A neuro-fuzzy approach to vehicular traffic flow prediction for a metropolis in a developing country

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Abstract: Short-term prediction of traffic flow is central to alleviating congestion and controlling the negative impacts of environmental pollution resulting from vehicle emissions on both inter- and intra-urban highways. The strong need to monitor and control congestion time and costs for metropolis in developing countries has therefore motivated the current study. This paper establishes the application of neuro-fuzzy to predict traffic volume of vehicles on a busy traffic corridor. Using a case drawn from metropolitan Lagos, Nigeria, a traffic prediction system is designed such that the predicted values (output) can be accessed by the public through mobile phones. The best route to a particular route will also be advised by the system. In addition, the expected fuel consumption and travel time will be included in the output. Input data is pre-processed based on acquired real time traffic data, the network is trained and the fuzzifier module categorized the numerical output of the model. The advisory module of the traffic prediction model then computes the expected travel time and the fuel consumption cost. The results obtained established the non-linear nature of traffic flow along the routes and indicates that predicting the traffic situation is non-algorithmic. The travel time along the routes is averaged at 23.5 minutes, while the fuel cost is estimated at an average of $2.03. Thus, proper control of traffic time and cost could be obtained if monitoring is aided with neuro-fuzzy as a tool.

Keywords: *Prediction; Traffic volume; Lagos island; Traffic congestion; Urban traffic; Neural networks; Neuro-fuzzy; Fuzzy logic; Route; Vehicle*

1. Introduction

While research on traffic flow has been intensive, investigators have mainly focused on monitoring, prediction and the control of traffic (Siljanov, 1977; Kuchipudi and Chien, 2003). However, practical cases of traffic flow measurements for metropolis in the developing African countries seem missing. Even many of the existing studies seem to have omitted capturing uncertainty and often ignore the powerful support that data could be provided by training from past data in the practical analysis of problems; they failed to integrate uncertainty capture with past data. Inose and Xamada (1983) studied the traffic control problem from a practical perspective. The traffic control analysis discussed by Prigogive and Herman (1971) has orientation along the kinetic theory dimension. Siljanor (1977) also reported on traffic control. While these efforts are direct contributions towards controlling traffic flow, other indirect means have also been documented. The control of congestion as an indirect means of traffic control was demonstrated in Broderick *et al*. (2005) with the use of CALINE 4 model. An emerging fact is that none of these studies has given detailed insights on how traffic could be predicted. None has also discussed the presence of uncertainty in decision making in model formulation. The case with a metropolitan of a developing African country is still missing in the literature. Additional studies on traffic control include Panella *et al*. (2006) with fuzzy based control theory for vehicle flow on a street network. Lukanin *et al*. (2003) contributed to traffic control by providing information on energy consumption, intensity of pollutants emissions caused by traffic flow and the use of the same in decongesting traffic build up based on past data analysis. Further on control, Anjanayulu *et al*. (2007) proposed an intelligent control model based on decision support system that calculates traffic flow. Quian *et al*. (2006) also controlled traffic with the use of system dynamics approach. None of these additional studies by Panella *et al*. (2006), Lukanin *et al*. (2003), Anjanayulu *et al*. (2007) and Quian *et al*. have fully solved the traffic flow prediction problem since control is only a partial component of the traffic flow problem. None also has accounted for uncertainty

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and imprecision in model framework. The case of a metropolitan in an African setting is also missing.

The monitoring aspect of the traffic flow problem has also been studied by a growing number of investigations. Notable studies are due to Gauvin *et al.* (2001), Gokhale and Khaz (2007) and Sol *et al.* (2007). Others are Izdanevitch *et al.* (2001) and Sharma *et al.* (2007). Primarily, the monitoring aspect of the studies entails obtaining information on defined performance level on roads through moderate speed regulation, short trip time analysis of vehicles, queue characteristics of moving vehicles, and associated parameters. Additional studies on traffic flow monitoring include Helbing and Cansvier (1999), Tampere (2004) with respective focus on modelling and simulation of multi-lane traffic flow as well as the development of human-kinetic multiclass traffic flow theory. Further monitoring studies include that of Elefteriadon and Webster (2000). In conclusion, none of these monitoring studies has addressed the traffic prediction problem, particularly in terms of uncertainty prediction. The case with a metropolitan African setting is conspicuously absent in them.

The area of traffic flow prediction is small but growing (Zhao and Wang, 2007a; 2007b). Studies that have been implemented include Dongli *et al.* (2007), which proposed a radial basis function neural network model prediction control from freeway traffic system. The work did not track uncertainty and learning from history but only applied neural network and genetic algorithm. The limitation of not incorporating fuzzy systems in model development has not provided much insight into the more practical aspects of traffic flow. Van Hinsbergen *et al.* (2009) documented a rich literature review on traffic flow prediction models and argued that ARIMA-like time series approaches (Nichan, 1980; Lee and Frambro, 1999), nearest neighbourhood techniques (Smith and Demetsky, 1996; Clark, 2003) and the committee or ensemble approaches in which multiple model predictions are combined (Kuchipudi and Chien, 2003; Petidis *et al.*, 2001) are the most extensively applied approaches in practice. Van Hinsbergen *et al.* (2009) further identified Kalman filtering (Okutami and Stephanedes, 1984; Yang, 2005) and linear weighted regression (Zhong *et al.*, 2005; Nikovski *et al.*, 2005) as additional models that have extended the frontier of knowledge in traffic flow. While many of these models mentioned by Van Hinsbergen *et al.* (2009) have shown high accuracy for predicting traffic flow conditions,

some of them have shown imperfections when applied in real-time applications (Hinsbergen *et al.*, 2009). None of the models has appropriately incorporated uncertainties inherent in real-life applications. Also, cases that detailed investigations relevant to a metropolitan in a developing country in Africa are missing in the literature. There is therefore need to extend the frontier of knowledge with the missing tools and provide useful information in literature for traffic flow improvement.

Ran (2000) proposed an advanced traveller information system, which disseminates real time traffic information to travellers, assisting them to make choice decisions on routes to follow, thereby decongesting traffic flow in prone areas and hence controlling traffic indirectly. Zhao and Wang (2007a, 2007b) advanced efforts in furthering the results of earlier studies by Ran (2000). However, there is a major shortfall in the level of knowledge attained using the methodology of Zhao and Wang (2007a, 2007b) as well as Ran (2000). Majorly, the unique advantage of mobile phones in providing advanced traveller's information has not been utilized. Thus, irrespective of locations, the best route to a particular destination could still be advised using mobile phones. This gap in the literature is an important omission that should be investigated. Emerging from the traffic prediction literature is a number of principal parameters used in predicting traffic flow, which may be distinct from the parameters generally considered in the literature. Oke *et al.* (2008) emphasised the width of the road, D, as an important parameter. This is certainly reflected in the fact that when the road is enlarged, more vehicles would move through a traffic line per unit time and if the road width is reduced due to bad roads (potholes or construction work in progress), the traffic may build up. When cross-roads are involved in traffic analysis, such as a two-way cross-road, more complexity is introduced and modelling is done with modelling one-way one-line traffic flow interaction with two incoming and one outgoing and with one incoming and two outgoing traffic flows (Junevicius and Bogdevicius, 2007).

However, from the pool of knowledge on traffic flow, scholars have been advocating for models that account for uncertainties. This call therefore makes the current work relevant. Thus, the aim of this work is to predict traffic flow of vehicles with development of a practical application in a way that incorporates fuzzy logic and artificial neural network in an integrated way as neuro-fuzzy. This aim is achieved with the

application of the principles of neuro-fuzzy in a metropolitan of a developing country. The article is structured into five sections. Section 1 deals with the introduction and serves as the motivation for the work. The literature review is also documented in Section 1. Section 2 discusses the methodology for the study with the necessary assumptions made, theoretical framework and aspects of the neural network used. Section 2 also includes the algorithm for cost measurement. Section 3 is the case application drawn on routes to Lagos Island. The fuzzifier module framework is also discussed. It contains information on the advisory module of the traffic prediction model with the route advisor stated. Furthermore, calculation of gallons of fuel is made while the software used for analysis is also presented. Section 4 is the concluding remarks.

2. Methodology

2.1. Assumptions

The model application was made under a number of basic assumptions, which are similar in structure to those contained in Oke *et al.* (2008) and are stated in this section. Other assumptions are stated in the appropriate places. First, there is conservation of the number of vehicles for the study period, which does not permit accidents. When accidents occur, chaos result and sudden change in traffic flow from moving to slow-moving or temporary static flow exists.

The static nature of the vehicle population is maintained under this assumption as accidents introduce dynamism which would necessitate utilising system dynamics principles for the problem solution. The second assumption is psychologically-based as it relates to the sanity and normal behaviour of drivers. This assumes that drivers keep safety rules and regulations while on the road.

The third assumption concerns road expansion, which does not take place during the study period. The effect of this on traffic may be either negative or positive. During road expansion, certain sections of the road may be blocked while repair activities are carried out. The other side to this issue is that extending the road would permit more vehicles for the width of the road, therefore affecting traffic flow positively.

Fourth, traffic flow is often deliberately slowed down with police checks on highways. Such a check is assumed as non-existent on the roads studied as it is a highway designed for relatively high vehicle speeds. Fifth, the flow of traffic is

assumed to be one directional on a particular lane. Hence, no crossing of lanes to obstruct flow of vehicles approaching in an opposite way is allowed.

2.2. Notations

The following notations are used in the paper:

q	Traffic flow
K	Concentration of vehicles in a road network
V	Traffic flow speed
G	Gallons of fuel per 1000 net ton mile
K	Constant (0.048965 for a car)
R_T	Total resistance per 1000 net tons
E	Thermal efficiency ratio about 0.22
R	Resistance (lb/gross ton)
w	Gross weight of a car or velocity (tons/axle)
N	Number of axles per car
v	Velocity (mph) i.e. v_1, v_2
T_o	The number of output units
T	Total elapsed timed (elapsed time of travel along a route)
t_d	Periodic density count
t	The desired target output
$f[*]$	Function of
w_0	Initial weight values
x_i	Input vector
N	Total density or volume count, the sum of vehicles observed during periodic density count each t second
o_j	Network output for the jth element
P	Population (urban area population)
d_i	Mean (average) of d_is
β	Learning constant
α	The momentum parameter
σ	Standard deviation
P_i	Value of parameter at time i
P_{i+i}	Value of parameter at time $i+1$
d_i	The difference in value of parameter at period $i + 1$ and that of period i

L Length of road

ρ Number of vehicles per cubic meter

v Velocity

D Width of road

ΔP Change in traffic congestion or pressure on roads

a_1, a_2, a_3 Constants.

2.3. Theoretical framework

Traffic prediction models have been well studied (Junevicius and Bogdevicius, 2007; Zhang, 2000) in the literature but the model suggested here is based on three sets of modular operations, which includes acquiring traffic information for the route of interest. Prediction is then made based on input data. The next consideration is to send the prediction to the fuzzifier and the advisory modules. Traffic information is obtained based on a number of established expressions, which are shown to be the framework of the study.

The formulations are established from first principles. The elapsed time, T, which is also referred to as the expected time of travel along a route, has been expressed mathematically as a function of traffic flow, q, concentration of vehicles in a road network, K, traffic flow speed, V, and t, the periodic density count. Thus,

$$T = f(q, K, V, t) \tag{1}$$

The relationship among the variables in Equation (1) may be established by starting from the kinetics theory of vehicular flow, as defined by Prigogine and Herman (1971), which related q to K and V, and a further relationship established by TRB (Dharia and Adeli, 2003) for q, N and T, given respectively in Equation (2) as:

$$T = \frac{N}{KV} = \frac{Nt}{V} \tag{2}$$

which reveals that t is the reciprocal of K.

Notice that T is an important parameter in the determination of traffic flow and Equation (2) should be noted. Apart from time element in measurement, the current work also focuses on cost determination and utilises the framework established in the literature. The basis of the formula is that as vehicles move around, there is an equivalent fuel consumption that the vehicle utilises. The fuel consumption in terms of quantity is then established as:

$$G = \frac{J\left[a_1 + \dfrac{a_2}{w} + a_3 V + a_4 \dfrac{V^2}{wN}\right]}{E} \tag{3}$$

where G is the gallons of fuel per 1000 net mile.

All other variables are as defined in the nomenclature. However, for specific vehicular conditions, the substitution of $a_1 = 0.6$, $a_2 = 20$, $a_3 = 0.01$ and $a_4 = 0.07$ yields an expression, which has an equivalence of Expression (4), particularly when we consider acceleration resistance as the sum of the linear acceleration of the car and that of the angular acceleration of the wheels and axles of the car. Thus,

$$G = \frac{J\left[\dfrac{70(V_2^2 - V_1^2)}{s} + \dfrac{95(V_2 - V_1)}{T}\right]}{E} \tag{4}$$

We also note that for the case considered, V_2 and V_1 being initial and final velocities gives 80 km/hr and 0 km/hr, respectively. We should also note that T is known while s is unknown. It thus becomes necessary to utilise another expression for s, stated as:

$$Log(s) = 0.99 + 0.07 \, Log \, P \tag{5a}$$

Notice that P, which refers to population could be calculated as:

$$R = T = 0.98 \, i^{0.019} \tag{5b}$$

Recall that the development of Equations (3) to (5b) has been based on the possible estimation of fuel consumption by the vehicle on the road. However, there are more parameters that influence the fuel consumption than those currently considered. For example, the length of the road, L, width of the road and change in traffic congestion or pressure on roads has not been mentioned in the Expressions (3) to (5b). It thus implies that obtaining an expression for the equivalence of velocity for Equation (17) of Oke et al. (2008) expression for change in traffic congestion or pressure on roads and substituting it in Equation (4) of the current paper yields:

$$G = \frac{J\left[a_1 + \dfrac{a_2}{w} + a_3 \sqrt{\dfrac{D\Delta P}{4L\rho}} + \dfrac{a_4 D\Delta P}{4wNL\rho}\right]}{E} \tag{6}$$
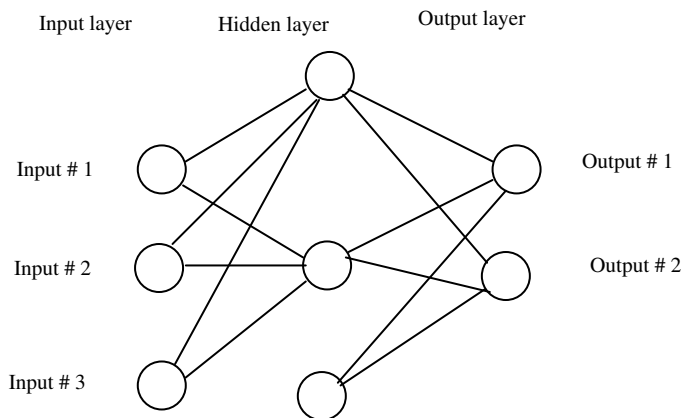
Figure 1: A generalised three-layer feed forward neural network.

Equation (6) has been developed based on Bernoulli's principle of flow and details could be found in Oke *et al.* (2008). An alternative equation, which is a variant of the first could be developed for Equation (6). This suggestion by Oke *et al.* (2008) could be used to modify the fuel consumption equation as:

$$G = \frac{J}{E}[a_1 + \frac{a_2}{w} + 0.5[K_i^{\frac{1}{5}}L^{-\frac{1}{10}}\rho^{\frac{1}{2}}Q^{\frac{2}{5}}\Delta P^{\frac{3}{10}}]$$

$$+\frac{0.25a_4 K_i^{\frac{1}{5}}L^{-\frac{4}{5}}Q^{\frac{2}{5}}\Delta P^{-\frac{4}{5}}}{wN}] \qquad (7)$$

2.4. Aspects of neural network used

Three principal steps are universally identified as appropriate when considering using neural network that is suitable as a building block for the current study. First, the network is tuned, pre-processing of data is made, and the training of data is embarked upon. In tuning the network, the first aim is to identify the set-up parameters for the network, which may include: (1) the number of hidden layers, (2) the size of the hidden layers, (3) the learning constant, (4) the momentum parameter, (5) the range, format and bias of data presented to the network and (6) the form of the activation function (sigmoid) used. Applied to the vehicle traffic flow problem in a metropolis, the output layer has a single unit, which is the expected total volume on a particular route for the next 30 minutes interval (see generalised network diagram – Figure 1).

From literature report, it has been suggested that the choice of the smallest number of neurons possible for a given problem allows for generalisation. The argument is that if there are too many neurons, there will be memorisation of patterns. Hence, the network may not be able to predict effectively outside the data in the training set. An observation from the literature suggests that as a general rule of thumb, the size of the first hidden layer is generally recommended as between one half to three times the size of the input layer. The next step in solving a neural network problem entails pre-processing of the acquired data. For the current work, the sigmoid activation function is used. Details of data-pre-processing include: (1) presenting a data set, which is a second derivative of the data set, defined as:

$$d_i = P_{i+1} - P_i \qquad (8)$$

The next stage is to normalise the data, where the normalised value,

$$t_i = \frac{d_i - \bar{d_i}}{\sigma} \qquad (9)$$

where σ = standard deviation;

The data is 'squashed' using the sigmoid function:

$$h_i = \frac{1}{1 + \exp(-x(t))} \qquad (10)$$

Image processing edge can be detected by accenting change with the function:

$$(a - b) / (a + b),$$

where *a* and *b* are adjacent pixel values. This enables feature detection and will be used to accent change in the data. Also,

$$s_i = \frac{P_{i+1} - P_i}{P_{i+1} + P_i} \qquad (11)$$

So all columns from the last (feature detection) procedure will be appended with the columns from the previous 'squashing' procedure. It will double the number of columns.

Training: The network is trained using the back propagation algorithm. The weights are initialized with random floating point numbers in the range (-1, 1) and the error function used is the mean square error defined as:

$$MSE = \frac{1}{T} \sum_{i=1}^{T} (\sigma_i - t_i) \qquad (12)$$

where T is the number of output units, o is the network output and t is the desired target output. This error will be propagated backward for each training pattern and for each epoch.

2.4.1. Back propagation algorithm used

The following are the step used in the back propagation algorithm utilized.

Step 1: Read first input pattern and associated output pattern: CONVERSE = TRUE

Step 2: For input layer – assign as net input to each unit in its corresponding element in the input vector. The output for each unit is the net input.

Step 3: For the first hidden layer units. Calculate the net input and output:

$$net_j = w_o + \sum_{i=1}^{n} x_i \, w_{ij} \qquad (13)$$

and

$$o_j = \frac{1}{1 + \exp\left(-net_j\right)} \qquad (14)$$

where w_o is initial weight values, and x_i is the input vector. Repeat Step 3 for all subsequent hidden layers.

Step 4: For the output layer units, calculate the net input and output (as indicated in Equations (13) and (14).

Step 5: Is the difference between target and output pattern within tolerance? If NO, THEN CONVERGE = FALSE

Step 6: For each output unit calculate its error:

$$\delta_j = \left(t_j - o_j\right) o_j \left(1 - o_j\right) \qquad (15)$$

Step 7: For the last hidden layer, calculate error for each unit:

$$\delta_k = o_j \left(1 - o_j\right) \sum_{k} o_k w_{kj} \qquad (16)$$

Repeat Step 7 for all subsequent hidden layers.

Step 8: For all layers, update weights for each unit:

$$\Delta w_{ij}(n+1) = \beta\left(\delta_j \, \sigma_j\right) + \alpha \, \Delta w_{ij}(n) \qquad (17)$$

If (last pattern is presented) & CONVERSE is TRUE, STOP.
Read next input pattern and associated output pattern and GO TO step 2.
The maximum number of training epochs used in this paper is 1000 for the traffic prediction problem.

2.4.2. Traffic prediction model

The traffic prediction model described above is what will be used to achieve the objectives of this paper. The operation of the system is as follows: (i) acquire traffic information for a particular route e.g. Lamata in intervals of 30 minutes; (ii) Get prediction based on input data. This implies that the network should have been trained for that route; (iii) The prediction will be sent to the fuzzifier and the advisory modules. The optimal choice will be the one with the lowest travel time of fuel consumption (Figure 2). These two are dependent variableson the traffic density for each route. Now, to compute the travel time for a car on Lamata (11:30 – 12:00), we have $T = Nt / v =$ (0.27942 x 30) / 0.447414 = 18.7 minutes. It is known that at 12:00 – 12:30, T = 28 minutes. The expected fuel consumption of a car with the speed of 80km/h is what will be used in this computation. The steady state fuel consumption is calculated by:

$$G = K * \frac{R_T}{E} \qquad (18)$$

To calculate R_T, Davis formula can be used:

$$R_T = a_1 + \frac{a_2}{w} + a_3 v + \frac{a_4 v^2}{wN} \qquad (19)$$

For a car $a_1 = 0.6$, $a_2 = 20$, $a_3 = 0.01$, $a_4 = 0.07$. Therefore equation (20) can be expressed by:

$$R_T = 0.6 + \frac{20}{w} + 0.01v + \frac{0.07v^2}{wN} \qquad (20)$$

Now acceleration resistance is the sum of the linear acceleration of the car and angular acceleration of the wheels and axles of the car. Hence, the equation below can be derived from the previous as:

$$R = \frac{70}{s}\left(v_2^2 - v_1^2\right) + \frac{95.6}{T}\left(v_2 - v_1\right) \qquad (21)$$

The difference between our model and that of Van Hinsbergen *et al.* (2009) is the Bayesian inference perspective in the later model, which defines the posterior probability distribution for the different weights after the observation of dataset *D*, denoted by $p(w/D)$, with the posterior component expressed as :

$$p(w/D) = \frac{p(D/w)\,p(w)}{p(D)} \qquad (22)$$

where $p(D)$ is the normalization factor, $p(D/W)$ represents the noise and $p(w)$ is the prior probability of the weight (Hinsbergen *et al.*, 2009).

2.4.3. Algorithm for cost measurement

The algorithm for the development of cost values is as follows:

Step 1: Initialize a queue (*Q*) with starting nose (*s*) as only entry.

Step 2: If *Q* is empty, fail. Else, pick some search node *N* (with the lowest cost) from *Q*.

Step 3: If state (*N*) is a goal, return N. Otherwise, remove *N* from *Q*

Step 4: Find all the children of state (*N*) and create all the one-step extensions of N to each descendant.

Step 5: Add all the extended paths to *Q*.

Step 6: Go to Step 2.

For example, if the optimum path from Lamata to Lagos Island is needed, Lamata and the goal state will be Lagos and cost used for computation will be the travel time. It should be noted that fuel consumption can also be used as cost, however since it is proportional to the travel time, it has not been utilized for finding the best route.

3. Case application

In this paper, the input to the network is considered as the volume of vehicle which consists mainly of eight (i) 14-passenger buses, which is commonly called Danfo or Kombi bus; (ii) 18-passenger bus, which may be a rebuilt form of that in category (i) but with more passengers seat; (iii) 22-27 passenger bus, which are special types of buses that accommodate passengers more than the kombi bus, but with less number of passengers than the coastal bus; (iv) Coastal bus, Molue, motorcycle, car, and truck. The input is acquired real time from traffic monitoring systems. The data is preprocess and the network trained with back propagation network. For this paper, however only two of these routes colloquially known as Western Avenue axis and the Third Mainland axis are used as case study (Figure 3).

From Figure 3, the Western Avenue axis consists of Idumota, Ojota, Yaba, Western Avenue and Eko bridge; and third mainland axis consists of Ogudu, Oworonshoki and Estate. There are also link routes. The primary problem is to predict traffic volume (density) for each of these routes for the next 30 minute interval with at least 80% accuracy. The traffic situation is a collection of millions of vehicles acting in a chaotic manner. The situation is neither mostly psychological as predicted by technical analysis nor logical as predicted by fundamental analyses. Having established the non-linear dynamic nature of this situation, it can be deduced that:

(i) predicting the traffic situation is non-algorithmic, that is, there is no step by step approach of logical recipe to give an answer;

(ii) the data provided to this prediction problem is complex, large, non-linear, dynamic may be noise or incomplete. From the traffic prediction model (Figure 2), it is obvious that the next stage of the process after neural network application is the fuzzifier module.

In the data obtained, the various vehicles are used for the training set and the test set. Results obtained for the different parameters are shown in Table 1. Figures 4 to 9 also indicates the details of the results obtained from the field observation.
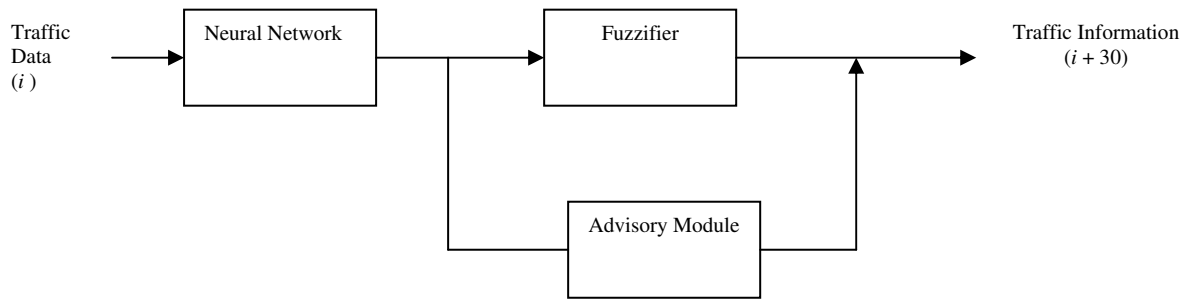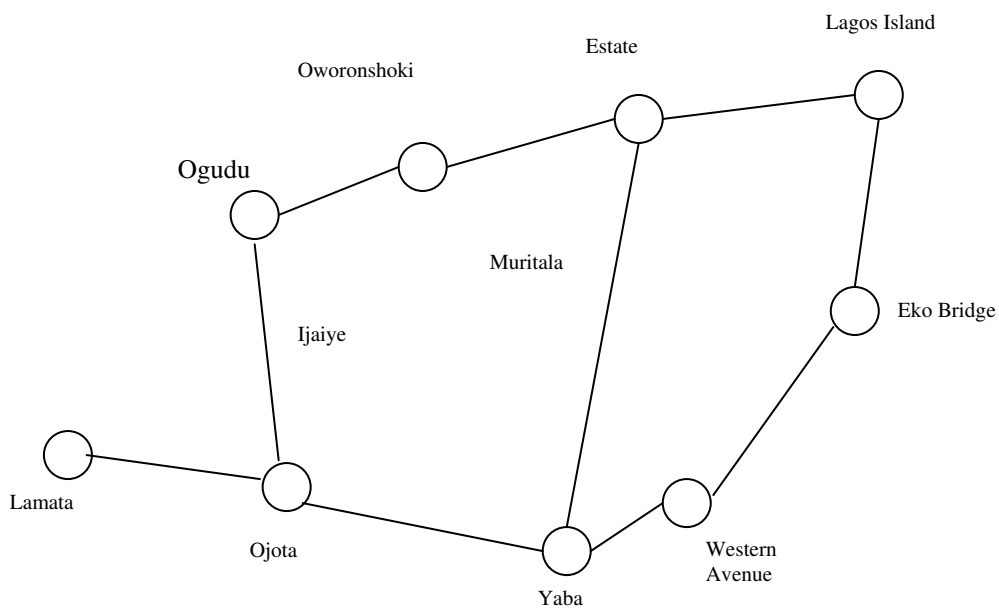
Figure 2: The traffic prediction model.

Figure 3: Schematic showing sub-routes that lead to Lagos Island.

Table 1: Network parameters for locations.

Location	Momentum	Learning Rate	Tolerance	No of Epoch	Architecture
Lamata	0.9	0.0001	0.002	800	17-19-1
Estate	0.9	0.0001	0.0002	1000	17-19-1
Ogudu	0.9	0.0006	0.0002	750	17-28-1
Western avenue	0.76	0.0088	0.0002	800	17-28-1
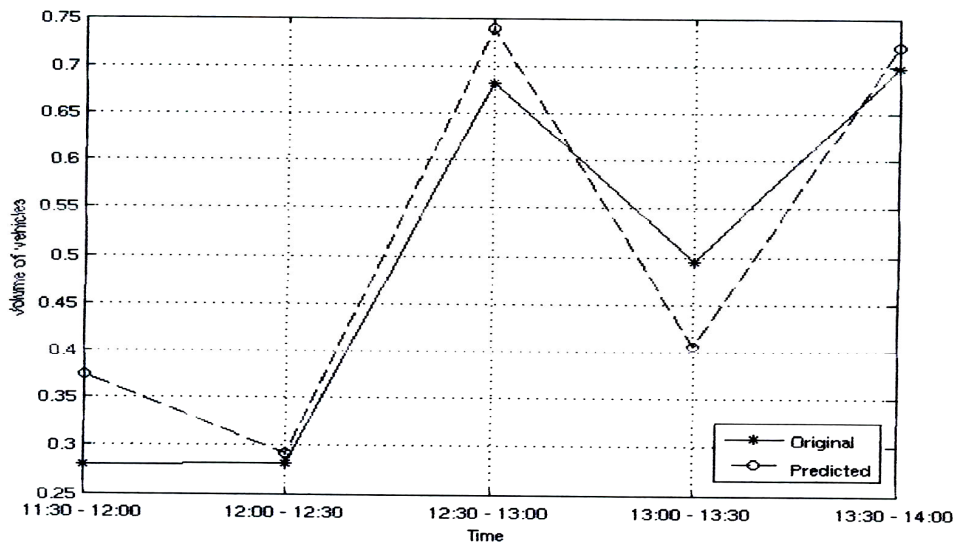
Figure 4: Lamata traffic prediction from 11.30 am to 2.00pm.
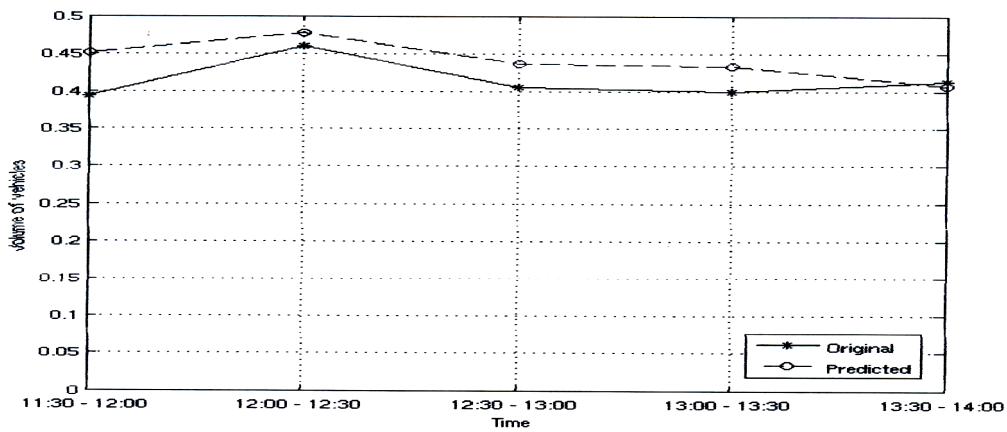
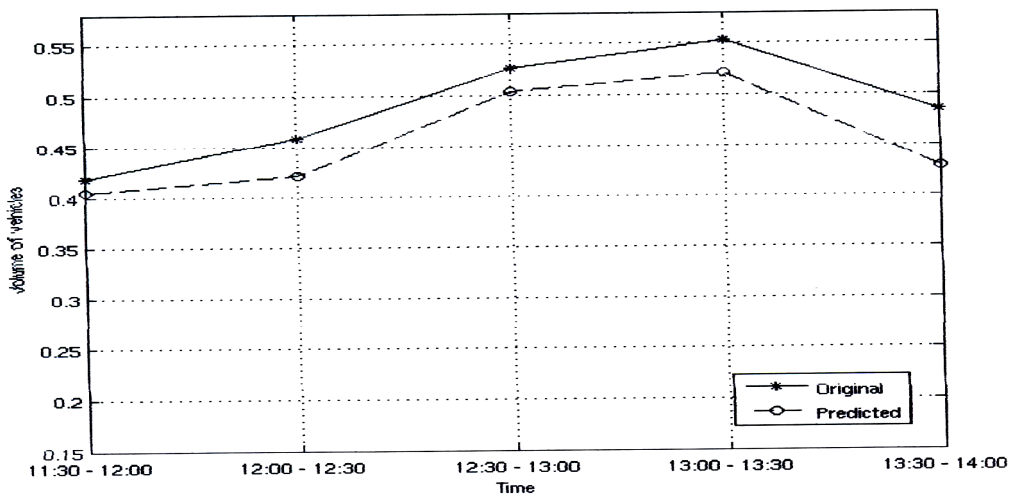Figure 5: Estate traffic prediction from 11.30am to 2.00pm.

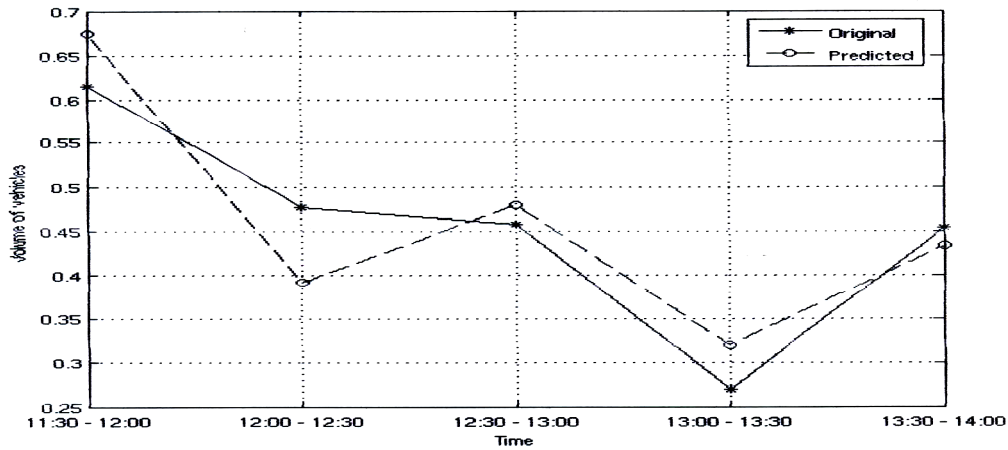Figure 6: Ogudu traffic prediction from 11.30amd to 2.00pm.

Figure 7: Western Avenue traffic prediction from 11.30am to 2.00pm.

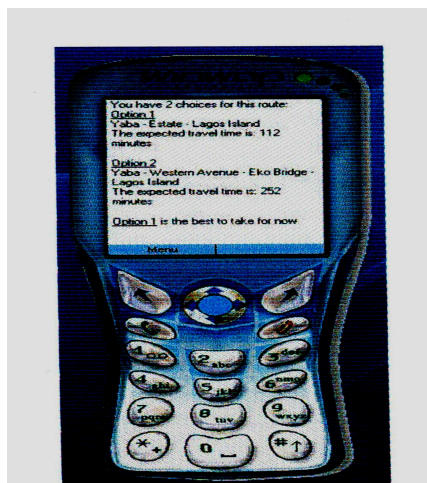Figure 8: Information for a particular route.

Figure 9: Route advisory screen.

3.1. The fuzzifier module framework

The function of the fuzzifier module is to categorise through interpretation the numerical output of the model; the categories being the various levels of the volume of traffic. The Essence of this is that the public is provided with easily understood information regarding the traffic volume. The backbone of the fuzzifier module is in the concept of set membership. Logical operations are performed on the set which is referred to as fuzzy set that consists of members which are presented as ordered pairs which includes information on the degree of membership. In this work, a triangular fuzzifier function is used to post-process the data from neural network using a triangular membership function distribution in order to implement the fuzzy logic with neural networks. Since the aim is to capture traffic volume for certain routes, the description of the different traffic information in fuzzy language could be weak, low and heavy (Figure 10) as shown with three overlapping triangles having minimum and maximum values as 0 and 0.1 respectively, along the y axis. For the x axis, the first triangle, which describes weak, has the lower boundary as 0 and the upper boundary as 0.3. The upper boundary of the triangle describing weak traffic overlaps that of low traffic, which starts form 0.2 and ends at 0.5. Again, the triangle that describes low traffic has it upper boundary overlapping with the next description (heavy traffic), which has a lower boundary of 0.4 and a higher boundary of 0.1. Naturally, road users would prefer a situation where weak traffic exists, where no traffic congestion on roads is experienced. However, the description "low traffic" may have some occasional thick congestion that may last for only few minutes. In heavy traffic situation, vehicles are characteristically in traffic congestion in most periods. This is an undesirable state. It could be stated that if the output of the network is in the interval [0, 0.2], it will be categorized as "weak

traffic." If it falls in the interval (0.2, 0.3), it can either be "weak or low traffic." It will therefore be important to choose which of them it is. A randomized probability value is used to determine which category it belongs to. A random value r, in the interval [0.2, (0.2 + 0.3)] generated. If r is in the interval [0.2, 0.3] it is "weak traffic" and if it is in interval (0.3, 0.5), it is "low traffic".

3.2. The advisory module of the traffic prediction model

This is an intelligent module that computes (i) expected travel time, (ii) expected fuel consumption. It also advises on the optimum path to a particular designation. From Figure 3, three main parts could be taken by a traveller from Lamata to Lagos Island. These are:

- Lamata – Ijaiye – Ogudu – Oworonshoki – Estate –Lagos Island;

- Lamata – Ojota – Yaba – Muritala – Estate – Lagos Island; and

- Lamata – Ojota – Yaba – Western avenue – Lagos Island.

Using fuel consumption as a criterion, if we assume that fuel consumption of a vehicle is directly proportional to the distance covered, then the optimal choice will be the paths with the lowest travel time and fuel consumption. These two criteria are dependent on the traffic density for each route. Thus, the expected travel time (T) along a route can be expressed mathematically as $T = nt/v$, where n describes the total density of volume count which indicates the sum of vehicles observed during period density counts at each t second. Also, t describes the time interval between density observations. The letter v is the vehicular volume in the route during the total elapsed study period. From the evaluation, the total volume prediction on Lamata routes as well as the volumes of cars on Lamata road are summarised in Tables 2 and 3.

The information obtained from Tables 1 and 2 are then used to computes travel time for the car between periods 11.30 – 12.00 and 12.00 – 12.30. The computation are $T = nt/v = 0.27942$ x $30/0.447414 = 18.7$ minutes and $T = 28$ minutes, respectively. For the expected fuel consumption of a car, the speed it's taken into consideration and the steady states formula for fuel consumption is then applied as $G = k*RT/E$. Here, G is the gallons of fuel per 100 netton mile. K is the constant given as 0.048965 for a car.

3.3. The route advisor

The route advisor (Figure 9) advises on the optimum path to a particular destination (Figure 11). To do this, an any-path uninformed search technique is used called the Best-First search technique. In figure below the numerical values are the costs (or penalties) attached to each route. Since the main objective is to reduce Travel Time, the optimum path will be the one that satisfies the objective.

Table 2: Total volume prediction on Lamata.

Time	Predicted Output	Un-normalized
11:30– 12:00am	0.27942	739
12:00– 12:30am	0.281145	551

Table 3: Volume of Cars on Lamata.

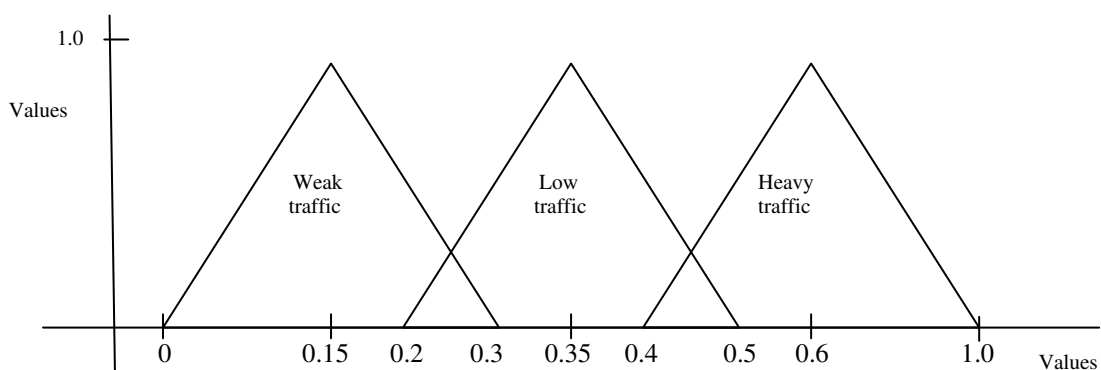| Time	Volume
11:30 – 12:00am	528
12:00 – 12:30am	388

Figure 10: Fuzzy language qualification of vehicle traffic.

3.4. Calculating gallons of fuel from formula

From equations 5a and 5b, *s* can be calculated. Consequently, *RT* can be calculated by substituting the value of s in equation (5a) to that in equation (3).

From the calculations above, it is found that the number of gallons per mile utilized by a passenger car is 0.0465 at a speed of 80km/h (50mph). This is a statistical data given by the US Environmental Protection Agency (EPA).

To determine a conversion rate for the number of gallons utilized per hour, 0.0465 gallons/mile x 50 gallons/mile = 2.325 gallons/hour. For Lamata, with time, *T* = 19min, number of gallons = (2.325 x19)/60 =0.73625 = 1 gallon (1s.f). When *T* = 28mins, number of gallons = 1.5. Also, the output is rounded up to the next whole number (using the (*x*) function). It is however inappropriate to present volume of fuel to the public as gallons since in Nigeria, litres is used. Conversion from gallons to litres is 1 gallon = 3.74 litres.
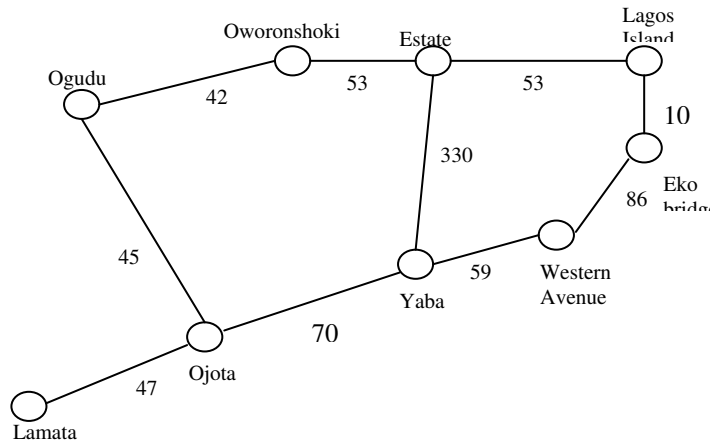

Figure 11: Graph showing cost on taking each link (route) for road network (Cost is based on total travel times between nodes).
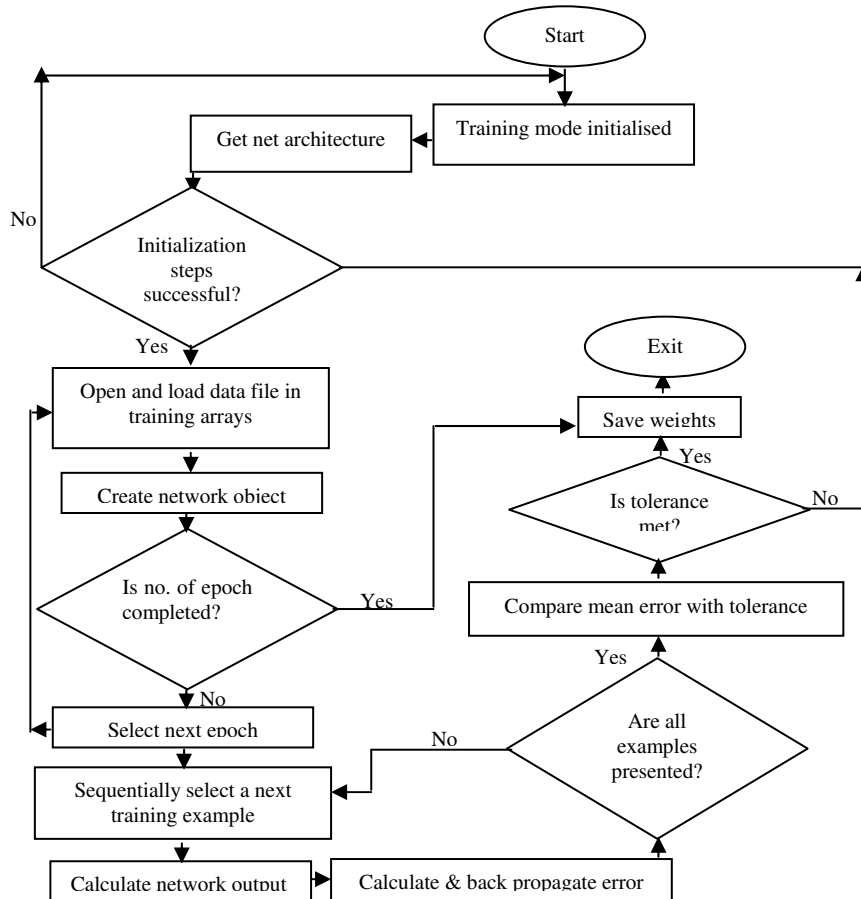

Figure 12: The algorithm for the software application.

3.5. The software used for analysis

The software used in coding the mathematical model and the framework presented in this work is written in C++ (Figure 12).

It should be noted that for the practical demonstration of the model application, the output used is the predicted travel time for the next 30 or 60 minutes interval. This is achieved in the programme by time shifting the original travel time by 30 or 60 minutes and using it for training. Using the concepts of object-oriented programming, classes were created in the header file to include network, middle layer, input layer and output layer. An object of the network class was then instantiated in the main programme. The concept of buffer was used so as to allow multiple inputs at different times. Some of the inputs of the programme are learning rate, architecture and number of layer. The programme was run in two modes: the training mode and the test mode. The data set obtained is splitted into training and test set for the prediction. Files, which include training, test, output and weight, were used to save the data. The results obtained from running the data is saved in the output file.

4. Conclusion

In this work, the problem of vehicular traffic prediction has been approached with a view to providing road users with a framework that could be relied on in order to avoid the high traffic situation of major roads in Lagos, Nigeria. The congestion that results from high traffic has devastating effect both on the individual and the community at large. First, the frustration and stress that built up in vehicle drivers during congestion period is often detrimental to the health of the concern and needs proper prediction of traffic flow. Second, a lot of time is lost in traffic, which could be converted into economic losses that are equivalent to the opportunity cost of not being in business activities during the traffic jam. Third, after a prolonged stay in traffic jam, the wear and tear of the vehicle is accelerated. This causes a gradual wear-out of the vehicle, leading to an early replacement. Thanks to the above reasons, a neuro-fuzzy approach has been used to capture the traffic situation for routes. The non-dynamic situation has been explored due to the non-algorithmic, complex, large non-linear nature of the traffic situation.

Verification to the model has been made using the movement of motorized and non- motorized vehicles along three specified routes in Lagos. These three routes are usually engaged by a large number of users who engage in commercial activities from Lagos Mainland to Lagos Island. There are different opportunities for future extension of the current work. Even in the neurofuzzy area, only an approach has been proposed.

There are countless approaches in the literature that have been applied in other areas such as electrical energy monitoring, wind control problems, among others. These methodologies could be applied and compared to the current approach. Apart, the application of genetic algorithm may find a favourable position on the vehicular traffic prediction. This could be used to optimize certain parameters. From the above discussion, researches in vehicular monitoring, have diverse opportunities for vehicular investigation and improvement on vehicular control. These studies will hopefully keep researchers busy for several years.

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