Traffic Flow Prediction at Signalized Road Intersections: a Case of Markov Chain and Artificial Neural Network Model

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Abstract*— Traffic congestion is a pre-existing problem globally, which threatens the wider community, especially in developing countries. Markov chain model (MCM) is a widely acknowledged and applied method used in traffic modelling, planning, and development of road traffic control systems. Traditional techniques like MCM have been used to reduce vehicular flow and traffic congestions. Nowadays, artificial intelligence techniques, have been recognized for solving traffic congestions and multivariate problems. The application of ANN in traffic flow prediction performance yielded positive results. The present study dwells on a comparison between the Markov Chain Model and artificial neural network model for predicting traffic flow of vehicles at signalized road intersections. Analysis of dataset collected at Mikros traffic monitoring (MTM) firm using vehicular speed, distance, and time as input and output parameters, gave a good performance with root mean square error (RMSE) of 0.0025 and a testing performance of (R^2) of 0.96417. The ANN model was adjudged capable of modelling traffic flow at road intersections.

Keywords*—Artificial Neural Network (ANN), Traffic congestion, Markov chain model, Artificial Intelligence.

I. INTRODUCTION

In the past few years, developed and developing countries have experienced elevated infrastructural and road network development levels. This development is accompanied by an increase in demand for mobility in urban cities [1][2][3][4][5], resulting in perennial problems such as high traffic demand mirrored by severe traffic congestions in metropolises [6][7][8]. These traffic congestion problems have led to a lack of travel efficiency (longer travel times), an upsurge in fuel consumption [9], and air pollution [10] caused by carbon monoxide discharging from exhaust pipes of vehicles stuck in traffic. Transportation researchers have tried to come up with both conventional and artificial intelligence approaches to address traffic-related problems such as traffic jams [11][12], urban planning [13][14], traffic prediction [15][16][17][18], and urban road system design. There remained a gap to be filled in tackling traffic congestion especially, traffic-related problems in road intersections. The application of an artificial neural network model in traffic congestion is not novel. However, many cogent questions have been raised by transportation researchers and academicians on the difference between a heuristics Markov model's strength and performance and a metaheuristics Artificial neural network model. This research study aims to carry out a comprehensive extensive analysis of the prediction performance of traffic congestion of non-autonomous vehicle by using ANN model and a heuristic markov model. A comparative analysis of the application of ANN and a heuristic markov model was done to predict traffic congestion of vehicles on South Africa Roads.

There are many definitions of the term “Transportation.” It was actually from two (2) Latin words, namely “trans” (which means going across) and “portare” (which means carry over). Transportation is when individuals move from one place to another, including goods and services from one place to another. Transportation can be an act of an individual or a systematic process or a means of transporting or being transported by people/goods/services. It is a means of conveying goods and services through air, road, sea, or rail. The transportation can either be a private or public transportation system. Nowadays, transportation is very significant to the day-to-day activities of humans. Various modes of transportation are applied worldwide to transport individuals and freight from one location to another. Each type of transportation has its specific features of initialization and mode of operation. Having a perfect understanding of transportation subsystems is imperative to have a concise understanding of transportation functions and the effects of the various stages of implementation and mode of operation of transportation systems, dependent on the physical, biotic, and anthropic environments.

Industrial revolution can be defined as the process whereby there is an elevated change in a country's economy, mostly due to the inception of power-driven machinery. Another alternative definition is that the industrial revolution is the instantaneous rudimentary change in an industrial organization, the displacement or repudiation of the first, second, and third industrial revolution, which have all been replaced by the fourth industrial revolution. Industrial organizations play a significant role in the economic development of any country. These organizations also play an essential part in the driving force of any country’s economic development. Any organizations' economic sustenance, albeit a small scale organization or a multinational organization, is all-dependent on innovative thinking resulting from information and communication technology (ICT). The technological innovation level is at a high number in developed countries. Hence, contributions to technological exports and the transfer of technological skills to developing nations are sustainable. Most technologically advanced equipment is manufactured, assembled, and produced in developing countries because of cheap labour and low taxation. This equipment is then sold to developing countries. In turn, these countries consume or use what is given to them by these developed countries. Manufacturing Industries are the economic backbone of a country. Suppose there are many industries in a country. In that case, the availability of manufacturing jobs will lead to the creation of efficient transportation systems. In the last 40 years, industrialization has adopted advanced information technology, which has led to all-encompassing technological innovations, modern digitization, automation, and nanotechnology. The industrial revolution was completed adopted in the early years of the 21st century because of the changes related to the adoption of technological innovation in the area of digital technology innovations and the increase in a surge of the transformation of electrical to electrons in all areas of the society and economic sector of the country. During the 1st, second, and third industrial revolutions, western civilization has witnessed industrial revolutions that can be termed as turbulent developments in industrial processes, leading to notably higher productivity. Explained below are the past and present industrial revolutions:

1. The First Industrial Revolution: This industrial revolution occurred towards the end of the 18th century in the year 1784, to be precise. This industrial revolution existed due to the invention of mechanical production equipment and techniques to assist with hydropower. The frequent utilization of steam power resulted in the evolution of steam engine driven machinery.

2. The Second Industrial Revolution: This industrial revolution occurred in the early years of the 20th century (1870). The second industrial revolution was introduced into the world by inventing large-scale production lines dependent on electrical energy multinational industries.

3. The Third Industrial Revolution: This came into actuality towards the twilight of the 20th century (1970) through the introduction of electronics and information technology systems for large scale automated production assembly lines in factories. This industrial revolution occurred in the era of sophisticated automation, advanced innovative technology, and experimental testing, semi-automated phase. In this type of industrial revolution, it is labour intensive and less automated.

4. The Fourth Industrial Revolution: Presently, the world is already experiencing, and using the fourth industrial revolution. This is when industrial processes are gradually tilting towards more automated equipment and global digitization, including artificial intelligence methods. Most industries are now using less labour-intensive methods for their production. The fourth industrial revolution is the period of connecting the pre-existing innovated methods of the first industrial revolution with the pioneered already existing second industrial revolution methods with the technological innovated pre-existing third industrial revolution techniques.

This connection will be carried out through the usage of efficient and effective information communication technologies via programming. The fourth industrial revolution is the inclination of automation and big data interchange in manufacturing advanced technological innovated industries. This comprises of cyber-physical frameworks, not excluding the internet of things and cloud computing technologies. It leads to the creation of what we called "smart sustainable transportation" in transportation systems.

The fourth industrial revolution is the age of automated machines and significant data exchange in advanced manufacturing technological companies. This industrial revolution consists of cyber-physical systems, the internet of things, artificial intelligence, machine learning, big data, etc. An advanced revolution established what is called an "intelligent factory." In a modular structural framework of intelligent industries, cyber-physical techniques supervised physical processes, created an automated virtual copy of the physical world, and made decentralization decisions. The fourth industrial revolution can be defined as the technological sustainability of innovation, automation, and advanced manufacturing mode of operation, which are the foundation of a booming industry. Innovative methods will be utilized to rebuild structures of mostly old-fashioned manufacturing companies, emulating business structures of accomplished countries by developing countries. The fourth industrial revolution is an additional developmental phase in re-arranging and managing complete value chain processes enmeshed in the manufacturing companies [9]. Some academic researchers believe that the fourth industrial revolution will mostly be widely acknowledged and utilized by the developed countries (United States of America, United Kingdom, China, Japan, Germany, and South Korea) due to their sophisticated technologies. Other academicians believed that underdeveloped and developing nations should have the capacity to participate in the fourth industrial revolution. Such developing countries should have the potential of moving from being a developing nation to a developed nation. Therefore, the fourth industrial revolution will not only be actualized by the developed countries of the world but also by the developing countries that have the potential to implement it. Mechanical engineering, Electrical engineering, and Information communication equipment will be connected via a radio frequency network. These primary components can be used to differentiate between the third industrial revolution and the fourth industrial revolution. These two components are:

- Technology
- Humans.

In the third industrial revolution era, there is more human-related work (labour intensive) than automated related work. However, during the fourth industrial revolution, it is the reverse. There is more of automated related components than a human component. Typical examples of the third industrial revolution inventions are 3D printing, Sensor Technology, Artificial Intelligence, Robotics, and Nanotechnology. All these inventions have been evaluated and tested at a high-efficiency level during the third industrial revolution. They are found to be in a fully working mode in the fourth industrial revolution. The fourth industrial revolution will improve the following:

- Machine Efficiency.
- Integrated Networking.
- Flexibility in employment opportunities.
- Global digitization and Optimization.

- Solutions to challenges facing advanced technological industries

This research study investigates and evaluates the ANN model's performance strength as an artificial intelligence technique and the Markov chain model as a conventional technique of solving traffic congestion. The application of this Artificial Intelligence technique will combat the recurring problem of traffic congestion, especially in developed and developing congested urban cities. It will help usher in a robust and more innovative fourth industrial revolution into the road transportation sector. This transportation study's theoretical and arithmetic findings are significant to road transportation researchers, pedestrians, and people that rely on the road network for their daily needs.

Artificial Neural Network

An artificial neural network consists of problematical mathematical processing units called neurons. These neurons can be found in the black box during a neural network operation on MATLAB. These neurons can form a relationship with each other via weights and biases. An artificial neural network consists of three primary layers: the input layer, hidden layer, and output layer. The neurons are placed in the hidden and output layers, while the input layers do not contain neurons. A typical artificial neural network architecture is shown in fig 1 below:

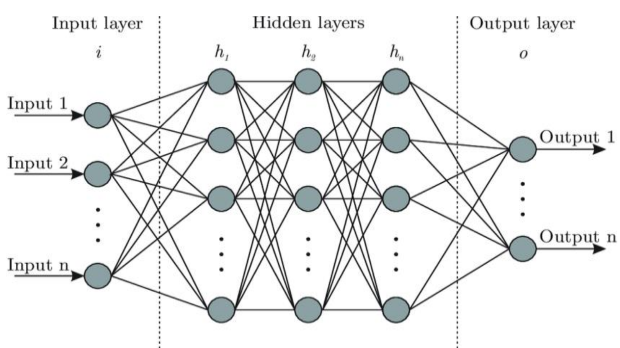

Fig 1*: Artificial Neural Network (ANN) Architecture*

Analysis of the ANN is usually performed using the ANN toolbox called from MATLAB, training is usually performed using input data and the corresponding output datasets. The inputs can be in two or three columns (depending on the datasets that are to be trained). The output datasets are in a single column on another excel sheet. These are all carried out to determine the appropriate weights and biases of the neurons. Neural network training of data (input and outputs) means determining the optimum variables of different weights and biases of the neural network. Different types of methods are generally applied to determine the Artificial Neural Network's appropriate parameters of weights and biases. In this conference paper, the network's suitable optimum training has been done by applying an artificial intelligence technique called Artificial Neural Network, found in the MATLAB software environment. Once the ANN training has been done adequately on the datasets, the network's validation is performed using independent variables called the testing data. An artificial neural network is perfect if the fitness function values are of lower values or closer to one for training and validating the traffic datasets.

II. MATERIALS AND METHODS

Traffic Datasets.

Traffic datasets were obtained from South African freeways, highways, and road intersections courtesy of the South Africa Ministry of Transportation. This traffic information was achieved using sophisticated Traffic surveillance equipment and techniques, such as inductive loop detectors, video cameras, and road-wide stationed GPS controlled equipment. The ANN model was trained tested and validated using the datasets available and the result obtained was compared with that obtained from the heuristics Markov chain model. The variables used for the ANN network are the vehicles' speed, distance covered by the vehicles, and the time taken by the vehicle to travel the road's length. The input and output variables considered were based on the approach used by [19], [20], and [21]. MATLAB user interface tools and command-line functionality facilitated the solution. In the ANN model, 100 traffic datasets were considered, 70% training, 15% testing, and 15% validation.

$$R^2 = 1 - \frac{\sum_k (y_k - \hat{y}_k)^2}{\sum_k (y_k - \bar{y}_k)^2}$$

$$MSE = \frac{1}{2}\sum_{k=1}^{n} (y_k - \hat{y}_k)^2$$

Where y_k ,$\hat{y}_k$, $\bar{y}_k$ n, represents the experimental data sample, the values predicted by the algorithm, the mean value of the experimental data samples, and the number of data samples, respectively.

Markov Chain Model.

The traffic data was collected from the South Africa Ministry of transportation using inductive loop detectors and video cameras on major highways and road intersections. The traffic volume data collected was based on three primary periods (morning, afternoon, and evening). Markov chain model is defined as the arrangement of random variables. This process is based on the markovian features defining only between adjourning periods ('chain'). Markov chain model can be applied in the description of systems that follow chain-like events. The events happening are dependent only on the current state of the system. It merely means it occurs when the next state of the system is dependent only on the current state and none on previous states. The probability transition matrix (Pij) is a significant feature of the Markov chain model. The probability of the traffic volume transitioning from state I to j (Pfeifer, 2000). The characteristics of a probability transition matrix are:

(i) The matrix takes a square shape due to all its possible states being used both as a row and a column.

(ii) All entries in the matrix are between 0 and 1. This is as a result of all entries represent probabilities.

(iii) The overall sum of all the entries in a row must be 1.

The probability of an average daily traffic volume conditions in a day, taking into consideration the traffic occurrences in the previous day, can be interpreted by a probability transition matrix which is shown in table 1 below:

Table 1: A Probability transition matrix of an average traffic volume per day

Average Traffic Volume (per day)	**Low**	**Moderate**	**High**
Low	P_{11}	P_{12}	P_{13}
Moderate	P_{21}	P_{22}	P_{23}
High	P_{31}	P_{32}	P_{33}

A Markov chain model is a progression of trials of an experiment if the following occurred:

(i) The results of each experiment are one group of discrete states.

(ii) The results of an experiment are dependent only on the current state and not on the previous state.

To envisage how a traffic flow metamorphoses on highways and freeways, the primary aim has to be on the probability of evolving traffic volume on South African roads. The movement of vehicles on South African roads is grouped into a three-transition matrix:

$$(e_1, e_2, e_3) = (e_1, e_2, e_3)$$

Each probability cell shows the evolving states of the traffic volume from one state to another, i.e., the traffic volume from low to moderate to high depending on the day's periods. The process of moving from one state to another can be derived by using this equation:

$$P(K) = P(0)\ Pij^k$$

P (0) = depicts the traffic volume for a low, moderate, and high vehicle movement.

P_{ij} = Probability transition matrix.

K = day.

P^k = Probabilities of transitional change in the average hourly traffic volume of entry into a low, moderate, and high traffic category is directly proportional to the average traffic volume of exiting from a particular traffic states. The low, moderate, and high traffic volume states are a 3-state traffic volume in developed countries. The application of a fixed point theorem resulted in a markovian model attaining equilibrium.

e = eP

$$e = (e_1, e_2, e_3)$$

e = is defined as the steady-state vector for a three-state markovian model [22], e_1 is the short term projection used for a low day to the daily traffic volume of vehicles, e_2 is the moderate short term projection of a vehicular traffic volume, e_3 is defined as the short term projection of a high daily vehicular traffic volume.

$$(e_1\ e_2\ e_3) = (e_1\ e_2\ e_3) \begin{matrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{matrix}$$

III. RESULTS AND DISCUSSIONS

Artificial Neural Network (ANN)

The ANN model was used for the prediction of the traffic congestion of non-autonomous vehicles. One hundred traffic datasets were applied for the ANN training, 70% (70 traffic datasets) of the traffic data was used for training, 15% of the datasets for validation, and 15% for testing. The validation and testing of the traffic data were carried out to verify the ANN model's proficiency. The ANN training, validation, and testing were effectuated in the MATLAB environment. The neural network model structure for the training, testing, and validation of the traffic dataset is illustrated in Fig 2. The best validation performance network for traffic datasets is shown in Fig 3. A regression value of R^2 of 0.96304 (2-8-1) is presented, clearly showing that the traffic data's inputs and outputs are well correlated.

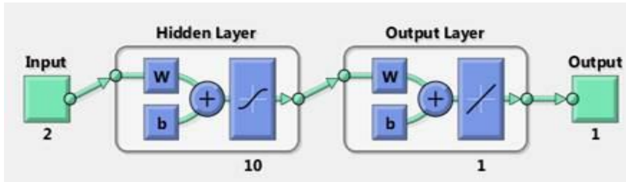

Fig 2: An Artificial Neural Network Structure with a 2-10-1.

A corresponding traffic performance evaluation indices of MSE and R^2 value for training and testing the traffic datasets have been presented from the ANN results. The ANN model training can be discerned that the best optimum training performance was obtained when the total number of hidden neurons is eight, i.e., 2-8-1. An evaluative observation made from the result is that the ANN parameters, number of hidden neurons, and the number of epochs significantly affect the traffic congestion datasets performance prediction. Therefore, the optimum networks obtained considering the traffic datasets training performance are training R^2 =0.96688. The traffic dataset's best testing performance testing R^2 =0.96417 have eight number of hidden neurons. Fig 3 shows the best optimum performance after the traffic data training by using the ANN model was presented (All: R = 0.96304). Fig 4 below shows the ANN training's best validation performance of 22.2915, at an epoch of 7.

Markov Chain Model

The total number of vehicles observed for possible prediction using the Markov chain model was 400. Observed vehicles in the morning hours = 150 vehicles, observed vehicles in the afternoon hours = 150 vehicles, observed vehicles in the evening hours = 100 vehicles. It is important to note the probability transition matrix for both morning, afternoon, and evening. Probability of Morning (PM), Probability of Afternoon (PA), Probability of Evening (PE).

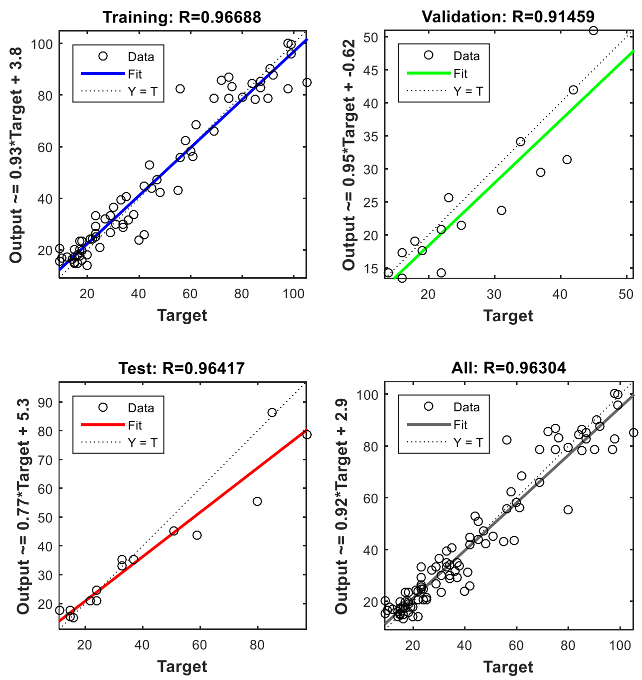

Fig 3: The ANN model results for the best prediction of the traffic datasets (2-8-1).

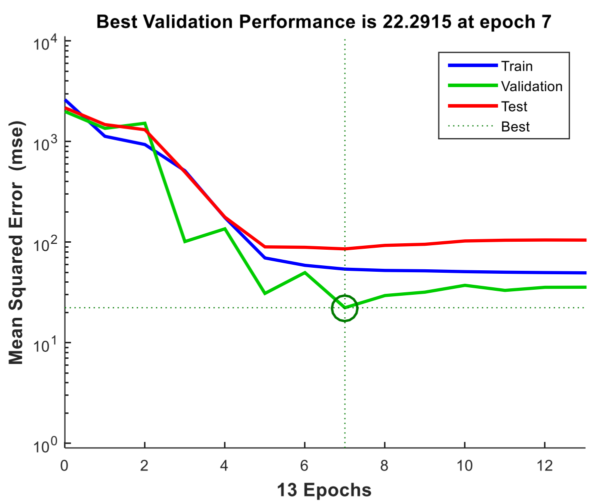

Fig 4: The ANN model results for the best prediction of the traffic datasets (2-8-1).

The overall number of the probability transition matrix = 0.375 + 0.375 + 0.25 = 1. This validates one of the characteristics of the Markov chain model, which states that "The addition of the entries in any matrix row must be equal to 1 since the number of the row gives the probability of changing from the state at the left to one of the states indicated across the top"[23]. Therefore, the probabilities of incoming and outgoing vehicles for both morning, afternoon, and evening are: P (M) = 0.375, P (A) = 0.375 and P (E) = 0.25.

IV. CONCLUSIONS

This study was carried out to effectively predict traffic flow performance at signalized road intersections using heuristic Markov chain model and ANN Model considering non-autonomous vehicles in Gauteng province. The traffic dataset obtained was analysed using ANN and Markov chain model with the current dataset obtained from South Africa's major highways and freeways. Two input parameters (speed and distance) and one output parameter (time) were considered. From the results obtained, the best training performance of the traffic datasets was achieved when the number of hidden neurons is 9, which gave a good coefficient of determination of 0.96304. A close view of the analysis of the study shows that the metaheuristic result seems marginally better than the heuristic model in the analysis of traffic flow at a signalized road intersection. It is recommended that researchers interested in this area of study should focus on unsignalized road intersections and traffic lights timing response optimization. In addition, demonstrating the strength and predictive power of other metaheuristic techniques will be very useful as a comparative measure for minimizing traffic issues in road transportation.

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