International Journal for Quality Research 17(3) 867–890
ISSN 1800-6450

Wallner Martin[1]
Peráček Tomáš

Article info:
Received 11.03.2022.
Accepted 09.04.2023.

UDC – 004.032.26
DOI – 10.24874/IJQR17.03-15

PREDICTORS OF AVERAGE WAIT TIME AT AN INTERSECTION USING ARTIFICIAL NEURAL NETWORK

Abstract: *This paper reports the results of the studies on identifying the predictors of average wait times of vehicles at intersections. The strength and direction of the relationship of these predictors were gauged from the values and sign of the predictor.*

Simulated data obtained using a JavaScript algorithm were used. The variables tested for predictability included the traffic light time (seconds), traffic density per minute, number of input tracks (1 or 2), and number of output tacks (1 or 2). The program can then simulate the average wait time in seconds for an intersection (down, right, up, and left). The programme simulated the average wait times for the four directions of traffic flows at the intersection. These data were used in an artificial neural network algorithm. About 70% of the data were used for training and the remaining 30% were used for testing. The ANN model used is called a multi-layer perceptron (MLP). All the 4 models developed have one input layer, one hidden layer, and one output layer.

The results indicated that density as the strongest predictor accounting for 100% importance among the variables tested. In some situations, traffic light times or the number of input or output tracks in some directions could also predict wait times to a lesser extent. Density was positively related to the wait times. These findings have been largely supported by the published literature when linked to traffic flow and travel times.

Keywords: *Average Wait Times, Predictors, Traffic Intersection, Simulated Data, Artificial Neural Network, Traffic Density*

1. Introduction

To be able to devise an adaptive intelligent traffic control system for smart cities, one needs to understand the predictors of average wait time and the strength and direction of the relationship between the predictors and average wait time. This information can then be optimized to design an adaptive intelligent traffic control system. The aspects of this study are adaptive intelligent traffic control systems more commonly implemented in smart cities and the average vehicle wait time at intersections and its predictors. Some recently available literature are discussed briefly on these aspects below.

[1] Corresponding author: Wallner Martin
Email: wallner4@uniba.sk

In a review paper, Mandhare, Kharat, and Patil (2018) discussed various adaptive and non-adaptive and simulation/real time/hybrid approaches of traffic routing and a signal controlling decisions, input and output variables like traffic volume, waiting time, previous and current traffic data for traffic routing, collection and communication methods of traffic data, smart traffic control at intersections and traffic management improvement to minimise congestion. RFID tags, readers and sensors were used, as fixed and pre-set traffic management system to detect and remove congestion in the studies of Atta, Abbas, Khan, Ahmed, and Farooq (2020). The study showed that a sensor based totally fuzzy judgment version can reduce the road traffic congestion to the minimum. This was achieved by letting the fuzzy device to decide on adjusting the signal timings. Simulation results confirmed the model.

Internet of Things (IoT) and Vehicular Ad Hoc Network (VANET) have emerged as promising technologies for an Intelligent Traffic Management System (ITMS). For prioritising emergency vehicles through congested traffic, Sumi and Ranga (2018) proposed a system which measures the gap between an intersection and the emergency vehicle and then dispatch the emergency vehicle (EV) from that intersection irrespective of whether the traffic signals are hacked, the type of incident and emergency car type. Thus, the EV bypasses heavy traffic and reaches its destination on time minimising delay in transmission of emergency messages. A separate mechanism exists to handle hacking problems. The model was tested using a simulation study. Internet of Vehicles (IoV) technology was used and practically demonstrated by Kumar, et al. (2018) to regulate traffic and identify the optimal route to destination. The street maps were segmented into a number of small distinct maps. Ant colony algorithm was applied to each map to find the optimal route. Fuzzy logic based traffic intensity calculation function was used to model heavy traffic. An intelligent traffic monitoring system using graph theory and formal methods was proposed by Latif, Afzaal, and Zafar (2018). Only proof of its correctness has been offered by the authors.

Thus, various types of intelligent traffic control systems have been developed and even used in different smart city contexts. These include, fixed, dynamic or vehicle-based systems and using conventional as well as modern technologies.

Harahap, Darmawan, Fajar, Ceha, and Rachmiatie (2019) proposed a model of queue at a road intersection with traffic lights. The appropriate traffic light duration can be determined based on the arrival of the vehicle. This helps to obtain the queue waiting time under the driver's time stress threshold. The waiting time in the queue was dependent on the accuracy of the traffic light time duration setting, both red and green lights on all intersection lines. The vehicle waiting time model in the queue at the red light phase, the waiting time model in the green light phase with the arrivals by Poisson process using M/M/1 queuing model and the waiting time of all vehicles for an entire traffic light cycle were determined. The queue waiting time model can facilitate estimation of the average wait time of vehicles at intersections. The average number of vehicles in the queue (density) was a variable included in this study.

A new approach of intelligent signal timing based on the traffic flow timing, in which, by temporally clustering optical flow features of moving vehicles using Temporal Unknown Incremental Clustering (TUIC) model reduced average vehicle wait time significantly compared to other algorithms in experiments (Kumaran, Mohapatra, Dogra, Roy, & Kim, 2019). A Reinforced Learning (RL)-based traffic signal control method that employs a graph convolutional neural network (GCNN) was tested by Nishi, Otaki, Hayakawa, and Yoshimura (2018) on a six-intersections environment. The policies learned using the proposed method could control the traffic flow with the shortest mean wait times under a wide variety of traffic demand conditions.

A model called Phase-Aware Deep Learning and Constrained Reinforcement Learning was proposed by Sur (2019) for optimization and constant improvement of signal and trajectory for autonomous vehicle operation modules for an intersection. The results obtained from the model helped to reduce the vehicle wait time significantly. The results of a case study on a novel smart traffic control framework using local traffic smart server and remote cloud server proved smooth progress of travel by reducing the waiting time for the green lamp onset (Kuppusamy, Kalpana, & Venkateswara Rao, 2019).

Experimental results on using two algorithms developed by Li, et al. (2019) indicated that these two algorithms outperformed the signal control method by reducing total traffic delays at intersections (vehicle wait times) leading to increasing intersection capacity and operation efficiency. In the trials of Liu S., et al. (2018) the average delay and average stop times of vehicles at intersections increased with increased traffic density with or without single-vehicle or multi-vehicle guidance systems in connected vehicles.

To determine the predictors of average wait time at intersections using artificial neural networks.

2. Method

A brief account of ANN methods and MLP models followed by using 70% of the data for training and the remaining 30% for testing are provided below.

2.1. ANN Models in General

A tutorial describing ANN methods was provided by Jain, Mao, and Mohiuddin (1996). Artificial neural networks (ANN) are used to solve several problems like pattern recognition, prediction, associated memory, and control. Conventional approaches are not flexible enough to apply beyond the context in which they were used. ANN is an answer for such situations. ANN can be applied to situations in which the normal numerical capabilities of computers are inadequate. ANN methods were developed to imitate some of the human neural network systems.

ANN is an engineering approach to biological neurons. It deals with situations of many inputs and one output. ANN consists of a large number of simple processing elements interconnected with each other and layered. A multilayered ANN was diagrammatically described by Sharma, Rai, and Dev (2012). ANN improves on the rules of computer algorithms and facilitates decision-making. The two basic types of ANN are feed-forward and feedback. In Feedforward Network, the signal travel in one way only but in Feedback Network, the signal travel in both directions by introducing loops in the network. Since ANN is used in this study, its use for predictive purposes is only explained further.

There are three layers in ANN structure: the input layer of the collected data, an output layer of computed information, and one or more hidden layers to connect the input and output layer. A neuron is a basic processing unit of a NN and performs both the collection of the inputs and the production of the output. Each input is multiplied by connection weights, and its products and biases are added and then passed through an activation function to produce an output. Bp algorithm is used for training feedforward ANN. The algorithm is based on supervised learning and hence learning occurs iteratively. It compares the estimated value with the actual value and iteration stops when the mean squared error is minimised using adjusted weights for each training model. Using the appropriate mathematical equations, each input in the input layer is multiplied by a connection weight between the neuron in the input layer to a neuron in the hidden layer and gets its products, and biases are summed formally to a net input, then passed to the hidden layer by a nonlinear sigmoid activation function to produce an output. A signal is sent from the hidden layer to all neurons in the output layer and computes the input to neuron function. Then the outer layer signals are computed using a sigmoid activation function. The error training between target output and measured data is estimated. The procedure is repeated for all pairs of the training set (each training cycle is known as an epoch) and repeated till the error value is reduced to a limit value. It is important to optimise the learning rate and stability. The performance of ANN can be measured using root mean square error (RMSE), the mean absolute percentage error (MAPE), mean absolute bias error (MABE) (minimum value better for all the three), and coefficient of determination (R2, higher better) (Mohamed, 2019).

2.2. ANN for Predictive Purpose

The need to be cautious about overtraining and recognise the limitations of extrapolation when using ANN for predictions was stressed and solutions were suggested by Yin, Rosendahl, and Luo (2003). The extrapolation problem was solved by the use of data with maximum and minimum values for training. The overtraining problem was solved by terminating the training by monitoring the training data and all the sample data. The training was terminated when both the energy function for the testing set and that for all the samples reduced to a relatively low value. But this procedure is cumbersome and may not be possible in all situations.

In a review, Ferrero Bermejo, Fernandez, Polo, and Márquez (2019) noted that ANN is used for ideal predictions, and prediction in presence of additional external variables like weather, asset reliability assessments for timely maintenance. ANN has the advantages of generating prediction models with high correlation coefficients, quick fitting, and flexibility to behaviour patterns, namely, by pattern-recognition and fault tolerance capability, especially, when data are absent and are noisy, can adapt to more complex and non-linear problems, can adjust to real-time dynamic changes, possible to process and integrate quickly and the possibility to predict the incremental output.

2.3. Analysis Methodology

The data for the research has been simulated using a JavaScript algorithm. The inputs in the program include the traffic light time (seconds), traffic density per minute, number of input tracks (1 or 2), and number of output tacks (1 or 2). The program can then simulate the average wait time in seconds for an intersection (down, right, up, and left).

ANN models were developed for 'down,' 'right,' 'left,' and 'up' intersections. Average wait time was the dependent variable, the number of input and output tracks were the factors, and traffic light time and traffic density were the covariates. 70% of the data was used for training and the rest for testing the models. The ANN model used is called a multi-layer perceptron (MLP). All the 4 models developed have one input layer, one hidden layer, and one output layer.

The 2 input and 2 output tracks scenario intersection is shown below in Figure 1.

The 2 input and 1 output tracks scenario intersection is shown below in Figure 2.

An example of a simulation run is shown in Figure 3.

ANN models were developed for 'down,' 'right,' 'left,' and 'up' intersections. Average wait time was the dependent variable, the number of input and output tracks were the factors, and traffic light time and traffic density were the covariates.

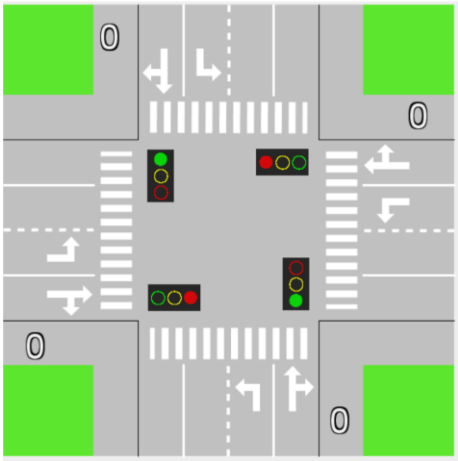


Figure 1. Two input and two output tracks scenario of the intersection

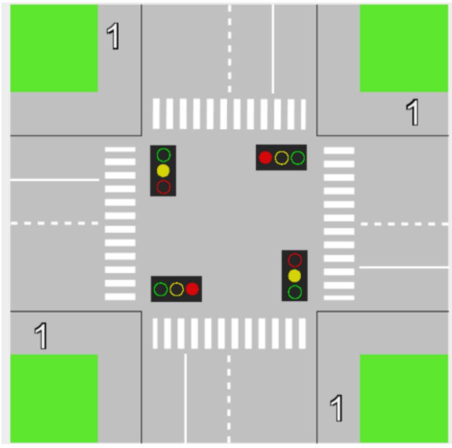


Figure 1. Two input and one output track intersection scenario

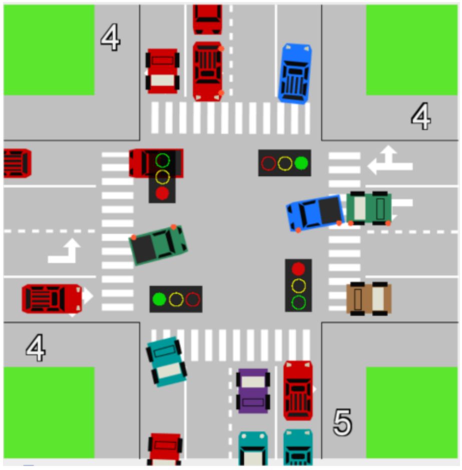


Figure 2. An example of a simulation intersection scenario

3. Results

3.1. Summary Statistics

The summary statistics are shown below.

Table 1 provides the descriptive statistics of simulation results consisting of minimum, maximum, mean, and standard deviation values for traffic flows in the four directions.

The minimum wait time was the highest (8 seconds) for up and down traffic flows.
The maximum wait time was the highest (215 seconds) for right and up traffic flows. The mean wait time was the highest for left (27.82 seconds) for down (27.04 seconds). Right flow recorded the lowest mean traffic flow of 20.70 seconds. As has been indicated by the minimum and maximum values over 75 observations, the standard deviation was higher than the mean values for all traffic flows.

In Table 2, the number of output tracks for all four directions of traffic flows are presented.

Table 1. Descriptive Statistics from simulation results

Direction		N	Minimum	Maximum	Mean	Std. Deviation
Down	Average wait time (seconds)	75	8.00	200.00	25.4833	35.51193
	Traffic light time (seconds)	75	5.0	25.0	15.000	6.1403
	Density (per min)	75	2.0	30.0	10.187	6.4655
	Valid N (listwise)	75				
Left	Average wait time (seconds)	75	7.00	150.00	27.8167	36.22642
	Traffic light time (seconds)	75	5.0	25.0	15.000	6.1403
	Density (per min)	75	2.0	30.0	10.187	6.4655
	Valid N (listwise)	75				
Right	Average wait time (seconds)	75	7.00	215.00	20.7033	31.31581
	Traffic light time (seconds)	75	5.0	25.0	15.000	6.1403
	Density (per min)	75	2.0	30.0	10.187	6.4655
	Valid N (listwise)	75				
Up	Average wait time (seconds)	75	8.00	215.00	27.0367	35.86948
	Traffic light time (seconds)	75	5.0	25.0	15.000	6.1403
	Density (per min)	75	2.0	30.0	10.187	6.4655
	Valid N (listwise)	75				

Table 2. Number of output tracks

Direction			Frequency	Percent	Valid Percent	Cumulative Percent
Down	Valid	1.0	42	56.0	56.0	56.0
		2.0	33	44.0	44.0	100.0
		Total	75	100.0	100.0	
Left	Valid	1.0	40	53.3	53.3	53.3
		2.0	35	46.7	46.7	100.0
		Total	75	100.0	100.0	
Right	Valid	1.0	38	50.7	50.7	50.7
		2.0	37	49.3	49.3	100.0
		Total	75	100.0	100.0	
Up	Valid	1.0	37	49.3	49.3	49.3
		2.0	38	50.7	50.7	100.0
		Total	75	100.0	100.0	

The number of vehicular output for down and left directions were higher for 1 track situations and right direction, it was marginally higher for 1 track situations. For up direction, the 2 track situation had a marginally higher vehicular output.

The number of input tracks for all four directions of traffic flows is given in Table 3.

Table 3. The number of input tracks

Direction			**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Down	Valid	1.0	31	41.3	41.3	41.3
		2.0	44	58.7	58.7	100.0
		Total	75	100.0	100.0	
Left	Valid	1.0	31	41.3	41.3	41.3
		2.0	44	58.7	58.7	100.0
		Total	75	100.0	100.0	
Right	Valid	1.0	41	54.7	54.7	54.7
		2.0	34	45.3	45.3	100.0
		Total	75	100.0	100.0	
Up	Valid	1.0	38	50.7	50.7	50.7
		2.0	37	49.3	49.3	100.0
		Total	75	100.0	100.0	

One track input had a higher input than 2 tracks in the case of right and marginally higher input in the case of up traffic flows. Two-track had higher input than one track in the case of both down and left traffic flows.

3.2. ANN results

The ANN models for ‘down,’ ‘right,’ ‘left,’ and ‘up’ intersections are shown below. The case processing summary in Table 4 shows the ratios used for different simulation scenarios.

Table 4. Case Processing Summary

Direction			N	Percent
Down	Sample	Training	53	70.7%
		Testing	22	29.3%
	Valid		75	100.0%
	Excluded		0	
	Total		75	
Left	Sample	Training	47	62.7%
		Testing	28	37.3%
	Valid		75	100.0%
	Excluded		0	
	Total		75	
Right	Sample	Training	56	74.7%
		Testing	19	25.3%
	Valid		75	100.0%
	Excluded		0	
	Total		75	
Up	Sample	Training	50	66.7%
		Testing	25	33.3%
	Valid		75	100.0%
	Excluded		0	
	Total		75	

Generally, an approximate 70:30 ratio was used for training and testing the data.

The detailed information on the network in the simulation is presented in Table 5 (See Appendix).

The factors and covariates for the prediction of the average wait time for different intersection scenarios are described in Table 5. These data are indicators of the ANN algorithms used in this study.

The network diagrams for the intersection scenarios are provided in Figure 4-7 (see Appendix).

4. Network Diagrams

4.1. Down

The factors and covariates are on the left side of the diagram. A hyperbolic tangent function is used for the hidden layer activation. The output is the average vehicle wait time at the intersection, which is identified by the outer layer activation function.

4.2. Left

In Figure 5 (see Appendix), the network diagram of the left scenario is presented. The hidden layer and the output layer definitions are kept the same.

4.3. Right

The network diagram for the right intersection scenario is presented in Figure 6 (see Appendix) with the same functional specifications as for the above two scenarios.

4.4. Right

The network diagram of up intersection scenarios with similar parameters as the above three is given in Figure 7 (see Appendix).

4.5. Parameter Estimates

The parameter estimates of the four intersection scenarios and variable importance analysis are given and explained below Table 6.

Table 6. Parameter estimates of the intersection scenarios using ANN

Direction- Down			
Predictor		Predicted	
		Hidden Layer 1	Output Layer
		H(1:1)	Average wait time seconds
Input Layer	(Bias)	-.877	
	[Number of output tracks=1.0]	-.346	
	[Number of output tracks=2.0]	-.892	
	[Number of input tracks=1.0]	-.113	
	[Number of input tracks=2.0]	-1.138	
	Traffic light time seconds	.057	
	Density per min	1.370	
Hidden Layer 1	(Bias)		.912
	H(1:1)		1.302

4.6. Down direction

The 'down' model is shown above. The model includes a bias (the equivalent of the contract in the regression models), and the other rectangles represent input variables (these are: number of output track=1, number of output track=2, number of input track=1, number of input track=2, traffic light time, and density per min).

For interpretation, we need to focus only on the positive or negative signs of the variables marked in yellow below. For example, the number of output track=1 is negatively associated with average wait time, vehicle density per min is positively associated with average wait time, and so on.

The independent variable importance analysis is given in Table 7 and the diagram on normalised importance is given in Figure 8 below.

Table 7. Independent variable importance- Down

Direction		**Importance**	**Normalized Importance**
Down	Number of output tracks	.035	3.9%
	Number of input tracks	.071	8.0%
	Traffic light time (seconds)	.011	1.3%
	Density (per min)	.883	100.0%

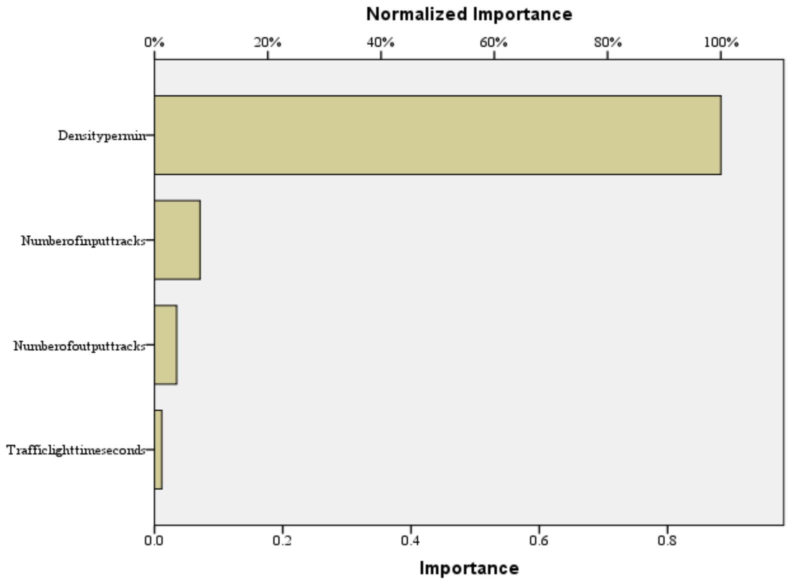


Figure 8. Independent variable parameters chart- Down

As both the table and the chart shows, the highest importance is for the density factor with 100% importance. The importance of all the other three factors is less than 10%.

4.7. Left direction

Similar tables and diagrams with similar explanations are given for the left intersection scenario below (Tables 8 and 9 and Figure 9).

Table 8. Parameter estimates of the intersection scenarios using ANN

Direction - Left					
Predictor		**Predicted**			
		Hidden Layer 1			**Output Layer**
		H(1:1)	**H(1:2)**	**H(1:3)**	**Average wait time seconds**
Input Layer	(Bias)	-.329	1.215	.468	
	[Number of output tracks=1.0]	-.318	-.388	.272	
	[Number of output tracks=2.0]	-.458	1.114	-.218	
	[Number of input tracks=1.0]	-.126	.576	.309	
	[Number of input tracks=2.0]	-.153	.527	.040	
	Traffic light time seconds	.003	-.050	-.284	
	Density per min	-.315	-1.331	-.339	
Hidden Layer 1	(Bias)				.763
	H(1:1)				-.706
	H(1:2)				-1.863
	H(1:3)				.278

The left model is shown above. The model includes a bias (the equivalent of the contract in the regression models), and the other rectangles represent input variables (these are: number of output track=1, number of output track=2, number of input track=1, number of input track=2, traffic light time, and density per min). There are three hidden layers.

For interpretation, we need to focus only on the positive or negative signs of the variables marked in yellow below. In the case of the hidden layer H(1:1), except for traffic light times, all others are negatively associated with the average wait time, the highest being for the number of output tracks (2.0) with -0.458 followed by density per minute with 0.315. The positive association between traffic light times is negligible.

In the case of the Hidden layer (H1:2), the number of output track 2.0 was positively associated with the average wait time with the value of 1.114. The highest negative relationship for the same dependent variable was obtained for vehicle density per minute with a value of

-1.331. While the number of output tracks 1.0 was negatively associated (-0.388), the number of input tracks 1.0 and 2.0 were positively associated with average wait time with their values around -0.5. The effect of traffic light was negligible.

In the case of Hidden layer H (1:3), the number of output tracks 1.0 (0.272), input tracks 1.0 (0.309), and 2.0 negligibly (0.040) were positively related to the average wait time. A negative relationship was obtained for the number of output tracks 2.0 (-0.218), traffic light times (-0.284), and vehicle density (-0.339).

The independent variable importance analysis using standardised relative values is given in Table 8 and the diagram on normalised importance is given in Figure 9.

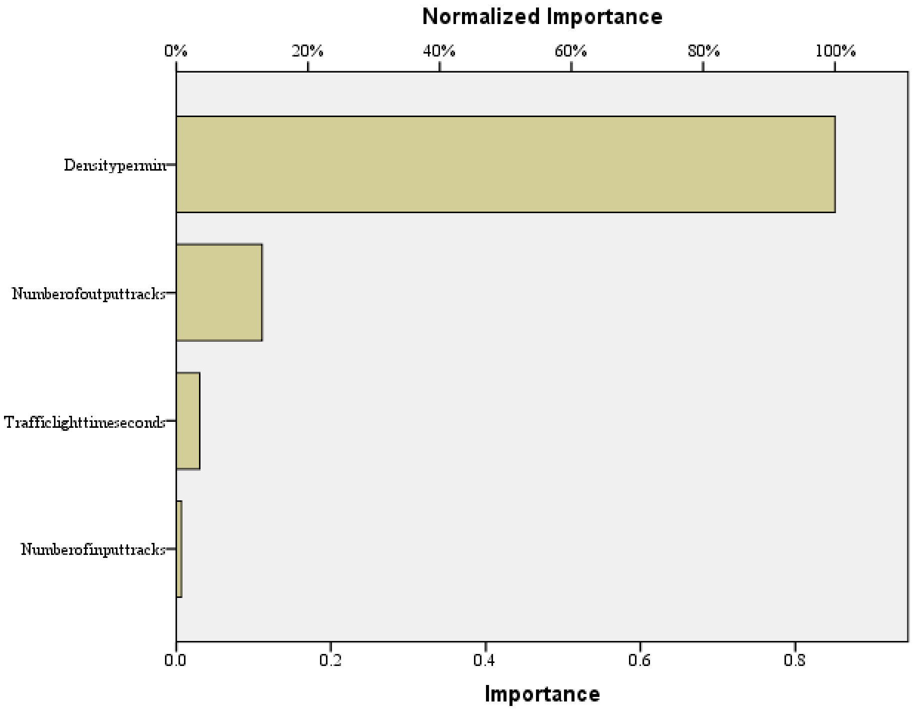


Figure 9. Independent variable parameters chart-Left

Table 9. Independent variable importance-Left

Direction		**Importance**	**Normalised Importance**
Left	Number of output tracks	.111	13.0%
	Number of input tracks	.007	0.8%
	Traffic light time (seconds)	.031	3.6%
	Density (per min)	.852	100.0%

Table 10 and Figure 9 reveal density as the most important predictor of average wait time with 100% normalised importance. The number of output tracks was the next important factor with 13% normalised importance. The importance of the other two factors was less than 5%.

4.8. Right direction

Table 10. Parameter estimates of the intersection scenarios using ANN

Direction-Right			
Predictor		Predicted	
		Hidden Layer 1	Output Layer
		H(1:1)	Average wait time seconds
Input Layer	(Bias)	2.016	
	[Number of output tracks=1.0]	.478	
	[Number of output tracks=2.0]	1.394	
	[Number of input tracks=1.0]	.766	
	[Number of input tracks=2.0]	1.402	
	Traffic light time seconds	1.445	
	Density per min	-2.182	
Hidden Layer 1	(Bias)		2.117
	H(1:1)		-2.457

There was only one hidden layer in this case. Positive associations for average wait time were obtained with four factors except for density. The highest two positive relationships were obtained for traffic light time (1.445) and the number of input tracks 2.0 (1.402), closely followed by the number of output tracks of 2.0 (1.394). Density had the highest association, but in the negative direction (-2.182).

The data on the relative importance and their normalised ranking are given in Table 11 and Figure 10.

Table 11. Independent variable importance-Right

Direction		**Importance**	**Normalised importance**
Right	Number of output tracks	.035	4.5%
	Number of input tracks	.024	3.1%
	Traffic light time (seconds)	.167	21.5%
	Density (per min)	.774	100.0%

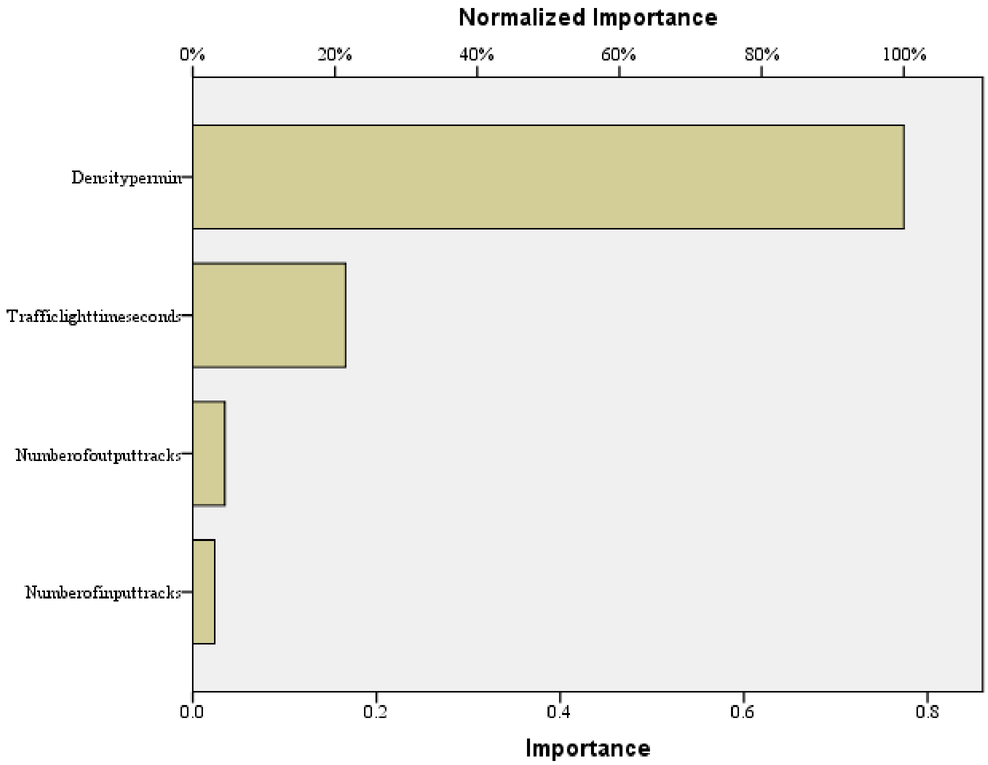


Figure 10. Independent variables parameters chart- Right.

As both Table 11 and Figure 10 reveals, the importance of density was the maximum at 100%, followed by traffic light times (21.5%). The importance of the other two variables was less than 5%.

4.9. Up direction

The ANN parameter estimates of the up direction are given in Table 10.

There were four hidden layers. In the case of H (1:1), a positive association for average wait times was obtained with the number of output tracks 1.0 (0.213) and density (0.993). Negative relationships were obtained for the remaining four factors, the highest being for the number of output tracks 2.0 (-1.519) and the lowest for traffic light times (-0.312). The other two were in the range of -0.6 to -0.7.

In the case of H(1:2), the highest positive relationship was obtained for the number of input tracks 1.0 (0.709) and the values for the number of input tracks 1.0 and 2.0 were in the range of 0.5 to 0.6. The highest negative value was obtained for traffic light times (-0.494), followed by density (-0.269). The negative relationship for the number of output tracks 2.0 was negligible.

In the case of H(1:3), there were four negative relationships and two positive relationships with average wait times. The highest two negative relationships were obtained for density (-0.498) and traffic light times (-0.436). The values for the number of output tracks 1.0 and 2.0 were -0.177 and -0.183 respectively.

Table 12. Parameter estimates of the intersection scenarios using ANN

Predictor		Predicted				
		Hidden Layer 1				Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	Average wait time seconds
Input Layer	(Bias)	-1.323	.642	.680	-.277	
	[Number of output tracks=1.0]	.213	.571	-.177	-.089	
	[Number of output tracks=2.0]	-1.519	-.066	-.183	.313	
	[Number of input tracks=1.0]	-.613	.709	.108	-.257	
	[Number of input tracks=2.0]	-.685	.568	.336	-.192	
	Traffic light time seconds	-.312	-.494	-.436	.283	
	Density per min	.993	-.269	-.498	.917	
Hidden Layer 1	(Bias)					1.234
	H(1:1)					1.981
	H(1:2)					1.048
	H(1:3)					-.208
	H(1:4)					.575

In the case of (H1:4), the highest positive association with average wait time was obtained for density (0.917), followed by the number of output tracks 2.0 (0.313). The values for input tracks 1.0 and 2.0 ranged from about -0.2 to -0.25. The negative relationship for the number of output tracks 1.0 was negligible.

Table 13 and Figure 11 provide the relative importance of independent variables using standardised values across all four layers.

As revealed by both Table 13 and Figure 11, 100% importance was obtained for density, followed by the number of output tracks with 15.1% and traffic light time with 12.4%. The number of input tracks had only 2.4% importance.

Table 13. Independent variable importance-Up

Direction		Importance	Normalised importance
Up	Number of output tracks	.117	15.1%
	Number of input tracks	.018	2.4%
	Traffic light time (seconds)	.095	12.4%
	Density (per min)	.770	100.0%

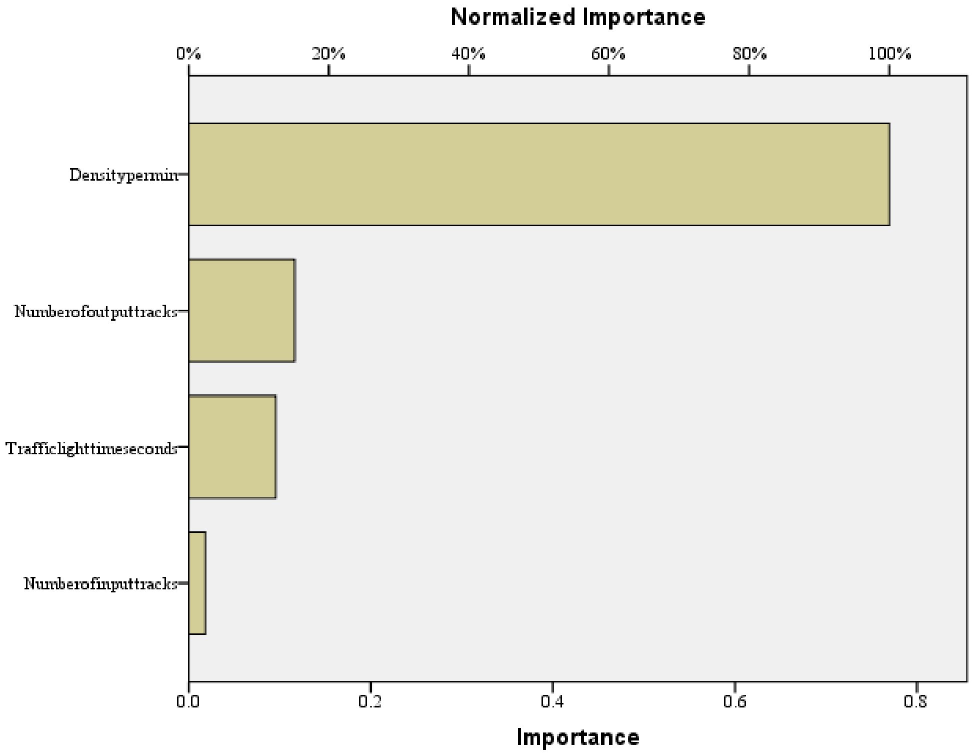


Figure 11. Independent variables parameters chart-Up

5. Discussion

Overall, the findings show 100% importance for density to predict average wait times at intersections in all directions of traffic. Such a consistent pattern may not be very common in actual situations. The differences among the four directions were noted only in the case of the subsequent importance rankings. In the case of both down directions, the other two factors had negligible importance. In the case of both left and up directions, the number of output tracks had significant importance ranging from 13 to 15%. Traffic light times were significant and second importance for right (21.5%) and up (12.4%) directions.

It is known that when vehicle density on the road increases, their speed is reduced delaying their arrival at the intersections. The effect of this on wait time at intersections depends on the number of vehicles, the number of input and output tracks, and traffic light times (if it is a traditional one). A significant reduction in wait times due to the use of a dynamic traffic light control system was reported by Chen, Chen, and Hsiungy (2016). Srivastava and Sudarshan (2013) analysed methods to build an intelligent system blending some of the existing technologies of traffic control thereby reducing the average waiting time of vehicles at intersections. The algorithms and models used were superior to the traditional methods in reducing the average wait times of vehicles at intersections and made the junction adaptive to the current density of traffic at the junction. Thus, vehicle density was used for adjusting the wait time automatically with an appropriate algorithmic model. In the studies of Patel and Ranganathan (2001), the average wait time was reduced using an integrated system of ANN and expert systems fuzzy logic in which dynamic traffic light control was an important part. The average delay (wait time) and vehicle queue length (density) were reduced significantly by using a dynamic predictive control framework in the studies by Yao, Shen, Liu, Jiang, and Yang (2019). These findings support the negative effect of density on wait time obtained in this research.

Liu and Zhang (2021) observed that the waiting time at an intersection is significantly associated with the final stopping location around the same time each day. In their study, the estimated and the actual waiting time compared well, when ANN models were used for the estimation of waiting time. It is known that waiting time mainly depends on the arrival time or the remaining time in a traffic light cycle. The ANN approach assumes that the vehicle's location can be used for the estimation of the arrival time under a constant traffic volume (density) condition. Since the vehicle locations are heavily affected by the accumulated space between the vehicles, precise estimation of the waiting time is challenging. Some factors affecting the relationship between wait times and density can be understood from these results. According to Dogan, Akgungor, and Arslan (2016), ANN models have the potential to estimate the vehicle delay time (wait time) and the number of vehicle stops. There was a good agreement between the estimated and simulated values. One important aspect for the continuation of the present study is the comparison of predicted relationships and values with the actual field data.

The capability of the Immune Network Algorithm-based Multi-Agent System (INAMAS) to predict vehicle queue length and wait times in different traffic scenarios was demonstrated by Darmoul, Elkosantini, Louati, and Said (2017). In this study, the different traffic scenarios are the traffic flow in the four directions.

In the studies of Perez-Murueta, Gómez-Espinosa, Cesar, and Gonzalez-Mendoza (2019), the use of platform continuous monitoring of the traffic flow situation in a specific geographic area led to a reduction in loss of travel time and wait time to provide a congestion detection and warning service. Deep neural networks can be used to obtain current traffic flow data if it is not already available with the existing system. Here, the deep neural network has been offered as a solution for the lack of historical data on the traffic in any specific geographical area.

Traffic volume and wait times were reduced by using a two-dimensional self-organizing neural network traffic classifier and a Hopfield neural network, according to Kaedi, Movahhedinia, and Jamshidi (2008). A model generated by Benhamza and Seridi (2015) reduced congestion by maximising traffic flows and minimising wait times in the simulation studies. The only way to reduce congestion is to minimise wait times, which will also lead to increased traffic flows. This is the importance of the findings in the present study.

6. Conclusion

This research aimed to predict wait times using ANN as the method. Density was found to be the strongest predictor accounting for 100% importance among the variables tested. In some situations, traffic light times or the number of input or output tracks in some directions could also predict wait times to a lesser extent.

Acknowledgment: This research was funded by the project National infrastructure for supporting technology transfer in Slovakia II–NITT SK II, co-financed by the European Regional Development Fund.

References:

Atta, A., Abbas, S., Khan, M. A., Ahmed, G., & Farooq, U. (2020). An adaptive approach: Smart traffic congestion control system. *Journal of King Saud University-Computer and Information Sciences, 32*(9), 1012-1019. doi:10.1016/j.jksuci.2018.10.011

Benhamza, K., & Seridi, H. (2015). Adaptive traffic signal control in multiple intersections network. *Journal of Intelligent & Fuzzy Systems*, *28*(6), 2557-2567. doi:10.3233/IFS-151535

Chen, Y.-R., Chen, K.-P., & Hsiungy, P.-A. (2016). Dynamic traffic light optimization and Control System using model-predictive control method. *IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), 1-4 Nov. 2016*, *Rio de Janeiro, Brazil* (pp. 2366-2371). IEEE. doi:10.1109/ITSC.2016.7795937

Darmoul, S., Elkosantini, S., Louati, A., & Said, L. B. (2017). Multi-agent immune networks to control interrupted flow at signalized intersections. *Transportation Research Part C: Emerging Technologies*, *82*(September), 290-313. doi:10.1016/j.trc.2017.07.003

Dogan, E., Akgungor, P. A., & Arslan, T. (2016). Estimation of delay and vehicle stops at signalized intersections using artificial neural network. *Engineering Review, 36*(2), 157-165. Retrieved May 31https://hrcak.srce.hr/file/229008, 2022

Ferrero Bermejo, J., Fernandez, J. F., Polo, F. O., & Márquez, A. C. (2019). A review of the use of artificial neural network models for energy and reliability prediction. A study of the solar PV, hydraulic and wind energy sources. *Applied Sciences*, *9*(9), 1844. doi:10.3390/app9091844

Harahap, E., Darmawan, D., Fajar, Y., Ceha, R., & Rachmiatie, A. (2019). Modeling and simulation of queue waiting time at traffic light intersection. *Journal of Physics: Conference Series, 1188*(1), 012001. doi:10.1088/1742-6596/1188/1/012001

Jain, A. K., Mao, J., & Mohiuddin, K. M. (1996). Artificial neural networks: A tutorial. *Computer*, *29*(3), 31-44. doi:10.1109/2.485891

Kaedi, M., Movahhedinia, N., & Jamshidi, K. (2008). Traffic signal timing using two-dimensional correlation, neuro-fuzzy and queuing based neural networks. *Neural computing and applications*, *17*(2), 193-200. doi:10.1007/s00521-007-0094-x

Kumar, P. M., Devi, G. U., Manogaran, G., Sundarasekar, R., Chilamkurti, N., & Varatharajan, R. (2018). Ant colony optimization algorithm with internet of vehicles for intelligent traffic control system. *Computer Networks*, *144*(October), 154-162. doi:10.1016/j.comnet.2018.07.001

Kumaran, S. K., Mohapatra, S., Dogra, D. P., Roy, P. P., & Kim, B.-G. (2019). Computer vision-guided intelligent traffic signaling for isolated intersections. *Expert Systems with Applications*, *134*(November), 267-278. doi:10.1016/j.eswa.2019.05.049

Kuppusamy, P., Kalpana, R., & Venkateswara Rao, P. V. (2019). Optimized traffic control and data processing using IoT. *Cluster Computing*, *22*(1), 2169-2178. doi:10.1007/s10586-018-2172-5

Latif, S., Afzaal, H., & Zafar, N. A. (2018). Intelligent traffic monitoring and guidance system for smart city. *International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), 3-4 March 2018, Sukkur, Pakistan* (pp. 1-6). IEEE. doi:10.1109/ICOMET.2018.8346327

Li, Z., Wu, Q., Yu, H., Chen, C., Zhang, G., Tian, Z. Z., & Prevedouros, P. D. (2019). Temporal-spatial dimension extension-based intersection control formulation for connected and autonomous vehicle systems. *Transportation Research Part C: Emerging Technologies, 104*(July), 234-248. doi:10.1016/j.trc.2019.05.003

Liu, S., Zhang, W., Wu, X., Feng, S., Pei, X., & Yao, D. (2018). A simulation system and speed guidance algorithms for intersection traffic control using connected vehicle technology. *Tsinghua Science and Technology*, *24*(2), 160-170. doi:10.26599/TST.2018.9010073

Liu, Y., & Zhang, J. (2021). A Repeated Commuting Driving Cycle Dataset With Application to Short-Term Vehicle Velocity Forecasting. *Journal of Autonomous Vehicles and Systems, 1*(3), 031002. doi:10.1115/1.4052996

Mandhare, P. A., Kharat, V., & Patil, C. Y. (2018). Intelligent road traffic control system for traffic congestion a perspective. *Intelligent road traffic control system for traffic congestion a perspective. International Journal of Computer Sciences and Engineering*, *6*(7), 908-915. Retrieved June 1, 2022, from https://www.researchgate.net/profile/Vilas-Kharat/publication/327073557_Intelligent_Road_Traffic_Control_System_for_Traffic_Congestion_A_Perspective/links/5bbd5754299bf1049b786b1b/Intelligent-Road-Traffic-Control-System-for-Traffic-Congestion-A-Perspectiv

Mohamed, Z. E. (2019). Using the artificial neural networks for prediction and validating solar radiation. *Journal of the Egyptian Mathematical Society, 27*(1), 1-13. doi:10.1186/s42787-019-0043-8

Nishi, T., Otaki, K., Hayakawa, K., & Yoshimura, T. (2018). Traffic signal control based on reinforcement learning with graph convolutional neural nets. *21st International conference on intelligent transportation systems (ITSC), 4-7 November 2018, Maui, HI, USA* (pp. 877-883). IEEE. doi:10.1109/ITSC.2018.8569301

Patel, M., & Ranganathan, N. (2001). IDUTC: An intelligent decision-making system for urban traffic-control applications. *IEEE transactions on vehicular technology, 50*(3), 816-829. doi:10.1109/25.933315

Perez-Murueta, P., Gómez-Espinosa, A., Cesar, C., & Gonzalez-Mendoza, M. (2019). Deep learning system for vehicular re-routing and congestion avoidance. *Applied Sciences*, *9*(13), 2717. doi:10.3390/app9132717

Sharma, V., Rai, S., & Dev, A. (2012). A comprehensive study of artificial neural networks. *International Journal of Advanced research in computer science and software engineering, 2*(10), 278-284. Retrieved May 30, 2022, from https://d1wqtxts1xzle7.cloudfront.net/32922006/V2I10-0117-with-cover-page-v2.pdf?Expires=1653910299&Signature=UYSew8jL0JWAO1cEYe4Z6U9qeBTdJBv2Jb6RQvRpf0LDmL-KMflyZ2P5i7NxAozXRqbzy3Lqry0tNuYBMibLg03x0Hrj4RfmJhPefoRxBzmunQ9BDLSUC1MEzSSkOlEtgvX0lBQs5~DNKpKCy

Srivastava, J. R., & Sudarshan, T. S. (2013). Intelligent traffic management with wireless sensor networks. *ACS International Conference on Computer Systems and Applications (AICCSA), 27-30 May 2013, Ifrane, Morocco* (pp. 1-4). IEEE. doi:10.1109/AICCSA.2013.6616429

Sumi, L., & Ranga, V. (2018). Intelligent traffic management system for prioritizing emergency vehicles in a smart city. *International Journal of Engineering, 31*(2), 278-283. doi:10.5829/ije.2018.31.02b.11

Sur, C. (2019). UCRLF: unified constrained reinforcement learning framework for phase-aware architectures for autonomous vehicle signaling and trajectory optimization. *Evolutionary Intelligence*, *12*(4), 689-712. doi:10.1007/s12065-019-00278-7

Yao, Z., Shen, L., Liu, R., Jiang, Y., & Yang, X. (2019). A dynamic predictive traffic signal control framework in a cross-sectional vehicle infrastructure integration environment. *IEEE Transactions on Intelligent Transportation Systems*, *21*(4), 1455-1466. doi:10.1109/TITS.2019.2909390

Yin, C., Rosendahl, L., & Luo, Z. (2003). Methods to improve prediction performance of ANN models. *Simulation Modelling Practice and Theory*, *11*(3-4), 211-222. doi:10.1016/S1569-190X(03)00044-3

Wallner Martin
Comenius University Bratislava
Faculty of Management
Department of Information
Systems
Bratislava
Slovak Republic
wallner4@uniba.sk
ORCID 0000-0003-4367-8711

Peráček Tomáš
Comenius University Bratislava
Faculty of Management
Department of Information
Systems Bratislava
Slovak Republic.
tomas.peracek@fm.uniba.sk
ORCID 0000-0002-3498-5640

Apendix:

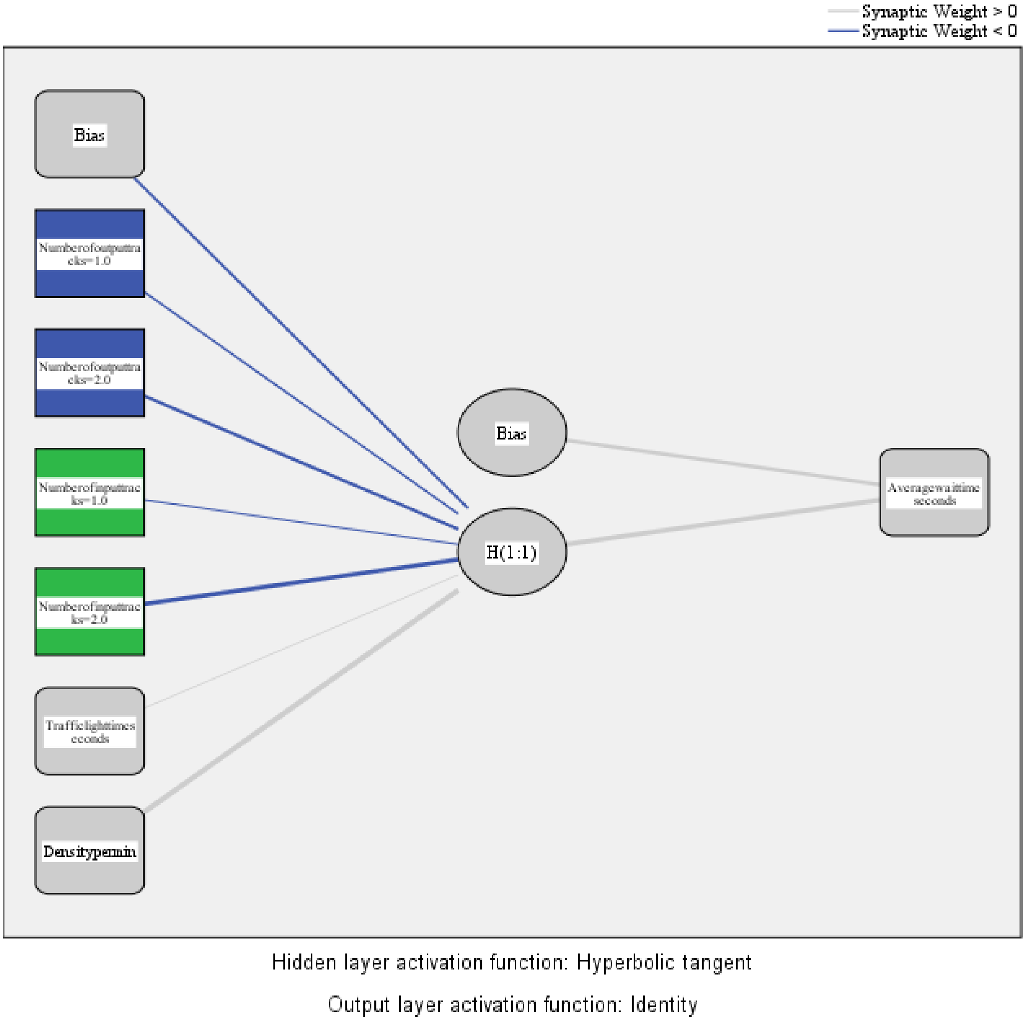
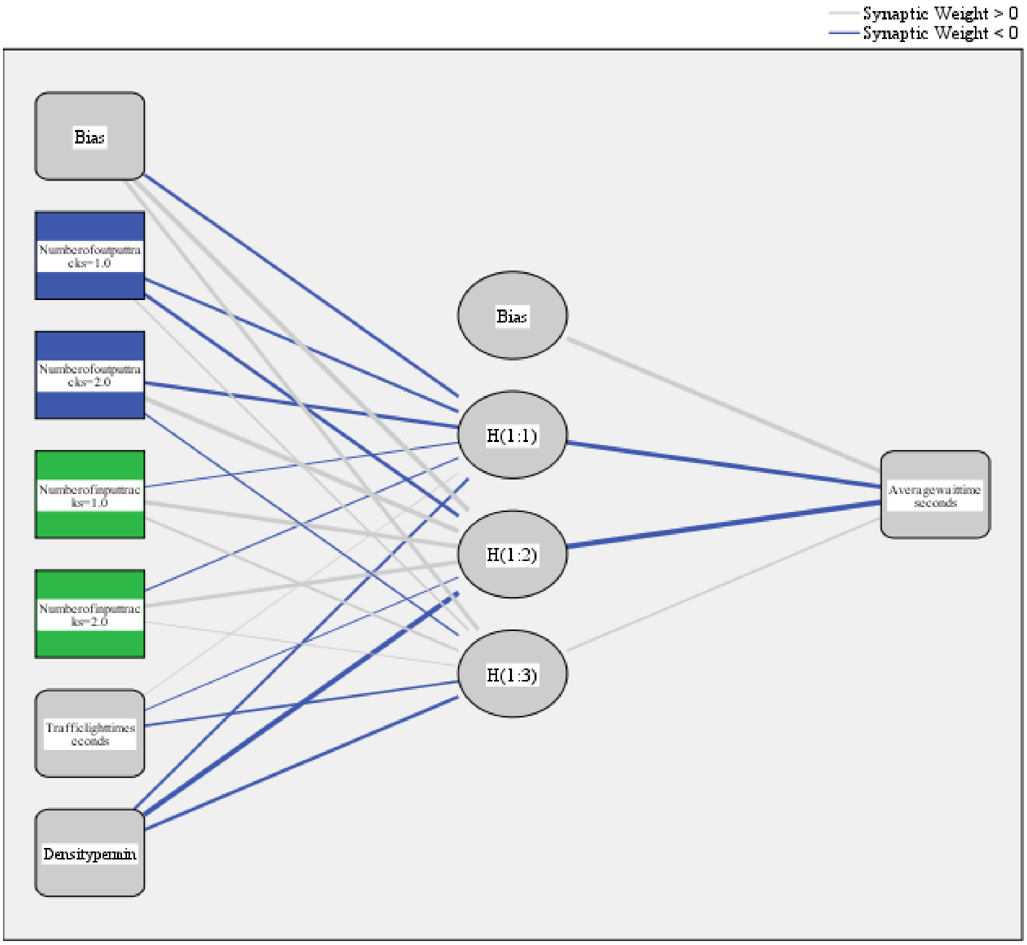


Figure 4. The network diagram of the down intersection scenario



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Figure 5. Network diagram of left intersection scenario

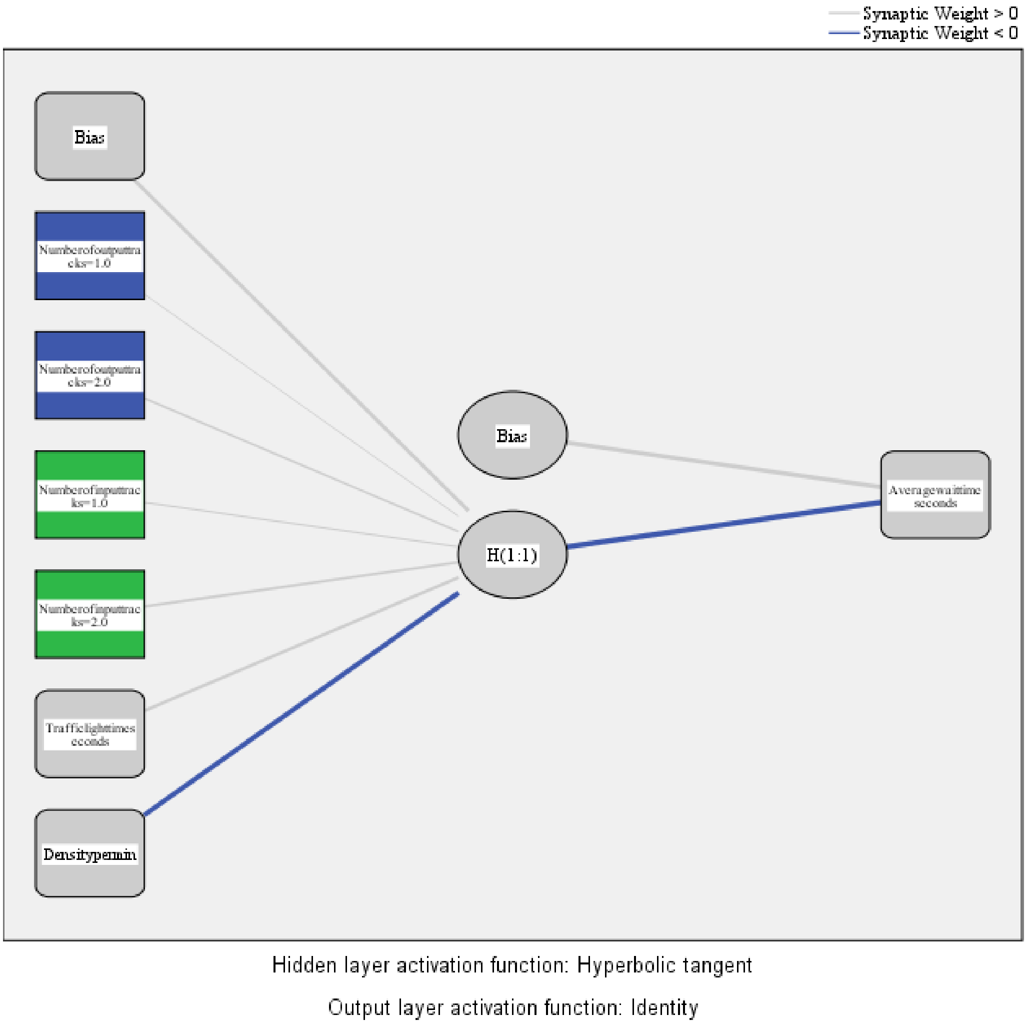
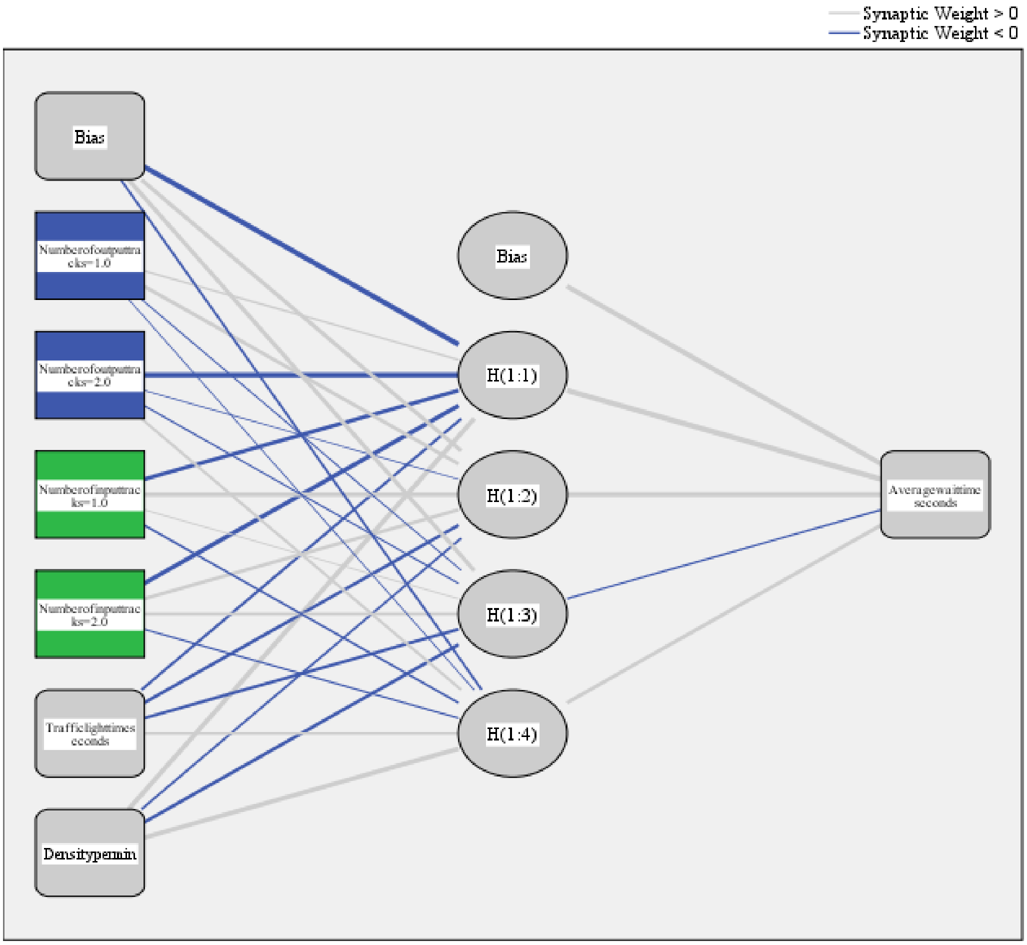


Figure 6. Network diagram of right intersection scenario



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Figure 7. Network diagram of up intersection scenario