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Forecasting of Short-Term Traffic Flow Using Artificial Neural Network (ANN) in Iraq

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ABSTRACT

Short-term traffic forecasting is one of the significant subjects in order to create more sophisticated transportation systems that regulate traffic volume and prevent congestion. The number of vehicles in Karbala City is growing quickly, which raises wait times and decreases Level of Service (LOS). It is essential to predict the traffic performance to ensure a correct traffic operation. The aim of this work is to create a short-term traffic forecasting model for intersections within a study area based on an Artificial Neural Network (ANN). The data has been used to create and train a number of ANN models. Two models were selected based on the most effective parameters that cause traffic congestion, longer travel times, and accidents for each type of vehicle, serving as the main input for the models. The results of models to predict the traffic volume and travel time found that the neural network performed in a good way, achieving R^2 values of 0.9101,0.9748 and 0.8877, which is a good score. Sensitivity analysis was adopted to evaluate the model's performance when the input values are changed. It was found that the passenger car (PC) was the most effective parameter for both models.

1. INTRODUCTION

Globally, the transportation networks of urban civilizations serve as the primary engines of economic activity. Roads are the most essential component of urban transportation infrastructure, which additionally encompasses trains, airways, and canals. Undoubtedly, the majority of research focuses on road systems and planning studies. The economic activities of most urban areas are greatly impacted by the system of vehicle transportation. The demand for transportation has markedly risen in numerous cities recently, resulting in a reduction in the traffic system's capacity and operational inefficiency [1]. Traffic flow data is crucial for implementing policies related to traffic control and management. The more information that is accessible, the more precise traffic predictions that can be produced, and the more successful the strategy will be. However, they are sometimes insufficient for collecting sufficient data, as the number of sensors (or road segments viewed) considerably determines the system cost. Certain monitoring systems also make advantage of portable detectors in addition to stationary detectors [2, 3].

Traffic flow characteristics are detected by monitoring systems, but they also need to forecast future trends. Keeping that in mind, short-term forecasting is the act of projecting future events (usually on an hourly basis) and utilizing the resulting data to develop a strategy to satisfy those demands in developing countries. The term "short-term forecasting" refers to this issue, which has received extensive research [4-6]. After reviewing the literature, we find that ANNs were frequently employed to address this issue.

Gallo and De Luca [7] have suggested a technique using ANNs that yielded encouraging results in a computerized setting where data collected at some monitored links is used to anticipate traffic flow on unmonitored road linkages. In particular, on a real-world network, multiple Artificial Neural Networks (ANNs) were trained using sample datasets produced from 139 connections' traffic flow as the basis for a traffic assignment technique, subsequently employed to forecast traffic flow on 1,186 other links. Theoretically, all information from monitored links was used to estimate the traffic flow on an unmonitored link, regardless of the distance or reciprocal influence between links. It was expected that all links in the network, monitored and unmonitored, were there and that there would be no assumptions about mutual influence.

In addition to saving drivers' time, traffic forecasting also helps to lessen air pollution and traffic congestion. For the modeling process to predict traffic factors, historical data is required. Several studies have developed a variety of methods and examined short-term traffic flow forecasting. Some of the techniques utilized for prediction are Kalman filtering [8], linear regression [9], neural networks [10] and fuzzy logic-based models [11]. Machine learning techniques [12] have garnered significant attention because of the extremely non-linear and stochastic style of traffic streams. As a result, they are being considered as a viable alternative for prediction. Backpropagation neural networks were built by Guido and

Waqar to build a traffic flow, occupancy, and speed prediction model [13].

Jiang and Luo [14] conducted a comparison study utilizing statistical models and neural networks to forecast short-term traffic flow on highway traffic data. Neural networks that are object-oriented were presented by Dia [15] for estimating the traffic circumstances on a route in the near future segment in Queensland, Australia, that runs between two main regions. The support vector machines (SVM) model was used by Wang and Shi [16] to estimate short-term traffic. They proposed that choosing this technique is a difficult task. They presented a novel method for building a novel kernel function that captures the non-stationary features of traffic speed data gathered over a brief period of time using wavelet theory. They also evaluated this strategy using actual traffic speed data from the real world.

Theja and Vanajakshi [17] examined homogeneous traffic flow on Indian roads with mixed and less-lane regulated traffic data. To create a traffic prediction model, they employed back propagation ANN and SVM. They stated that their investigation found the SVM method to be more accurate. Using traffic data gathered in Turkey, Çetiner et al. [18] created a model for short-term traffic forecasting using an ANN model, taking into account the homogeneous traffic flow. They stated that the prediction of traffic volume is greatly affected during daily peak hours and the minutes within that hour. Kumar et al. [19] examined how well neural networks predict traffic volume in the short term on four-lane roadways with multi-traffic flow characteristics. The following input parameters were used by Kumar et al. [19] while looking at the model for predicting traffic flow, such as the amount of traffic, its speed, and time during the week. They stated that even when they increased the forecast time interval from five to fifteen minutes, the ANN's performance remained constant.

Guo et al. [20] quantified uncertainty and predicted short-term traffic flow rates using an adaptive Kalman filter technique. Utilizing actual traffic information gathered from four distinct highway networks in the UK, they created a short-term traffic forecast model. They proposed that in situations with extremely erratic traffic, the adaptive Kalman filter works extremely well. For the purpose of predicting short-term traffic flow rates, Habtemichael and Cetin [21] developed a model of non-parametric prediction with an improved k-nearest neighbors' method. They used 36 datasets that were gathered from various locations, 24 Americans and 12 from the United Kingdom, to apply and evaluate this approach. They discovered that their model performed better than the other intricate parametric models that were employed in their research.

Furthermore, Ma et al. [22] noted that when predicting short-term traffic flow, precision is crucial. They suggested applying Kalman filtering to historical traffic data to create a 2-dimensional prediction approach. They stated that their recommended approach performed better than the conventional Kalman filtering approach with respect to accuracy. As indicated by Guo et al. [23], they created a modeling tool for interval and point forecasting using the use of fuzzy data accumulation method in the ANN, SVM, and KNN methods on actual traffic information gathered from American field transportation systems. These outcomes demonstrated the prediction system's stability improved with time interval. These kinds of studies are made feasible by the availability of high-quality data and the advanced technology seen in intelligent transport systems (ITS) in the United States and Europe, where users are disciplined about following traffic laws. A different picture emerges when thinking about Karbala City, where most people do not adhere to traffic laws, in addition to all the highways being poorly built. This is what the world is facing today as a major challenge due to the development of industries in general and the automobile industry in particular, the tendency of most individuals to own private cars and adopt them as a primary means of transportation, and abandon public transportation and the lack of infrastructure such as metros, trains, and trams.

A model of short-term traffic flow prediction was created by integrating particle swarm optimization (PSO) with a bidirectional long-short-term memory (Bi-LSTM) neural network [24]. PSO operates by globally searching for optimal model parameters. The BI-LSTM model functions as an optimization network for the prediction model utilizing PSO, noted for its rapid convergence, substantial resilience, and global search capabilities. Data was gathered from the study area of Delhi, India, to evaluate the model's performance, revealing superior accuracy and stability relative to existing ANN methodologies, such as (Extreme Learning Machine (ELM), Gated Recurrent Unit (GRU), Wavelet Neural Network (WNN), Multilayer perceptron (MLP), and Autoregressive Integrated Moving Average (ARIMA).

Jiang et al. [25] suggested statistical models, shallow ML models, and deep ML models are among the forecasting approaches in the literature. Modern traffic forecasting methods have shifted their focus to graph neural networks (GNNs) due to their superior performance in graph-structured traffic systems. The purpose of this review is to provide an overview of the current state of research and emerging trends in the field of graph neural networks used for traffic forecasting. The research compiled a list of previous studies' goals, graph types, datasets, and neural networks in addition to summarizing their findings. Predicting the flow and speed of road traffic remained the most popular traffic forecasting problem. The GAT, GCN, and GNN were among the potential answers to these issues. Introduced were new dataset collections and coding resources meant to inspire more investigation.

Shaik et al. [26] created an ANN model to forecast short-term traffic flow on a two-lane highway in Bangladesh. The data was gathered from March 1, 2021, to June 30, 2021, between 600-900 and 1200-1500 hours. Every vehicle along the entire specified length was captured by high-quality electronic cameras. The network outputs were shown in regression graphs with the targets for the training, validation, and test datasets. The model performed well with respect to the speed level parameters, which had acceptable fits across all data sets (R values of 0.98426). The traffic volume parameters were fairly fitted across all data sets (R values of 0.96758). The model's effectiveness was shown by its minimal mean squared error values.

Bing et al. [27] created a CNN-Transformer model and secondary decomposition strategy for short-term traffic flow forecasting. In order to do global modeling and analysis of long-term relationships, the Transformer model makes use of the local spatial characteristics extracted by the CNN model. The final findings are obtained by adding up the forecasts from all of the IMF's parts. The following results are indicated by the experimental data: Notable improvements have been made to the forecasting performance. When it comes to making predictions, the suggested CNN-Transformer model is light years ahead of the competition. When evaluated using MAPE, the CNN-Transformer approach showed a decrease of 13.58%, 11.88%, and 11.10% in three-step-ahead forecasting compared to the other methods.

Traffic congestion has caused a decline in the quality of community life of people when they are forced to spend more time in traffic jams and tend to be angry since they will be delayed from reaching their destination and that has had a significant negative influence on day-to-day routines, particularly since the roads within the city are narrow in addition to the lack of parking lots, as most vehicles are on-street parking, thus reducing the road's capacity for vehicles. Also, places that suffer from congestion are more susceptible to pollution that affects human health as a result of emissions from vehicles, which affects the city's economy and residents.

The current rise in traffic congestion in Karbala has been acknowledged as a severe problem in the city. This problem has an impact on the economy, travel time, and driving behavior, and it also causes discomfort to drivers and visitors. Although there has been a rapid increase in the number of cars in Karbala, there has not been a significant expansion in the capacity of the road network. Additionally, there has been inadequate geometric design and planning, which has resulted in an increase in delay times and a decrease in the Level of Service (LOS).

Previous studies used an ANN model for the short-term traffic flow predictions for two- or four-lane highways. Here, we are trying a new methodology related to the nature of the problem in the ANN model to investigate its performance for short-term traffic prediction on intersections and streets with mixed traffic conditions for a selected zone in Karbala City, which has never been applied before in that zone.

This study's main objective is to determine whether using the ANNs technique may help bridge this significant decision-making gap for the city of Karbala's major road network and intersections. Through the technology, they can notify drivers about the expected traffic congestion for the upcoming time.

2. MATERIALS AND METHODS

2.1 Study area and data collections

Karbala stands out as one of the most compelling cities within the Islamic world, renowned for its profound history. It is approximately 36 meters above average sea level. It left Baghdad around 110 km to the southwest. Al-Anbar province borders it on the north and west, Al-Najaf city borders it on the south, and Babylon city borders it on the east. There are four intersections with various urban streets and one roundabout in the chosen study area. The existence of numerous centers of activity, including schools, government offices, shopping malls, and houses of worship, contributed to the area's growing traffic demand and congestion [28, 29].

Within the chosen study area are four intersections with different urban streets and one crossroads. These study areas have a lot of activity centers, including schools, government buildings, shopping malls, and houses of worship, which have led to a rise in traffic demand and congestion. Figure 1 shows the research region. Table 1 and Figure 2 list the names of the intersections and the type of traffic control for each intersection, while Table 2 shows that the kind of traffic control for each intersection is signalized, and all streets are divided.

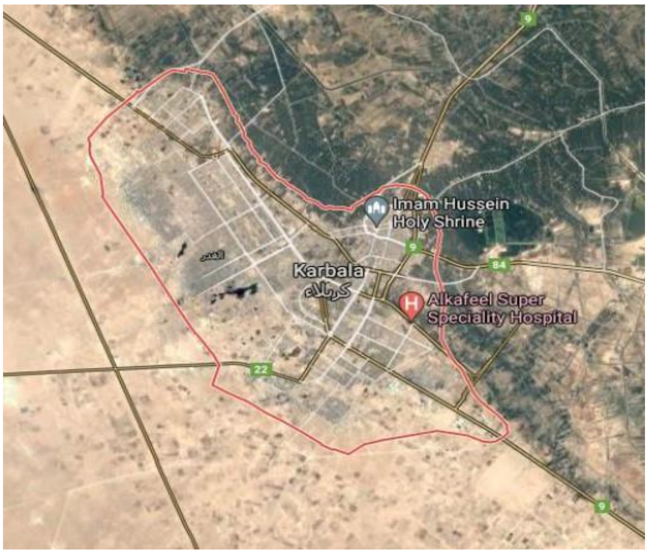


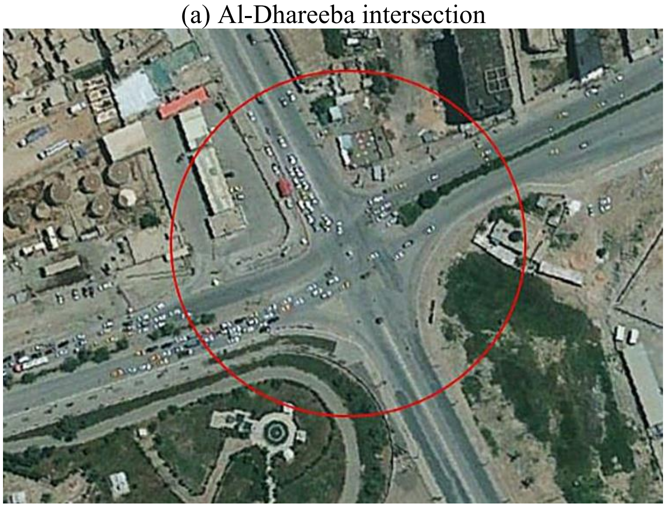
Figure 1. Karbala City's location and satellite image

Table 1. The name of intersection and control type [29]

No.	Intersection Name	Control Type
1	Al-Dhareeba	S.I
2	Al-Sayed Jawda	S.I
3	Central Al-Hussein	S.I
4	Saif Saad	S.I

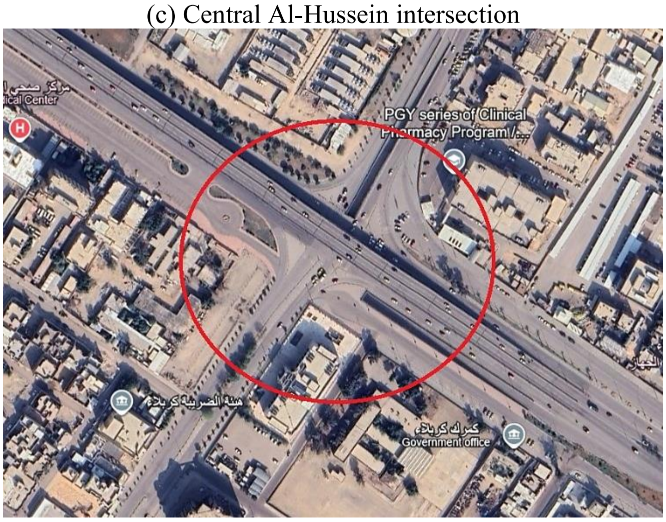
*S.I refer to a signalized intersection

(a) Al-Dhareeba intersection



(b) Al-Sayed Jawda intersection

(c) Central Al-Hussein intersection



(d) Saif Saad intersection

Figure 2. Site plan of the study area

Table 2. The details of the divided street [29]

No.	Street Name	Lane/Direction
1	Fatima Al-Zahraa Street	3
2	Al-Abbas Street	3
3	Al-Iskan Street	3
4	Ramadan Street	3

The goal of the data-collecting phase is to compile all the information needed to assess the research area's traffic flow conditions. The necessary data are gathered in two months (January and February, 2024) during morning and evening peak hours. Since bad weather might alter the regular traffic flow pattern, all necessary traffic data are gathered during favorable weather.

To predict the busiest time of the day for gathering traffic data, a number of in-person observations, pilot surveys, and in-person interviews with pertinent parties, including local traffic officers and other road users, were undertaken in the research region. These data showed this study region is distinguished by peak times in the morning (8:30–11:00 a.m.) as well as (4:00–6:00 p.m.) on average weekdays for each direction of the intersections (east, west, south, and north), while in the main streets, observation data has been taken at each segment of the road, and it's representing the typical traffic patterns in Karbala.

The video camera was used to get the traffic flow data from the field. This method is preferred for a number of reasons, including the convenience with which the data may be acquired. A great deal of scenarios is able to be accurately documented. The gathered data can always be updated and subjected to a more thorough analysis. It is possible to visually extract data from the videotapes, such as capacity, traffic flow, and all moves. In order to guarantee optimal coverage for every intersection approach, a survey was conducted to determine the best view position from which to install video recording on the traffic signal-carrying overhead bridge. When recording, a number of factors should be taken into account, such as clear skies and favorable weather.

To ascertain the value, kinds, and actions of road vehicles at a given site, traffic volume studies are conducted. Part of the traffic volume information is the counting of the traffic numbers taken out of video recordings for every approach at the selected network's junctions. These statistics can be used to pinpoint peak flow times and assess how big cars affect traffic flow.

Vehicle speeds on a street segment with traffic control typically drop less than the typical running speed. Average travel speed is the speed metric that most accurately depicts the impact of traffic management. This speed is calculated by dividing the section's length by the average travel time. The amount of time required to conclude the road section, taking into account any stop-time postpones, is known as the travel time. The distance between the border intersections that constitute a segment is its length [30].

These statistics incorporate the assessment of journey times for every internal link in the chosen network. Roads are divided into several parts prior to the calculation of journey time. The length of each segment as well as the quantity of selected routes and sections for every route as explained in Table 3.

Table 3. Classification for the chosen roads based on the Highway Capacity Manual (HCM) 2000 [30]

Road No.	Name of Street	Segment No.	Lanes/Direction	Length (m)
1	Fatima Al-Zahraa	1	3	234
		2		443
		3		790
		4		811
		5		418
		6		269
2	Al-Abbas	1	3	964
		2		572
		3		777
		4		776
		5		568
		6		944
3	Al-Iskan	1	3	1430
		2		1380
4	Ramadan	1	3	1670
		2		1710

One of the most important metrics in transportation is time spent traveling, or the amount of time needed to complete a journey between any two sites of interest. Consequently, following the determination of each road's segment in the research zone, the average trip time has been determined using the floating car method and measured using a stopwatch, as well as congestion measured by establishing the vehicle's journey length. Table 4 shows the calculated travel time for each segment.

Table 4. Computed the typical travel time

Road No.	Segment No.	Average Travel Time (seconds)
1	1	114
	2	57
	3	97
	4	109
	5	120
	6	51
2	1	128.5
	2	97
	3	80
	4	86.5
	5	95.8
	6	127
3	1	121
	2	133
4	1	147
	2	166

When traffic volume is low enough to prevent drivers from being swayed by other cars and when intersection traffic control is either absent or far enough away to have no influence on drivers' decisions about how fast to drive, the traffic stream's average speed of travel is known as free flow speed (FFS) [30, 31]. Using a speed gun, the free flow's speed was measured. An apparatus for measuring the speed of moving cars is called a speed gun. Over the course of the investigation, it was used to gauge the vehicle's speed. The speed values that were calculated in this study are approximate values of the inability to calculate it in other methods due to the current situation in the country for the base year. It is utilized in law enforcement to determine the speed of moving vehicles [32].

3. MODEL FORMATION

An ANN is composed of up consists of three levels: An input layer that accepts signals from the outside world, an output layer, and one or more hidden layers that carry out nonlinear input transformations that transmit and receive external signals included in the network [33]. Figure 3 displays a graphic representation of the created ANN system.

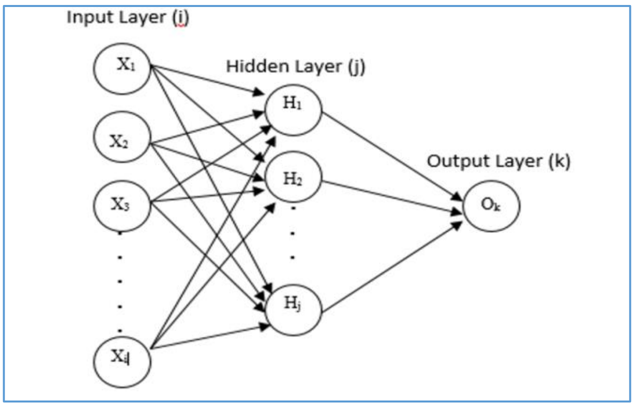


Figure 3. Simple ANN architecture

A popular ANN network design that has a hidden layer is the Multi-Layer Perceptron (MLP). Back propagation is one of the most well-known learning methods utilized by MLP Neural Networks, and it was employed in this study. In order to investigate how well an MLP Neural Network model predicts brief traffic on a two-lane, unbroken road with a variety of traffic situations, we are working to construct one. Figure 4 depicts the training Architecture of the developed system.

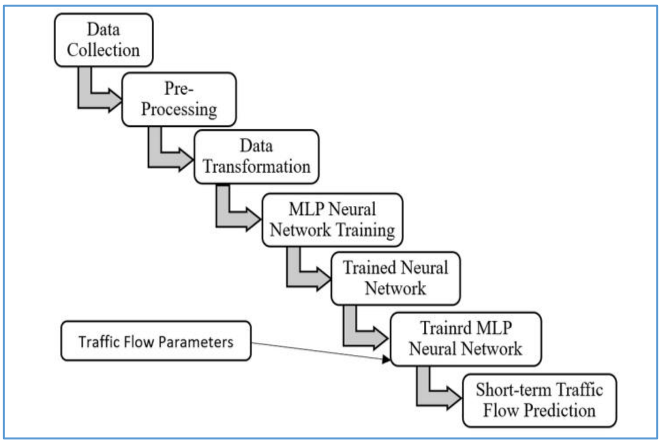


Figure 4. The training architecture of the developed system

When it comes to training MLP Neural Networks, the primary goal is to obtain ANN output weight values that are as close as possible to the actual target values. This research utilized the MLP Neural Network to make predictions on the flow of traffic. This model was constructed using each of the 4,510 data samples, each of which possesses various variables. These features include the geographic location, the time of day, eight different types of vehicles, and the average speed of each type of vehicle.

An undivided two-lane highway's traffic flow is predicted by applying the average speed of several vehicle classifications. MATLAB, SPSS, and Microsoft Excel were utilized in the formulation and development of the ANN model. To ascertain the right value for the network variables, a trial-and-error method was employed. It was decided to use the lowest Mean Square Error (MSE) as the completion requirement for training sessions.

4. DEVELOPMENT OF ANN MODELS

Multilayer perceptron networks are employed in this study to estimate future traffic flow for four intersections, as indicated in Table 1, and for four major streets, as indicated in Table 2. The 4,510 data samples, each with eight features (location, five different vehicle kinds, period of day, and the average speeds for every category with the average journey duration), were collected in order to create the ANN model. Since Iraq does not have a single road designated for a single class of vehicle, a speed flow model for a single class is insufficient to explain traffic circumstances there. All samples (4,510 data), including all types of vehicles (PC, MB, B, HV and MT), were distributed across locations (at each intersection and segment of the streets) with respect to peak time duration from 8:30 a.m. to 11:00 a.m. and 4:00 p.m. to 6:00 p.m. on average weekdays for each direction of the intersections. There is no restriction placed on the number of input variables that can be used. The nature of the problem should be taken into consideration when choosing the number of variables to be used for input and output in ANN.

In addition, various vehicles, both motorized and non-powered, use the same road, and their speeds vary. To forecast the multiclass traffic flow of streets and contractions, the average speed of several vehicle classes is taken into consideration. After multiple training of the network with different training, testing, and validation ratios, different logarithms were used. Till to get two different ANN models have been created to forecast the traffic volume for intersections, in addition to the average travel time for streets.

The criteria for selecting input variables for each ANN model (three models) were selected based on the most effective parameters that cause traffic congestion, longer travel times, and accidents for each type of vehicle, as the main input to the models. The selection of input parameters for the model was based on a real problem in Karbala City, which is the total reliance on private transportation rather than public transportation, which was confirmed through interviews with officials in the Karbala traffic department, and thus the rise in the numbers of cars compared to the lack of road development, so it was logical for the network structure to be derived from reality.

For the first model: 70.3% training, 18.8% testing and (validation) holdout 10.9%, where input variables (time, destination as main factors, PC = passenger car, MB = mini bus, B = bus, HV = heavy vehicle, MT = motorcycle) with one hidden layer (one node) and traffic volume as a single output layer. In the hidden layer, the activation function was a hyperbolic tangent and identity for the output layer, which gives the best prediction result. The specification of the first model has been presented in Figure 5.

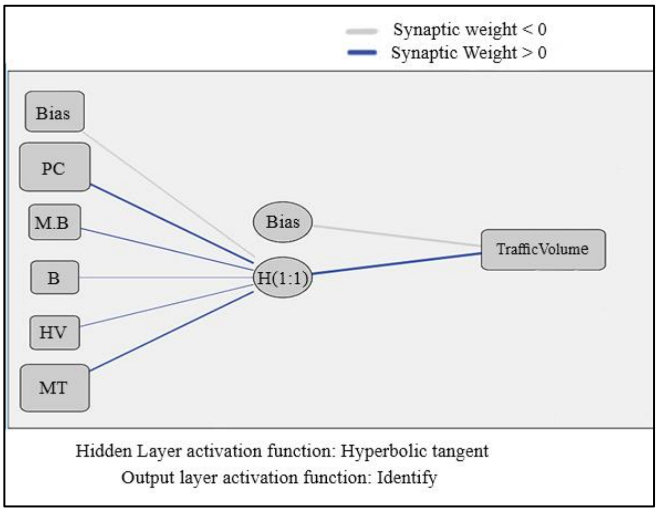


Figure 5. The specification of the first model

For the second model: 69.2% training, 20.3% testing and (validation) holdout 10.5%, where input variables (time, segment numbers as main factors), with one hidden layer (five nodes) and traffic volume with average travel time for streets as output layer. For the hidden layer, the activation function was a hyperbolic tangent, and for the output layer, it was identity, which gives the best prediction result. The specification of the first model has been presented in Figure 6.

ANN models' performance was assessed by testing and cross-validation data sets. The efficiency of the results was assessed using the Coefficient of Determination (R^2), Mean Absolute Error (MAE), Mean Square Error (MSE), and Normalized Mean Square Error (NMSE).

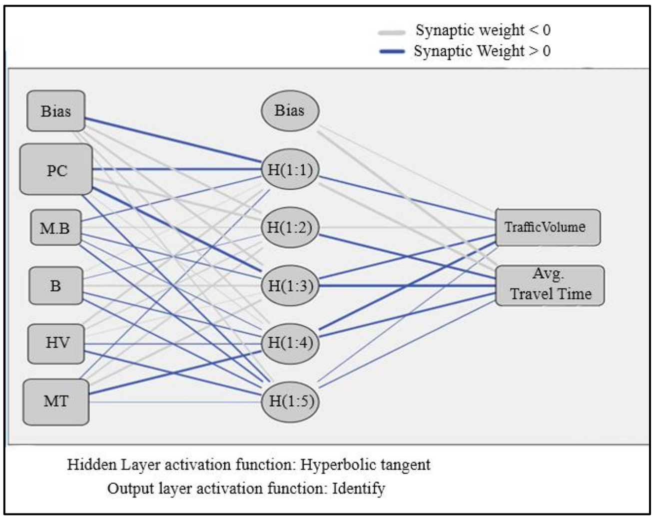


Figure 6. The specification of the second model

5. SENSITIVITY ANALYSIS

This analysis evaluates how the model's efficiency varies when the input value changes. Sensitivity analysis applied to a trained network can remove irrelevant inputs. Reducing unnecessary inputs may save data-gathering costs and enhance network performance. Sensitivity analysis also helps to identify the underlying relationships between variables that are input and output [34, 35]. The ANN model (first model) was used in this inquiry. Among seven significant input factors, PC is the most sensitive (important) among other input parameters, and time is less, as explained in Figure 7.

In the same way, for the second ANN model, among seven significant input factors, PC is the most important among other input parameters, and B is less, as depicted in Figure 8.

In the field of information available, there is no universal methodology for developing an optimal neural network architecture. At first, trial and error means picking weight settings for each neuron in the hidden layer at random. Further, these weights are modified by propagating the prediction error backwards. Certain parameters like the number of input variables, number of hidden layers, activation or transfer function and learning rate play an important role in designing neural network architecture. The values of learning rate, epoch count, and optimizer started with the default values, and then we changed the values till we got a more acceptable pattern of network and closely matched the output. Every time a neural network is trained, it can give a different result because the starting weight and bias values are different and the data is split into training, validation, and test sets in different ways. This training can be stopped after a certain number of epochs if the accuracy of the predictions doesn't improve further.

Previous studies discuss the comparisons between regression and ANN; others discuss SVM and ARIMA with ANN. They found that ANN models are more efficient than others. This study could be improved by adding more detailed and useful data about traffic flow for data collection and model development in future research. The vast data set should be evaluated using deep neural networks, such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN), which are renowned for their ability to effectively manage massive data sets.

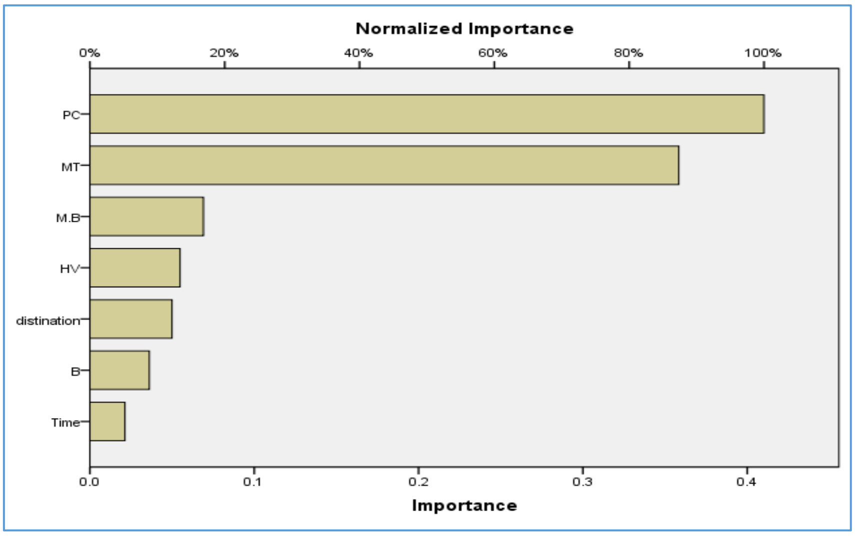


Figure 7. Sensitivity assessment of the first ANN model's input variables

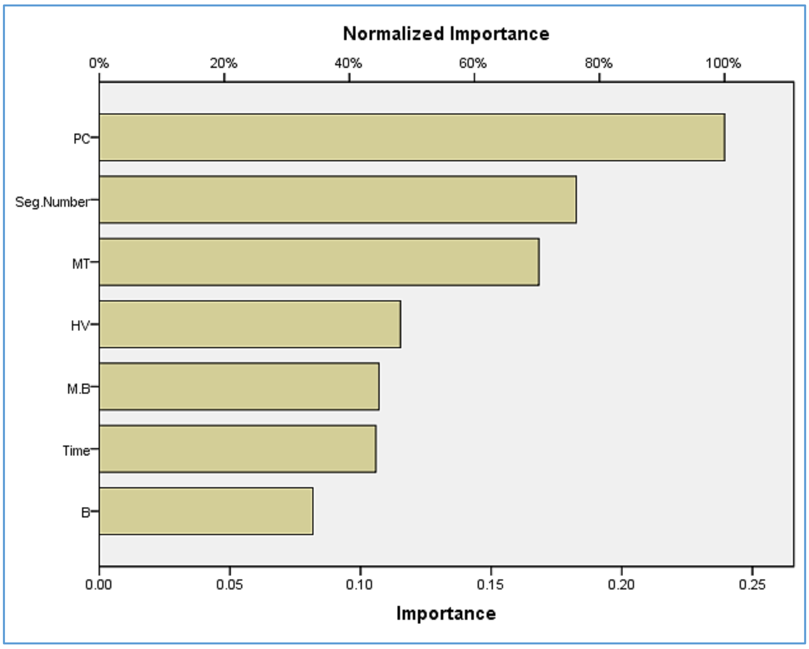


Figure 8. Sensitivity inspection of the second ANN model's input variables

6. RESULT AND DISCUSSION

The data has been used to create and train a number of ANN models. To modify the network's weight parameters, each of these models underwent training at various testing, validation, and training conditions using various algorithms and activation functions.

The regression plot for the first and second models between the simulated and observed traffic volume is displayed in Figures 9-11. It is evident that the model with the highest prediction accuracy (R^2 values of 0.9101, 0.9748, and 0.8877) was reached. R^2 is a parameter that shows how well the regression line fits the data can be defined. It is believed that a prediction model would be more accurate the closer its R^2 value is to 1. Moreover, mean absolute percentage error (MAPE) and mean absolute error (MAE) are used to evaluate each produced model's performance. The MAPE was 0.04, 0.032, and 0.08 for all models, while the MAE was 0.54,0.36, and 0.31.

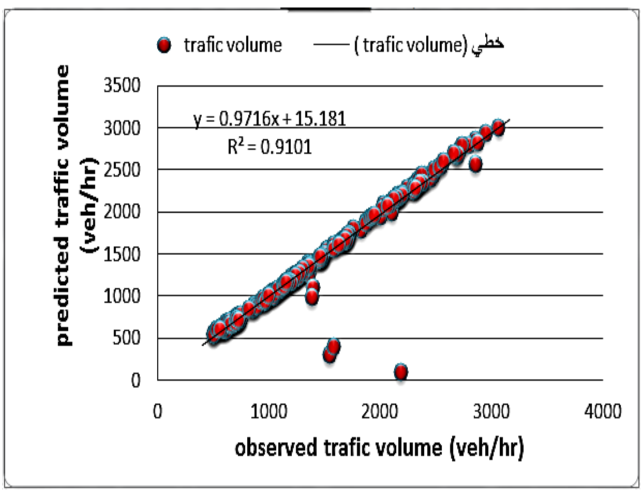


Figure 9. The first model's regression diagram comparing the traffic volume observed and simulated

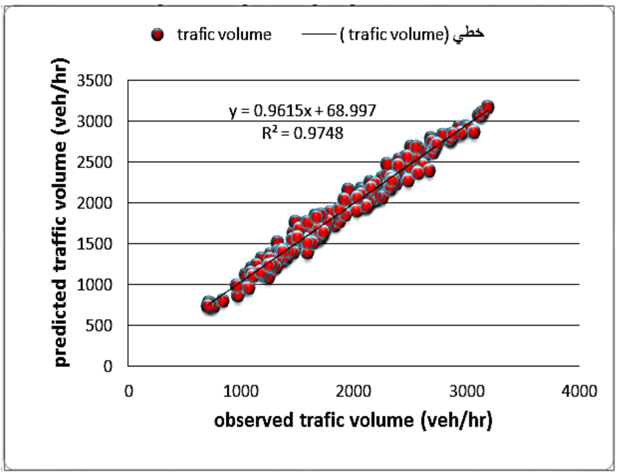


Figure 10. The second model's regression diagram comparing the traffic volume observed and simulated

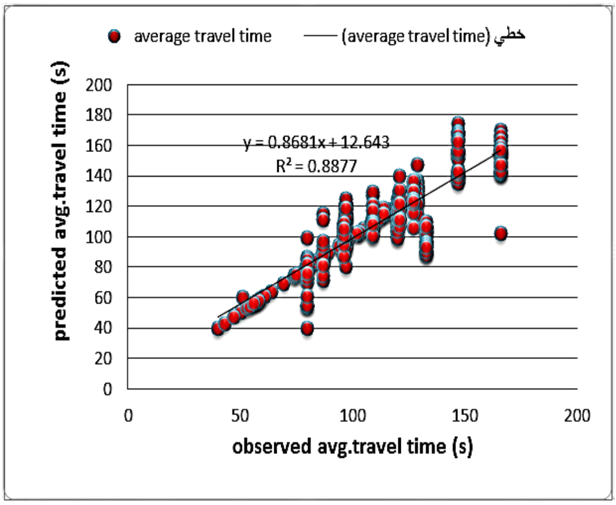


Figure 11. The second model's average journey time regression plot, comparing the simulated and observed travel times

Specific strategies in current research offer a chance to offer a good substitute for anticipating short-term traffic flow on main streets and intersections in Karbala City by introducing the number of vehicles for each type, thus contributing to the creation of a more sophisticated transit system that can monitor traffic, including potential integration with existing traffic control systems that include sensors and available cameras.

This data collection process necessitates significant human and technology resources, including deep neural networks, which are adept at managing extensive data sets efficiently. Enhancements to the model. Future research will focus on evaluating the training of ANNs using extensive data from broad regions, proposing deep learning methodologies, and integrating spatial analysis with short-term forecasting.

The practical implications of the developed models can be implemented in real-world traffic management systems in Karbala in both medium and large areas and each neighborhood can be studied independently from the others, but the management system in the study area suffers from weakness and keeping pace with the development in the field of road management. The implementation of traffic management and control policies heavily relies on traffic flows among all the data; the more data accessible, the more accurate the traffic forecasts are, and the more effective the strategy. On the other hand, the number of sensors (or road segments being monitored) has a significant impact on the monitoring system's cost; therefore, it is frequently insufficient to gather necessary data. Therefore, the application of such a model saves in terms of cost, time, and proper management of the traffic system for practitioners and policymakers.

7. CONCLUSIONS AND RECOMMENDATIONS

This research offered a short-term traffic volume prediction model for major intersections and streets in Karbala City with mixed traffic that is based on artificial neural networks. Samples of data were gathered and computed. The study created a two-zone short-term forecasting model with varied traffic circumstances using a back propagation neural network approach. The outcomes of the artificial neural network models showed great promise, with R^2 values of 0.9101, 0.9748, and 0.8877. Advanced traveler information systems (TIS) are used for short-term traffic forecasting.

The study may surely give an accurate short-term traffic forecast solution for important crossings and streets in Karbala City with mixed traffic conditions. Nevertheless, the study's dataset is limited to a particular number of weekdays and road segments. The study might benefit from further precise data on traffic flow on selected days in the week, during peak and off-peak hours, as well as for other seasons or months. The information collection procedure will surely result in a larger and more meaningful dataset, even though it requires a significant amount of technological and human labor. Moreover, a more suitable method would be employed to analyze this massive data set because deep neural networks are known to manage large datasets well.

This study would help highlight the contributions of using advanced TIS to forecast traffic in the near future. The study can undoubtedly offer a useful solution for intersection traffic prediction in the short run and on main streets with multiple traffic conditions in developing countries.

The more specific recommendations for future research are to maintain road capacity. Encroachments must be prevented and removed from the on-street parking, and there is a need to use advanced transportation systems such as Tram.

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