – 14 persons, unlike standard bus services in modern cities in Europe, USA, Canada, etc. that use coaches whose capacities range between 20 – 60 persons. In most cities of developing countries, the minibuses usually shuttle along routes to pick-up and alight passengers at non-designated stops that are rather convenient to the passengers as they alert drivers whenever they wish to alight. These buses operate in an interrupted and heterogeneous traffic stream characterised by mixed traffic flow and pedestrian interferences (crossing at non designated spots). This disorderly and continues stop-and-move movement of mini-buses along routes in search of passengers, boarding and alighting has significant impact on the smooth flow of traffic, hence affects travel time significantly (Izadpanah, 2010; Ibarra-Rojas et al., 2015). Also, while commuters hope to arrive at their destinations quickly, bus travel time is basically influenced by time used for walking from/to the bus stops, waiting time at the stop, in-vehicle travel time, and mode transfer period, etc. These processes are associated with traffic congestion and affects the certainty of travel time estimation which makes its prediction more complicated (Ibarra-Rojas et al., 2015). In such a mixed traffic situation with a lot of complications, it is more meaningful to attempt a short term bus travel time prediction which falls within the range of 0 to 60 minutes so as to minimise the impact of variability among estimated variables (Izadpanah, 2010; Gurmu, 2010). In line with previous researches, it has been observed that all essential parameters employ for estimation of (bus) travel time exhibit stochastic properties with high degree of uncertainty (Jeong, 2004; Ramezani and Geroliminis, 2012), which therefore requires sophisticated method of analysis.

The importance of travel time in assessing road network performance by transport planners and engineers for efficient operation management and for developing travellers' information system for commuters cannot be overemphasised. This is because most travellers' are keen about trip planning and wish to optimise or minimise waiting time due to their high value of travel time (Schiller et al., 2010; Zheng, 2011; Zaki et al., 2013; Mannini et al., 2015; Gudmundsson et al., 2015). According to Bonsall et al. (2005), the act of modelling behaviour of transport systems using realistic assumptions is very essential, "it is better to use values that are realistic-but-unsafe than values that are safe-but-unrealistic".

Like many other prediction models, researchers have stated that accurate prediction of bus travel time is very difficult, especially in a system where public transport system is not given priority (Liu, 2010), only average value could be easily estimated since most factors affecting the estimation of travel time are stochastic in nature (Ramezani and Geroliminis, 2012; Bharti et al., 2017). These factors include weather condition, time of the day, driver behaviour, traffic volume, vehicle characteristics, etc. (Izadpanah, 2010; Liu and Sinha, 2007). Technically, major factors that can influence bus travel time include; intersection delays due to queues and traffic control operations, delay caused by turning vehicles, on-street parking of vehicles, crossing pedestrians and cyclists, etc. (Zheng, 2011; Liu et al., 1999). Others include travel distance, number of stops,

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dwell times, number of boarding passengers and alighting passengers and weather description (Gurmu and Fan, 2014). Though a difficult task to achieve, technologies used for data collection in developed countries for the purpose of travel time prediction have improved accuracy of estimations. Morden devices used for data collection include; probe vehicles, loop detectors, digital cameras, Automatic Number Plate Recognition (ANPR) camera, Bluetooth scanners, speed sensors (Coifman, 2000; Zheng, 2011; Bharti et al., 2017).

There are several bus travel time prediction models developed by previous researchers. Analytical techniques such as probability theorem (Bharti et al., 2017), regression models (You and Kim, 2000; Wu et. al., 2004; Bharti et al., 2017), Artificial Intelligence techniques (Gurmu, 2010; Gurmu and Fan, 2014; Bharti et al., 2017; Zaki et al., 2013; Kumar et al., 2017), etc. have been used in the past. The degree of accuracy of these models depends on the level of variability of input parameters and the reliability of the analytical technique used (Izadpanah, 2010; Gurmu, 2010; Kumar et al. 2017). Zaki et al. (2013) combined the Neural Network (NN) and the Kalman Filter Techniques to form a hybrid methodological algorithm for estimating arrival time at bus stops using Global Positioning System (GPS) data and historic travel speed data, the study yielded satisfactory results.

Bharti et al. (2017) considered traffic volume and car percentage composition in traffic stream as independent variables for travel time estimation modelling. The authors recommended the use of Artificial Intelligence method such as the Artificial Neural Networks (ANN) and the use of Stochastic Response Surface Methods (SRSM) since they yielded relatively accurate results compared to the multiple linear regression model. Though, the multiple linear regression model dose not predict bus travel time accurately as stated by other researches (Gurmu and Fan, 2014; Bharti et al., 2017), its approach is capable of measuring the degree of sensitivity of all the input variables used for predicting the bus travel time (Gurmu and Fan, 2014).

It is not certain if the transferability of calibrated and validated bus travel time prediction models built by previous researchers for other locations will suite cities like Makurdi town, Benue state of Nigeria. Major challenges of bus services in cities of developing countries like Makurdi town include poor services characterised by disorderly and uncertain/non-organised operations on routes without designated bus stops (Zheng, 2011). It therefore becomes a challenge for concerned persons or organisation to develop local models that actually suits the unique properties of developing societies. Some of the peculiar properties that may weaken the strength of other existing models for use in developed cities include the use of bus rapid transport (BRT), bus assigned lanes, designated bus stops, bus time table, etc. Efficient public transport system in cities is important because it improves their liveability and boost economic and social growth of the cities (Gurmu, 2010). Because there is no previous research work which attempted to predict bus travel time on routes without designated bus stops in a heterogeneous traffic stream associated with several uncertainties in estimating model input parameters, in this part of the world, this study is relevant and justified.

The study aims at developing a multiple linear regression model for predicting bus travel time on urban roads without designated bus stops based on bus services in Makurdi town and, then validate the model using ANN technique. Objectives of the study include; to assess bus travel time on routes without designated bus stops, to examine geometric features of roadways, to assess bus dwell time and travel speeds in a heterogeneous traffic stream on routes in Makurdi town, to validate the built model and examine sensitivity of all input variables.

2. Literature Review

2.1 Multiple Linear Regression Model

The multiple linear regression model is a mathematical function that defines the relationship between independent (input) and the dependent (output) variables that explain the behaviour of a system (Rohatgi and Saleh, 2001; Soong, 2004). Development of multiple linear regression model usually employs statistical tools such as; Statistical Product for Service Solution (SPSS), R Programming, Microsoft Excel, etc. which are capable of defining the relationship between the independent and dependent variables in form of a function. The strength of the function is usually examined using it coefficient of determination (also known as r square – R^2) value which ranges from 0 – 1, with 0 defining a weak relationship and 1 showing a stronger relationship between variables (Rohatgi and Saleh, 2001). Another relevant model performance indicator is the measure of sensitivity of input variables using their respective p-values. The p-value tests the null hypothesis that coefficient of a variable is equal to zero, meaning the variable has no effect on the model; such that a low p-value (< 0.05) indicates that the null hypothesis should be rejected, that is, the variable is likely to be meaningful to the model. Multiple linear regression models are generally expressed as mathematical function in the form shown in Equation 1;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n \qquad - \quad - \quad - \quad - \quad - \qquad (1)$$

where, Y is the dependent variable, X_i and β_i for i = 1, 2, . . n denote the independent variables or input parameters and their respective coefficients, β_0 is the constant value which defines the average behaviour of the system when the magnitude of all other variables is zero. n represents the total number of input variables used in the model. The use of multiple linear regression model for property or performance prediction of engineering systems has been in use over a long period of time (Ramakrishna et al., 2006; Gurmu and Fan, 2014). The model best suites systems that exhibits deterministic behaviour rather than those that are stochastic in nature, since stochastic systems exhibit behaviours that are nonlinear or uncertain and difficult to predict (Zheng 2011).

2.2 Artificial Neural Network (ANN) Models

The ANN method is an Artificial Intelligence (AI) technique used for analysing systems (Munakata, 2008; Russell and Norvig, 2010). The application of ANN models in predicting bus travel time has gained acceptance decades ago (Balaubramanian and Rao, 2015; Amita et al., 2015). It is an iterative simulation process which has gained wide acceptance in predicting system behaviour due to its ability to handle system complexities of nonlinearity and challenges of missing or incomplete dataset, inaccurate data, etc. The network consists of numerous layers of parallel processing neurons. Hidden layers exist between input and output layers. Neurons in one or more hidden layers are connected to the neurons of the neighbouring layers by weighted factor that is adjustable during model training process. ANN model could adopt a sigmoid performance function which is probabilistic in nature having multilayer processing framework capable of accepting multiple inputs to produce the desired outputs. Running an ANN model is an iterative and a trial-and-error process which requires specifying the number of layers which are usually more than one (Gurmu and Fan, 2014). The training process requires a feed forward-backward propagation algorithm, specification of the maximum number of training epochs and number of iterations which describes the number of times a batch of data passes through the algorithm for forward and backward propagations. From the process, mean square errors and

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biases of estimations are usually computed using the model function specified. Figure 1 is an architectural presentation of a typical ANN model.

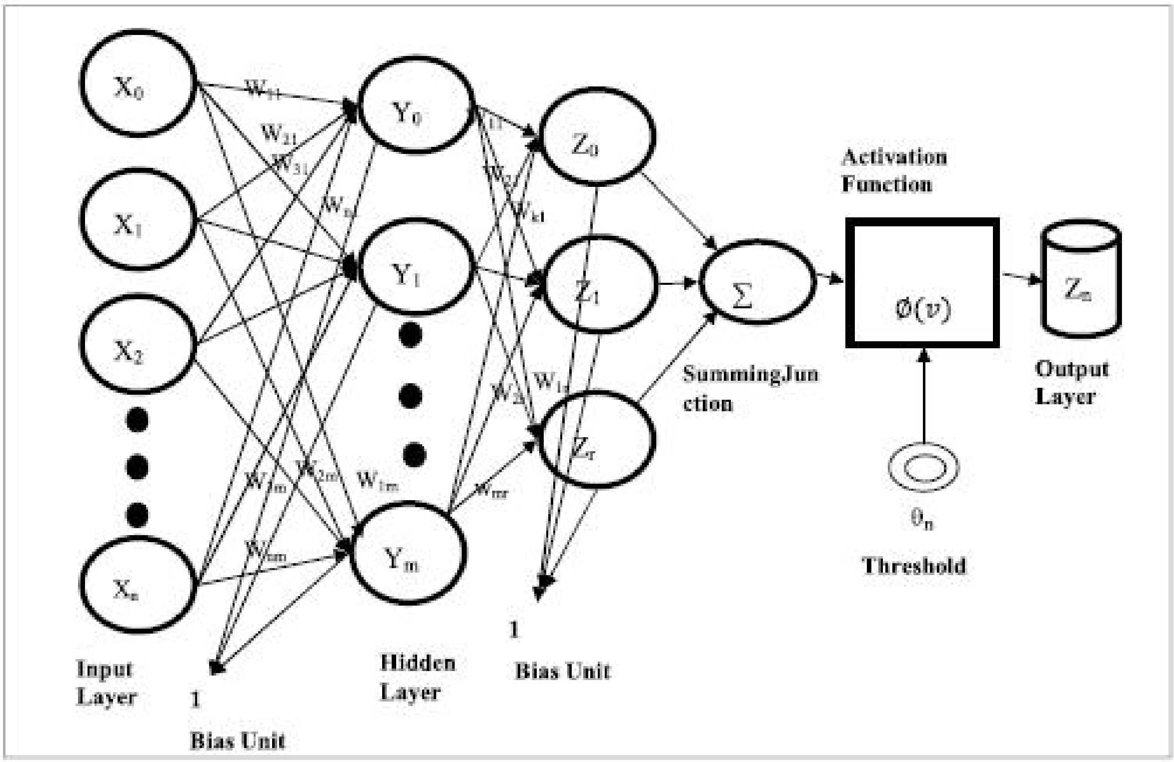

Figure 1: The Architecture of an ANN Model (Amita et al., 2015)

The ANN method is usually implemented using software that are capable of simulating the probabilistic behaviour of the systems such as the ANN tool found in MATLAB (Zheng, 2011; MATLAB, 2018). The ANN tool in MATLAB is used to simulate systems based on the ANN model. It requires input parameters, targeted output values, then validate results to a certain degree of accuracy. It is therefore relevant to employ such technique in this study for model validation to check for variations caused by the probabilistic nature of some input variables such as dwell time, bus headway, traffic composition, etc. as they influence the regression model significantly (Gurmu and Fan, 2014; Amita et al., 2015).

3. Materials and Methods

3.1 Description of Study Area

This study was carried out in Makurdi town, Benue state of Nigeria. Makurdi town is an urban area known to be the capital city of Benue State, Nigeria. The city located on Latitude 7° 43′ 56″ and Longitude 8° 32′ 21″ (Google Earth, 2018) has an estimated human population of over 367,588 persons with a land mass of approximately 800 km^2 (NPC, 2006). Traffic streams in Makurdi town are described as being heterogeneous since they comprise private cars, mini buses, Heavy Goods Vehicles (HGV) and Light Goods Vehicles (LGV), motorcycles, tricycles and pedestrians. Though mini-buses are the major mode for mass transit in Makurdi town, the design and construction of roadways in the town does not provide special road facilities such as bus lane for the mini-buses therefore, the buses travel and share lanes with other traffic components. This is described as a mixed traffic stream since it comprises different modes including pedestrians. Traffic flow in Makurdi town is generally characterised by interruptions from differed sources such as pedestrian crossing, the stop-and-move pattern of mini-buses that have no designated stopping spots (bus stops) along the routes, operations of intersection, etc. Town shuttle mini-buses operating within the city travel along the arterials conveying commuters along the routes. The routes in Makurdi town considered by this study as presented in Figure 2 included; the High Level roundabout – School of Remedial Studies Junction (HL - SRS), High level roundabout – Federal medical centre junction (HL – FMC), Wurukum roundabout – Coca cola complex (W - CCC) and Wurukum roundabout – Welfare quarters (W – WQ).

Figure 2: Sampled Routes on An extract Map of Makurdi town (Google Earth, 2018)

3.2 Data Collection

Trained traffic enumerators carried out the field survey. The road network in Makurdi town was divided into routes namely; HL - SRS, HL – FMC, W – CCC and W – WQ. The movement of mini-buses used for public transport services in Makurdi town within the traffic streams was examined from 07:00 am to 05:00pm daily. The geometric characteristics of bus routes such as; route length, average lane width and number of lanes in both directions. Other essential model parameters and methods of measurements were as following;

Traffic volume in one direction (veh/h) - This was measured using manual traffic count technique. The composition volume of motorcycles, private cars and trucks in the traffic stream were estimated. Materials used were basically record sheets, stop watch and writing instruments.

Bus travel speed (km/h) – It was estimated using the plate number matching methods. This involved identifying the bus plate number from its journey origin, then total travel speed was estimated using time lapse during the journey period, and the route length measured using a meter counter wheel.

Average Bus headway (s) – It is the average time lapse between the passage of a sampled lead bus and the following bus measured from bomber-to-bomber using a defined reference spot marked on the road pavement as buses pass over along the routes.

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Average dwell time (s) – This is the time lapse between stops for pick-up of passengers and start-up movement of buses. It was measure by an enumerator who travelled along with the bus from its origin to the destination.

Bus Travel time in minutes (min) – This is the time required for a mini-bus to travel from its origin to the terminal point of the journey or destination of the trip.

Number of intersection (unit) – These were counted by the enumerator who travelled along with the bus. Types of intersection identified included; roundabouts, cross-intersection and T-intersections.

Total distance travel (m) – This is the distance between the origin and destination of the journey measured along the travel route using the meter counter wheel. For a given road segment, it was measured in meters (m).

3.3 Data Analysis

A multiple linear regression model for estimating short term bus travel time along routes without designated bus stops was developed using SPSS. The process involved creation of a spreadsheet in Microsoft Excel for the raw data which comprised the independent and dependent variables. The Excel file was then imported into SPSS for statistical analysis to build the regression model. Results of the analysis revealed the data characteristics which was used to check for accuracy of the built model. The built model was first validated using goodness of fit test based on the measured (on field) and predicted (using model) bus travel times. It was further validated using ANN tool simulated in MATLAB. The simulation process involved series of iterations at several times to arrive at a better fit for the network model testing, validation, training and estimation of the overall coefficient of determination of variables. The validation process aimed at comparing outputs of the multiple linear regression model and those of the ANN model using, coefficient of determination value for best fit.

4.0 Results and Discussion

Table 1 shows the geometric characteristics of bus routes in Makurdi town as considered by this study.

Table 1: Geometric Characteristics of Minibus Routes in Makurdi Town

Name of Bus Route	Carriageway Share (Dual/Single)	Number of lanes in one direction	Avg. Lane width (m)	Route Length (m)	Number of Intersections		
					Roundabouts	Cross	Tee
HL – SRS	70%/30%	2	3.60	6420	1	3	2
HL – FMC	80%/20%	2	3.47	4000	1	1	3
W – CCC	100%/0%	2	3.70	5000	0	3	4
W - WQ	0%/100%	1	3.50	4000	0	1	5

Table 1 revealed that, only few bus routes in Makurdi town have dual and single carriageway along the entire route length. Some routes have alternating type of carriageway for dual and single. Only major cross and Tee intersections connecting the highways and arterials were counted. Intersections connecting minor streets supplying less than 50 Veh/h were ignored. Only traffic flow in the direction of movement of sampled mini-buses with corresponding geometric features were considered.

4.1 Model Development

This study employed the multiple linear regression and ANN methods of modelling for the prediction of bus travel time along routes in Makurdi town.

4.1.1 The Multiple Linear Regression Model

A multiple linear regression model for estimating short term bus travel time on routes within Makurdi town was developed using SPSS software, the summary of results from the statistical analysis were as shown in Table 2.

Table 2: Summary of Statistical Results of the Multiple Linear Regression Model

Model	Unstandardized Coefficient		t-statistic	p-value	95% Confidence interval for β_i	
	β_i	Std. Error			Lower bound	Upper bound
Constant	14.962	1.604	9.328	0.000	11.757	18.167
J_s	-0.024	0.002	-13.292	0.000	-0.027	-0.020
R_l	0.002	0.000	8.281	0.000	0.002	0.003
T_m	0.001	0.002	0.744	0.460	-0.002	0.005
T_{pc}	-0.006	0.003	-1.959	0.055	-0.013	0.000
T_t	-0.029	0.019	-1.531	0.131	-0.066	0.009
A_{Dt}	0.008	0.006	1.363	0.178	-0.004	0.020
C_j	0.507	0.256	1.978	0.052	-0.005	1.018
B_h	-2.374	2.305	-1.030	0.307	-6.980	2.232
R^2 = 0.954						
Adjusted R^2 = 0.949						

Table 2 revealed that journey speed, composition of private cars and trucks in a traffic stream and bus time headway affects bus travel time negatively, in other words, the variables are inversely proportional to bus travel time. This implies that the higher the magnitude of these aforementioned variables the lesser the bus travel time. On the other hand, the higher the magnitude of route length, composition of motorcycle and tricycles in the traffic stream, average dwell time and number of cross-junctions along the route the higher the bus travel time. These results agreed with findings of Gurmu and Fan (2014). This model indicates that, the estimated average bus travel time along routes in Makurdi town without considering the impacts of other variables is approximate 15 minutes (constant).

Table 2 also shows the statistical strength of the built multiple linear regression model. Though the coefficient of determination obtained from the analysis (Adj. R^2 = 0.949) showed a strong relationship in estimating output using the input variables considered by the study, only p-values for the journey speed and route length variables showed a stronger relationship (having value of 0.00) between the input and output variables in the model. The p-values for traffic composition of private cars and number of crossed intersections along the route showed a slight (> 0.05) variation which indicates it significant strength in determining short term bus travel time using this model. Other independent variables such as the composition of motorcycle and trucks in the traffic stream, average dwell time and average bus headway showed less importance in

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estimating bus travel time using this model, which agreed with findings of previous researchers (Gurmu and Fan, 2014). Therefore, the developed mathematical model for predicting short term bus travel time is as shown in equation 1;

$$T_T = 14.962 - 0.024J_s + 0.002R_l + 0.001T_m - 0.006T_{pc} - 0.029T_t + 0.008A_{Dt} + 0.507C_j - 2.374B_h \quad (2)$$

Where: T_T is the estimated bus travel time measured in minutes, J_s is journey speed of the bus measured in meter per minute, R_l is the bus route length measured in meters, T_m is the volume of motorcycles in the traffic stream measured in units per hour, T_{pc} is the volume of private cars in the traffic stream measured in vehicles per hour, T_t is the volume of trucks in the traffic stream measured in vehicles per hour, A_{Dt} is the average dwell time measured in seconds. Some variables such as the number of roundabout along routes,, number of Tee intersections along routes and the composition of motorcycles in traffic stream as obtained from the field work were ignored by the statistical tool (SPSS) used for the analysis which indicated their irrelevance to a great extent in predicting bus travel time using the built model.

4.1.2 Model Validation

Statistical test for goodness of fit using the actual and estimated dataset was carried out using the plot shown in Figure 3. The coefficient of determination obtained from the plot was 0.95 which indicated that, the model discribes up to 95% of the vaiables considered in the study which shows a statistically good fit.

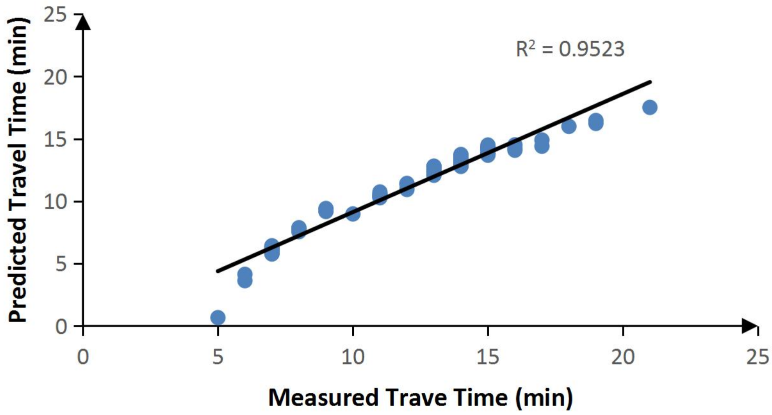

Figure 3: Model Validation using Statistical Method

An intelligent approach was also employed to further examined the fitness of the built model since p-values of some variables considered by the model such as the composition of motorcycle and trucks in the traffic stream, average bus dwell time and bus headway did not show statistically satisfactory relationship between the input and output variables of the model (p–value > 0.05). This involved developing an ANN model using the MATLAB tool to further check for accuracy of the built multiple linear regression model.

4.2 The ANN Model

A MATLAB tool based on the nntool command was used for this study. The tool used for simulating the ANN models is capable of estimating weighted mean values, mean square errors and biases from the input variables. Model validation using the ANN approach implemented in MATLAB yielded results as shown in Figure 4.

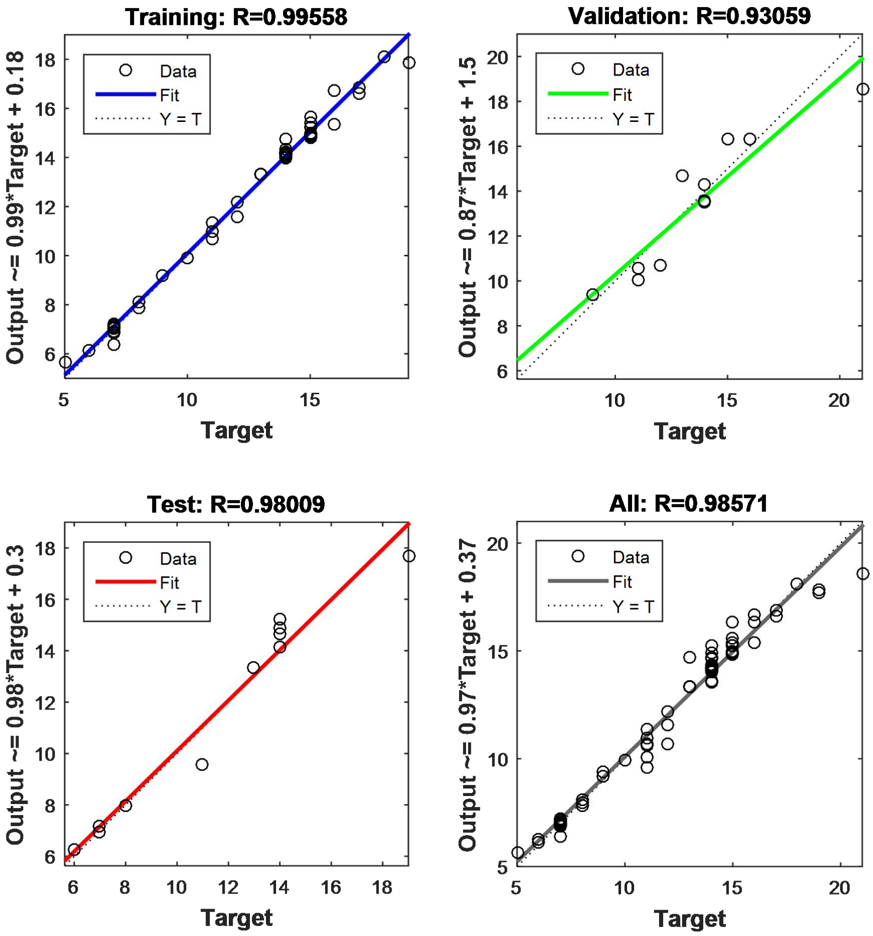

Figure 4: Model Validation using ANN Model

Figure 4 showed fitness of the built model in defining the relationship between the input and output variables considered by the study. The training, validation and testing of the model using 1000 iterations for a sigmoidal function gave satisfactory output measured at levels 100%, 93% and 98% respectively. The entire performance of the model is measured at 99% approximately, which showed a strong relationship between variables. Thus, using this model, all performance indicators of the model showed satisfactory results.

5.0 Conclusion

This study developed a multiple linear regression model for predicting bus travel time using SPSS software. Input variables required by the model included; bus route length, bus travel speed, average dwell time at random stops for pick-up and alighting of passengers, bus headway, volume of motorcycles in the traffic stream, volume of private cars in the traffic stream, volume of trucks in the traffic stream and the total number of cross intersections along the route. Based on the built model, an average bus travel time of 15 minutes approximately was established as bus travel time for all bus routes in Makurdi town (assuming all other variables have zero magnitude). Goodness of fit test in statistics and ANN model were used to confirm the accuracy of the built model for predicting short team bus travel time on bus routes within Makurdi town, in Benue State. It was therefore concluded that, bus travel time on major routes in Makurdi town could be accurately estimated using the built multiple linear regression model

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provided all essential input parameters required by the model were available. The following recommendations were therefore made;

Establishment of designated bus stops along bus routes within Makurdi town was recommended to minimise bus dwell frequency and for more accurate estimation of travel time in line with the design and development of modern cities.

Travel information bill boards should be erected at strategic locations along bus routes in Makurdi town stating their average bus travel time to help enlighten commuters that have high value of travel time.

References

Amita, J., Singh, JS. and Kumar, GP. 2015. Prediction of Bus Travel Time Using Artificial Neural Networks. International Journal for Traffic and Transport Engineering, 5(4): 410 - 424.

Balaubramanian, P. and Rao, KR. 2015. An Adaptive Long-Term Bus Arrival Time Prediction Model with Cyclic Variations. Journal of Public Transportation, 18(1): 1 -18.

Bharti, AK., Sekhar, CR. and Chandra, S. 2017. Modelling Travel Time of Car with varying Demand on an Urban Midblock Section. Journal of Intelligent Transport Systems, 22(2): 99 – 105.

Bonsall, P., Liu, R. and Young, W. 2005. Modelling safety-related Driving behaviour impact of Parameter Values. Elsevier, Transport Research Part A, 39: 425 – 444.

Ceder, A. 2007. Public Transit Planning and Operation Theory, Modelling and Practice, Elsevier, London.

Coifman, B. 2000. Estimating Travel Times and Vehicle Trajectories on Freeways Using Dual Loop Detectors. Transportation Research Part A: Policy and Practice, 36(4): 351 - 364.

Cullinane, S. 2002. The Relationship between Car Ownership and Public Transport Provision: a case study of Hong Kong. Transport Policy, 9: 29 – 39.

Google Earth. 2018. Google Earths Inc.

Gudmundsson, H., Hall, RP., Marsden, G. and Zietsman, J. 2015. Sustainable Transportation. Indicators, Frameworks and Performance Management. Printer Texts in Business and Economics, London.

Gurmu, ZK. 2010. A Dynamic Prediction of Travel Time for Transit Vehicles in Brazil Using GPS Data. MSc. Dissertation, Department of Civil Engineering and Management, University of Twente, The Netherlands.

Gurmu, ZK. and Fan, W. 2014. Artificial Neural Network Travel Time Prediction Model for Buses Using Only GPS Data, Journal of Public Transport, 17(2): 45 – 65.

Ibarra-Rojas, OJ., Delgado, F., Giesen, R. and Munoz, JC. 2015. Planning, Operation and Control of Bus Transport Systems: A Literature Review. Transport Research Part B, 77: 38 – 75.

Izadpanah, P. 2010. Freeway Travel Time Prediction using Data from Mobile Probes. PhD Thesis, Department of Civil Engineering, University of Waterloo, Waterloo, Ontario, Canada.

Jeong, RH. 2004. The Prediction of Bus Arrival Time Using Automatic Vehicle Location Systems Data. Ph.D. Thesis at Texas A&M University, Texas.

Kumar, BA., Jairam, R., Arkatkar SS. and Vanajakshi, L. 2017. Real time bus travel time prediction using K-NN classifier. Transport Letters, The International Journal of Transport Research, 7: 1 – 11.

Liu, R. 2010. Traffic Simulation with DRACULA. In: Barcelo, J. ed. Fundamentals of Traffic Simulation, International Series in Operations Research and Management Science. Springer New York.

Liu, R. and Sinha, S. 2007. Modelling Urban Bus Service and Passenger Reliability. In: The Third International Symposium on Transportation Network Reliability, 19-20 July, The Hague, Netherlands.

Liu, R., Clark, SD., Montgomery, FO. and Watling, DP. 1999. Microscopic Modelling of Traffic Management Measures for Guided Bus Operation, Selected Proceedings of 8th World Conference on Transport Research, 2: 367 – 380.

Mannini, L. Carrese, S., Cipriana, E. and Crisalli, U. 2015. On the Short-term Prediction of Traffic State: An Application on Urban Freeways in Rome. 18th Euro Working Group on Transportation 14 – 16 July, 2015, Delft, the Netherlands.

MATLAB 2015. User Guide Manual. Mathworks Inc., Natick, Massachusetts, USA.

Munakata, T. 2008. Fundamentals of the New Artificial Intelligence: Neural, Evolutionary, Fuzzy and More, 2nd Edition. Gries, D. and Schneider, F. B. (Eds.). Springer, Cleveland, USA.

NPC. 2006. National Population Commission. Federal Republic of Nigeria Official Gazzette, 94.

Ramakrishna, Y., Ramakrishna, P. and Sivanandan R. 2006. Bus Travel Time Prediction Using GPS Data. The 9th Annual International Conference and Exhibition Map India, 30th Jan. – 2nd Feb., 2006, Proceedings Map India, pp. 23 – 35, New Delhi, India.

Ramezani, M. and Geroliminis, N. 2012. On the Estimation of Arterial Route Travel Time Distribution with Markov Chains. Transport Research Part B., 46: 1576 – 1590.

Rohatgi, VK. and Saleh, AKE. 2001. An Introduction to Probability and Statistics. 2nd Edition, John Wiley and Sons, Inc. New York.

Russell, SJ. and Norvig, P. 2010. Artificial Intelligence: A Modern Approach, 3rd Edition. Prentice Hall Series, London.

Schiller, PL., Bruun, EC. and Kenworthy, JR. 2010. An Introduction to Sustainable Transportation – Policy Planning and Implementation. Earthscan, New York, USA.

Soong, TT. 2004. Fundamentals of Probability and Statistics for Engineers. John Wiley and Sons, Ltd., England.

Wu, CH., Wei, CC., Su, DC., Chang MH. and Ho, JM. 2004. Travel Time Prediction with Support Vector Regression. IEEE Transactions on Intelligent Transportation Systems, 5(4): 276-281.

You, J., and Kim, TJ. 2000. Development and Evaluation of a Hybrid Travel Time Forecasting Model. Transportation Research Part C: Emerging Technologies, 8: 231-256.

Zaki, M., Ashour, I., Morkany, M., and Hesham, B. 2013. Online Bus Arrival Time Prediction using Hybrid Neural Network and Kalman Filter Techniques. International Journal of Modern Engineering Research, 3 (4): 2035 – 2040.

Zheng, F. 2011. Modelling Urban Travel Times. PhD Thesis, Faculty of Civil Engineering and Geosciences, Delft University, Netherlands.

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