Traffic Occupancy Prediction Using a Nonlinear Autoregressive Exogenous Neural Network

Nazhon Ismael Khaleel[1], Uthayasooriyan Anuraj[2], Joanna Hartley[3]
[1]College of Education for women, University Of Anbar, Ramadi, Iraq
[2]Department of Interdisciplinary Studies, University of Jaffna, Jaffna, Sri Lanka
[3]Nottingham Trent University, UK

Article Info

Article history:

Received Apr 17, 2022
Revised Jul 6, 2022
Accepted Jul 26, 2022

Keyword:

Intelligent Transportation System
Scoot system
Traffic occupancy
Deep learning
Neural Network.

ABSTRACT

The main aim of intelligent transportation systems is the ability to accurately predict traffic characteristics like traffic occupancy, speed, flow, and accident based on historic and real-time data collected by these systems in transportation networks. The main challenge of a huge quantity of traffic data collected automatically, stored, and processed by these systems is the way of handling and extracting the required traffic data to formulate the prediction traffic characteristic model. In this research, the required traffic data of a specified road link in the UK are extracted from the big raw data of the Split, Cycle, and Offset Optimization Technique *(*SCOOT) system by designing a C++ extractor program. In addition, short-term traffic prediction models are created by using a deep learning technique called a Nonlinear Autoregressive Exogenous (NARX) neural network to find accurate and exact traffic occupancy. Three scenarios of time intervals which are 10 minutes, 20 minutes, and 30 minutes are considered for analyzing the prediction accuracy. The results showed that the prediction models for the 30 minutes interval scenario have very good accuracy in estimating the future traffic occupancy compared to other scenarios of time intervals. In addition, the testing and validation study showed that the prediction models for 30 minutes intervals for particular road link yield better accuracy than 10 minutes and 20 minutes intervals.

Corresponding Author:

Uthayasooriyan Anuraj,
Department of Interdisciplinary Studies,
University of Jaffna,
Jaffna, Sri Lanka,
Email: uanuraj@eng.jfn.ac.lk

1. INTRODUCTION

Transport infrastructures are the backbones of the cities and countries to improve the environment and their living standards in addition to increasing the growth rate of the economy. Although transportation introduces these advantages, there is a substantial issue associated with this development represented by traffic congestion because of the growing quantity of vehicles over the past five decades (1). Therefore, it is required to obtain solutions that are able to decrease traffic congestion and improve mobility performance and the environment. One of these solutions is the forecasting of short-term traffic characteristics like traffic flow, occupancy, and speed. Moreover, another solution to transportation issues is Intelligent Transportation Systems (ITS) (2).

In developed countries and large cities, transportation agencies allocate financial resources to develop the transportation infrastructure and employ modern technologies including cameras, sensors, and other traffic monitoring techniques to record traffic conditions on highway networks. With developments in communication and computing technologies, intelligent transportation systems (ITS) are developed to collect traffic information easily comprising congestion, vehicles flow, speed, and accident reports and to make decisions not only to reduce traffic jams and to decrease the number of accidents on the highway but to ensure the smooth traffic flow as well. Traffic control devices generate a huge amount of information that could be employed to study the traffic characteristics on those highway networks. It also supports the transportation agencies to supply real-time statistics of traffic that not only help travelers to make decisions but the authorities to choose the right and required actions (1,2).

Traffic characteristics such as traffic occupancy, speed, etc. on a highway network could be forecasted by exploring the information collected from the ITS system and other traffic monitoring devices. Consequently, the number of researchers have been using different modeling techniques and algorithms to forecast traffic characteristics. some of these techniques showed decent results represented by the high accuracy in predicting traffic characteristics under different situations like the changing in accidents and weather or natural circumstances (3).

Recently, ITS has substantial improvement and supports individuals to think to make more choices to increase the speed of traveling and decrease congestion, Artificial Neural Network (ANN) has become essential in the prediction of traffic control. Different neural network techniques were applied to predict a single traffic characteristic like traffic speed (3,4), traffic flow (5), traffic volume (6) and traffic accident (7). However, prediction models were developed using a single ANN technique to forecast more than a single characteristic like traffic flow and speed (8), traffic flow, speed, and occupancy (9) and traffic speed, travel time, and accident (10).

To attain more reliable and robust prediction results, fuzzy logic has been frequently applied to solve traffic problems. Therefore, it was used to forecast traffic volume or flow (11,12) traffic accidents (13), and occupancy (14). Moreover, to address the disadvantages of expert systems, the hybrid system which combines the strength of neural networks with other AI techniques were considered to solve traffic control issues. Different types of fuzzy neural networks like the pseudo-outer-product fuzzy neural networks to predict short-term traffic flow (15,16) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) method to forecast short–term traffic occupancy (17) were applied.

With developments in communication and computing technologies, a huge quantity of collected traffic information can be generated easily. The availability of big data considers opportunities to considerably increase the accuracy improvement of prediction (18). These can promote focus and the use of the deep learning concept for traffic characteristic prediction. Deep learning which is a type of machine learning technique based on learning data representations can quickly process the large-scale raw data and extract features automatically from these data (18). For these reasons, deep learning methods have been used to predict traffic characteristics such as traffic speed (19–21), traffic Flow (18,22) vehicle occupancy (23), and accidents (24). There are number of deep learning methods like the autoregressive, vector error correction and vector autoregressive models applied as forecasting methods in various fields (25–30) (e.g. in real estate sector (31–34), agriculture sector (35,36) and energy sector (37,38)).

In the majority of mentioned studies, different Computational techniques like fuzzy logic, ANN, etc. were used widely to build models of traffic characteristics prediction. However, these methods can capture the statistical traffic features and need to improve their accuracy. Therefore, it is required to use advanced technology like deep learning methods that can capture traffic patterns from a huge amount of existing data with improving prediction accuracy significantly.

The key challenges of the SCOOT system are the massive amount of traffic data and also the extraction of the desired traffic data. In addition, another main challenge is how to select the effective input variables that can be considered to develop an accurate prediction model and which technique can be considered to build the prediction model. Developing a short-term traffic occupancy prediction model is essential to the huge quantity of available historical data and advanced computational techniques that can deal with the high dimensional and nonlinear nature of traffic occupancy data.

For the development of a model, the traffic data of a specified link of a road in the UK were collected from the SCOOT system. The big raw data of this system are extracted by using a C++ extractor program that is designed to bring out the necessary data from the database and export them to Text File format. In this study, traffic occupancy is predicted for the short term using a deep learning technique to find accurate and exact traffic occupancy. Different time interval scenarios which are 10 minutes, 20 minutes, and 30 minutes time intervals are considered for analyzing the prediction accuracy.

This research is organized as follows. Section 2 describes the ITS system which is the SCOOT system. In Section 3, the method used for the prediction is demonstrated by defining the NARX neural network model. Section 4 describes the traffic database. Results are presented in Section 6. Finally, Section 7 shows the conclusions and future works.

2. SCOOT SYSTEM

The Split, Cycle and Offset Optimization Technique (SCOOT) is the Intelligent Traffic System (ITS) applied to collect information on real traffic for training, designing, and executing predictions. Now, The SCOOT urban traffic control system is working in over 30 cities in the UK and overseas. In addition, it estimates and implements the settings that decrease stops and delays (1,25).

It is developed for cities having large congestion cities and also applied in a small area that has fluctuating traffic that is difficult to predict. The efficiency of this control system depends on the quality of traffic data to find the accurate result. The detector which is the fundamental element of the system sends information on the traffic stream to SCOOT. Then, this information will transform into its internal elements after the cars across the detector and the SCOOT system acquire information, then that will apply to generate a cycle flow profile for every link as shown in Figure 1 (25). This traffic system consists of three procedures that give this name. Firstly, the function of the Split Optimizer is to estimate the quantity of green for each approach. Moreover, the Offset Optimizer limits the time between adjacent signals. Finally, the Cycle Time Optimizer is the allowable time for all approaches (25).

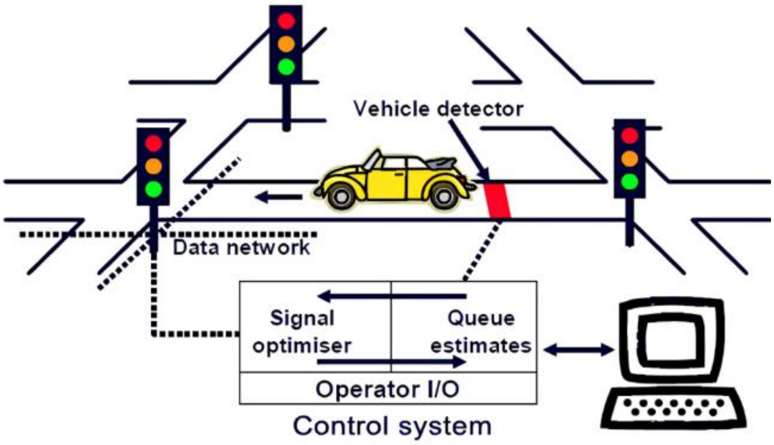


Figure 1. Basic SCOOT traffic control system (25).

3. ARTIFICIAL INTILLEGENCE NETWORKS (ANN)

ANNs perform an understanding of data like the way that the human brain works. They learn the context and relate information based on the examples which are fed to them. This is where an ANN model and a computer program which executes the task based on defined rules vary. For the need of addressing sophisticated problems which possess non-linear properties, ANNs play their productive role (26–28).

A neural structure which is a replica of the biological brain is built with the basic elements called artificial neurons or processing elements. They are the building blocks of an ANN and each neuron processes data. The artificial neurons incorporate weights at the input side that decide the effect of individual input data which is being provided to a certain artificial neuron. In simple terms, the artificial neuron is an equation that creates a balance between the input data and output data (26). A neural structure is comprised of a layer of input neurons, a set of hidden neuron layers, and a layer of output neurons. An artificial neuron model is depicted in Figure 2 in which the inputs are referred by (I_1, I_2, I_3,…, I_n) and the respective weight are referred by (W_{j0}, W_{j1}, W_{j2}, W_{j3}, …, W_{jn}). The activation function is aided by W_{j0} to produce the right relationship between inputs and outputs (y); the column number of the input vector is indicated by the subscript j (29). The summation function produces a weighted sum by adding the multiplication of inputs and their respective weights. The output value of a processing element is calculated by a suitable activation function from the weighted sum. This process happens in the hidden layer of neurons on the output side.

3.1. NARX Neural Network (NARX net)

The traffic prediction problem is a time series. The NARX neural network is applied in modeling various nonlinear dynamic systems (30) and it is known for its ability to forecast time series (31–33). NARX falls under recurrent dynamic neural network (RNN). The memory ability of NARX net is prominent as it can remember the past values of forecasted time series or true time series. This property enables a great performance to NARX in forecasting the nonlinear time series.

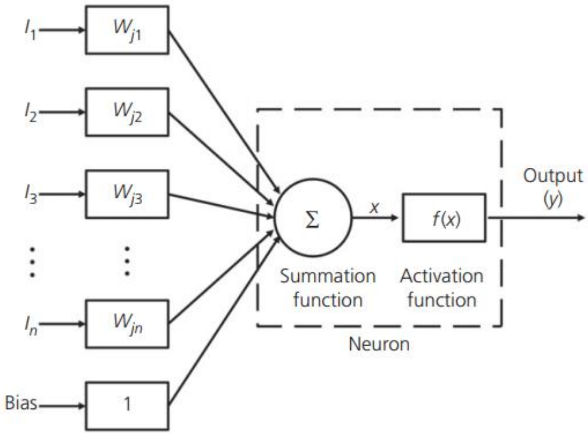


Figure 2. Artificial neuron model.

NARX net has two forms (architectures) that are open-loop architecture (series-parallel architecture) and closed-loop architecture (parallel architecture). The elementary building block of the NARX net is also a neuron). When true past values of the respective inputs are known, the open-loop NARX net can be implemented (34) otherwise one should opt for close-loop architecture. Figure 3 and Figure 4 depict the open-loop architecture and close-loop architecture respectively. Figure 5 shows the elaborated version of the open-loop architecture. In our work, the open-loop architecture has been used since the true outputs are known. Open-loop NARX net architecture can be mathematically explained using the function f.

$$\boldsymbol{y(t+1) = f\left[y(t), y(t-1), \ldots, y\left(t-d_y\right); u(t+1), u(t), u(t-1), \ldots, u(t-d_u)\right]} \quad \textbf{(1)}$$

The components of the open-loop architecture equation are defined as follow: f is the mapping function, $y(t+1)$ is the guessed value at the time (t+1) for the input $y(t)$ at the time t, and the desired outputs (true past values that are already known) are represented by $y(t), y(t-1), y(t-2), \ldots\ldots, y(t-d_y)$, the inputs (independent variables) to which the prediction to be done are referred by $u(t+1), u(t), \ldots, u(t-d_u)$ and, d_u and d_y represents the input delays and output delays.

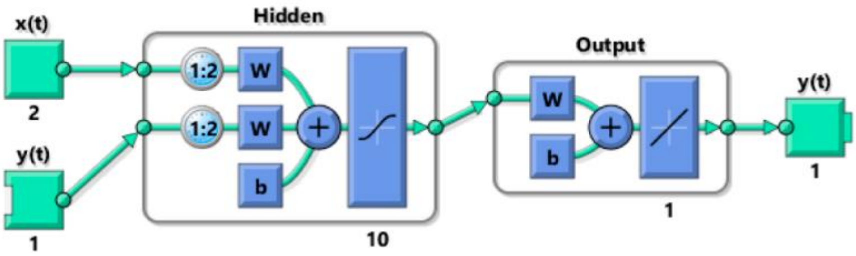


Figure 3. The open-loop architecture of NARX net.

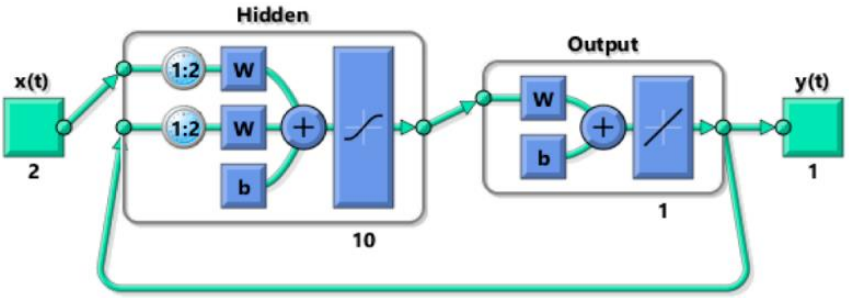


Figure 4. The close-loop architecture of NARX net.

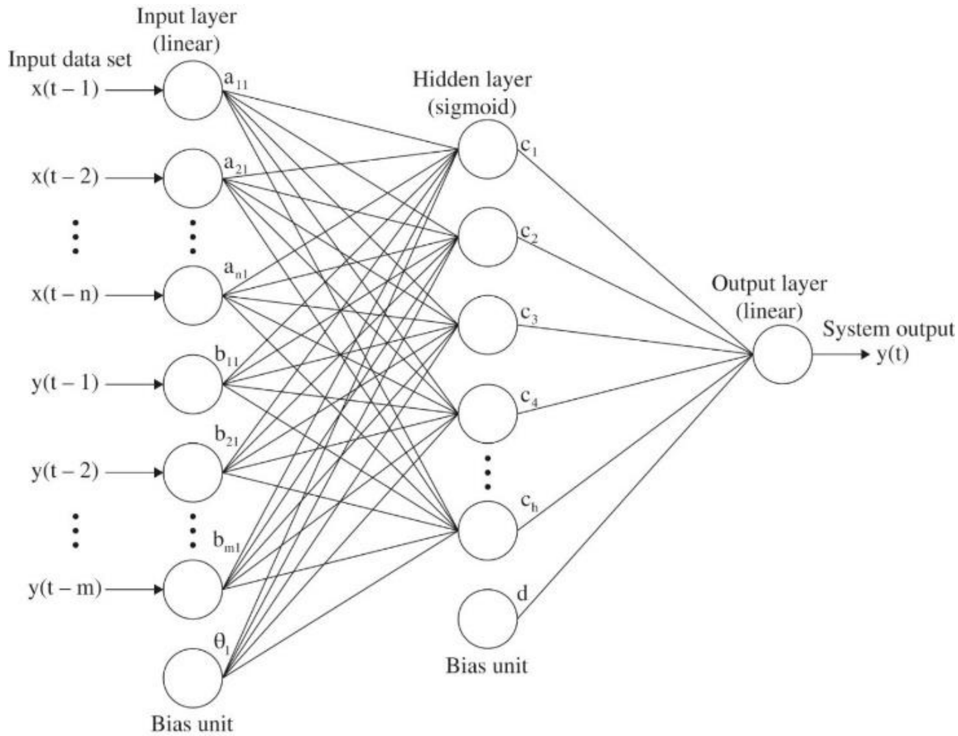


Figure 5. The elaborated version of the open-loop architecture.

4. TRAFFIC DATABASE

For the development of a model, the traffic data of a specified link (N60531A) and road (M14) in the UK in June and July 1998 were collected from the SCOOT system. The raw data are big data imported from the SCOOT system as Zip Files and then transform these raw data into the C++ Extractor program. C++ Extractor program is designed to extract the required data from the database and export them to Text File format. To predict the number of vehicles passing the place of interest, the presence of the number of vehicles at 10 minutes time intervals on weekdays was considered. However, to analyze the prediction accuracy at different time intervals, the data were then manipulated to have traffic data for 20 minutes and 30 minutes time intervals. This manipulation was done by adding up the two subsequent time intervals and relevant traffic, and three subsequent time intervals and the relevant traffic to obtain the traffic data set for 20 minutes and 30 minutes time intervals respectively. Table 1 and Table 2. show the number of original data samples relevant to each of the weekdays.

Table 1. Number of set of data samples relevant to each of the weekdays.

Day	Month	Number of set of samples				Total number of set of samples
		CT	CT - 10 Min.	Last Week CT + 10 Min.	CT + 10 Min.	
Monday	June	16	0	0	0	969
	July	13	37	7	6	
Tuesday	June	0	34	0	19	1100
	July	3	0	0	0	
Wednesday	June	2	3	3	10	828
	July	0	0	14	0	
Thursday	June	35	0	0	11	1078
	July	0	0	11	3	
Friday	June	0	24	0	10	870
	July	0	40	0	3	

Table 2. Total data samples in each data set.

Day	Number of samples 10 minutes data (Data set 1)	20 minutes data (Data set 2)	30 minutes data (Data set 3)
Monday	969	485	323
Tuesday	1100	550	367
Wednesday	828	414	276
Thursday	1078	539	360
Friday	870	435	290

Each set of samples of the data contained three sets of instances as input variables, that are (1) the occupancy of vehicles at the current time (CT) for a specific day, (2) the occupancy of vehicles before ten minutes of CT for a specific day (CT - 10 Minutes) and (3) the occupancy of vehicles after ten minutes of CT for the same day in the last week (Last Week CT + 10 Minutes). There was one dependent variable which is the occupancy of vehicles after ten minutes of CT for the specific day (CT + 10 Minutes).

5. RESULTS

The traffic prediction model was derived by feeding three input variables and one output variable. The model was synthesized by implementing the artificial neural network NARX in MATLAB using the NN toolbox. The modeling process encompassed three steps that are training, validation, and testing. While the training data set was used for training the network while tuning it, the validation data set was in place for determining the network's generalization and stopping training when optimum conditions appeared. The network performance was computed using testing data set.

Out of the total samples employed for each day, 70% of samples were defined as the training set, 15% of samples defined as the validation set, and 15% as the testing set. The selection of samples for each set was randomly done. Total samples available for each weekday from Monday are 969, 1100, 828, 1078, and 870 respectively. The model development was done in three different schemes. The first scheme was to run the NARX with the original data samples which explain the traffic in 10 minutes intervals. The second and third schemes were to run the network with the manipulated data samples which provide traffic data in 20 minutes intervals and 30 minutes intervals. Details of the number of samples for 10 minutes intervals, 20 minutes intervals, and 30 minutes intervals are tabulated in Table 2 (Data set 1), Table 3 (Data set 2), and Table 4 (Data set 3), respectively. In all the schemes, the target was to determine the NARX in terms of several hidden neurons and the input delay value, which provides optimum performance.

The training was done with the standard NARX net while changing the number of combinations between hidden neurons and input delays. This was achieved by first fixing a certain number of neurons and changing the value for input delay. Once the training was completed with a range of input delays, the next value for neuron numbers was set and the process was repeated. For performing training with each of the three data sets described in Data set 1, Data set 2, and Data set 3, the NARX network configuration with 4 neurons in the hidden layer was trained while changing the input delay from 1 to 20 with the increment of 1 and found the best network performance. This strategy was made recurring until the network was taken through all the combinations of the number of hidden neurons and input delays. For this purpose, neuron count was varied from 4 to 20 with the increment of 1. Thus, the range of neuron numbers was chosen as a minimum of 4 and a maximum of 20. Input delays were tried from a minimum of 1 to a maximum of 20. The network configuration that output the best result for each day under each data set was recorded. After the training, the produced results were analyzed separately, using Mean Squared Error (MSE) and coefficient of correlation (R) of regression as performance indicators. Best configurations for MSE-based evaluation and best configurations for R-based evaluation were found, listed, and compared. The tables from

Table 3 to Table 5 elaborate on the evaluated results.

From Figure 7 and Figure 8, it is evident that the model's best performance is seen with the data of 30 minutes intervals. The model shows poor performance on the 10 minutes data. Further, comparing Figure 6 and Figure 9, it can be concluded that the best model can be obtained by choosing it from a MSE-based evaluation. On the other hand, going for the network model configuration selection only based on regression R-value induces high MSE. Moreover, selecting the network configuration by prioritizing MSE enables a better R-value that is a good fit over the scattered data as well

Table 3. Summary of the results of selected trained network for 10 minutes data

Best configuration selection based on best regression value for validation

Day	Best Network Configuration: Number of neurons	Best Network Configuration: Value for time delay	R: Training	R: Validation (Deciding parameter)	R: Test	R: All	MSE: Training	MSE: Validation	MSE: Test
Monday	6	5	0.4857	0.5387	0.3665	0.4757	65.1626	54.2497	72.7255
Tuesday	5	3	0.3276	0.5217	0.0803	0.3104	74.6566	40.3522	94.8950
Wednesday	10	19	0.6021	0.5762	0.3708	0.5647	53.6446	43.3913	69.0544
Thursday	4	11	0.4932	0.5466	0.4778	0.4981	68.0561	57.9773	68.2695
Friday	5	9	0.5160	0.5678	0.1964	0.4721	67.4631	82.8938	109.3767

Best configuration selection based on best MSE value for validation

Day	Best Network Configuration: Number of neurons	Best Network Configuration: Value for time delay	R: Training	R: Validation	R: Test	R: All	MSE: Training	MSE: Validation (Deciding parameter)	MSE: Test
Monday	6	5	0.4857	0.5387	0.3665	0.4757	65.1626	54.2497	72.7255
Tuesday	18	19	0.4650	0.4254	0.3983	0.4488	66.7949	39.6898	73.7596
Wednesday	6	4	0.5274	0.4897	0.2123	0.4798	60.7628	40.7845	72.4553
Thursday	4	5	0.4908	0.5337	0.4131	0.4834	70.6159	47.7006	72.0606
Friday	16	6	0.5658	0.5106	0.3096	0.5175	68.9013	54.7553	102.1476

Table 4. Summary of the results of selected trained network for 20 minutes data.

Best configuration selection based on best regression value for validation

Day	Best Network Configuration: **Number of neurons**	Best Network Configuration: **Value for time delay**	R: **Training**	R: **Validation (Deciding parameter)**	R: **Test**	R: **All**	MSE: **Training**	MSE: **Validation**	MSE: **Test**
Monday	4	7	0.6018	0.6584	0.3700	0.5682	119.0927	129.4328	219.0259
Tuesday	20	11	0.6879	0.7098	0.3865	0.6327	87.9045	76.4418	217.1146
Wednesday	5	6	0.6849	0.7071	0.3971	0.6520	99.9424	99.2955	128.3266
Thursday	5	5	0.6704	0.6867	0.4869	0.6438	113.2091	110.2976	149.7440
Friday	4	2	0.6619	0.7341	0.4898	0.6521	137.6982	93.7541	134.3203

Best configuration selection based on best MSE value for validation

Day	Best Network Configuration: Number of neurons	Best Network Configuration: Value for time delay	R: **Training**	R: **Validation**	R: **Test**	R: **All**	MSE: **Training**	MSE: **Validation (Deciding parameter)**	MSE: **Test**
Monday	18	4	0.6676	0.6410	0.4725	0.6334	117.2321	100.6167	145.5364
Tuesday	17	16	0.6153	0.6866	0.4510	0.5964	115.1602	71.4765	153.8840
Wednesday	6	1	0.5974	0.6556	0.3241	0.5593	121.4363	81.0015	178.2216
Thursday	8	5	0.7149	0.6773	0.4288	0.6665	99.4839	94.8464	191.9789
Friday	4	2	0.6619	0.7341	0.4898	0.6521	137.6982	93.7541	134.3203

Table 5. Summary of the results of selected trained network for 30 minutes data.

Best configuration selection based on best regression value for validation

Day	Best Network Configuration: Number of neurons	Best Network Configuration: Value for time delay	R: Training	R: Validation (Deciding parameter)	R: Test	R: All	MSE: Training	MSE: Validation	MSE: Test
Monday	11	8	0.5069	0.6543	0.6523	0.5404	293.7729	162.3032	187.8768
Tuesday	12	13	0.6393	0.7291	0.5687	0.6393	195.2819	133.7239	224.3526
Wednesday	8	19	0.6235	0.7239	0.6117	0.6340	188.4919	159.3746	284.4737
Thursday	8	17	0.5555	0.7625	0.6920	0.6043	270.2165	121.5004	250.8954
Friday	6	1	0.7056	0.7878	0.1219	0.4835	201.4537	182.8167	139.8988

Best configuration selection based on best MSE value for validation

Day	Best Network Configuration: Number of neurons	Best Network Configuration: Value for time delay	R: Training	R: Validation	R: Test	R: All	MSE: Training	MSE: Validation (Deciding parameter)	MSE: Test
Monday	4	18	0.6232	0.5991	0.6127	0.6187	243.3642	146.0029	223.1288
Tuesday	6	12	0.6728	0.6762	0.4664	0.6428	179.9264	120.4922	306.1045
Wednesday	5	19	0.7630	0.6398	0.5451	0.7075	135.5145	131.4624	335.2813
Thursday	8	17	0.5555	0.7625	0.6920	0.6043	270.2165	121.5004	250.8954
Friday	5	5	0.7779	0.7870	0.5134	0.7444	181.8207	104.8877	269.6688

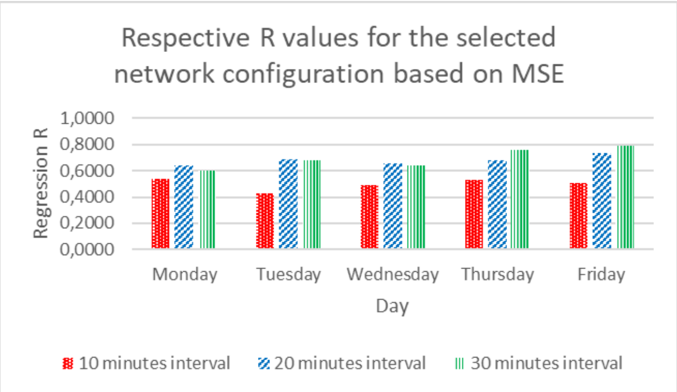


Figure 6. Comparison of regression R when the model was determined based on the MSE

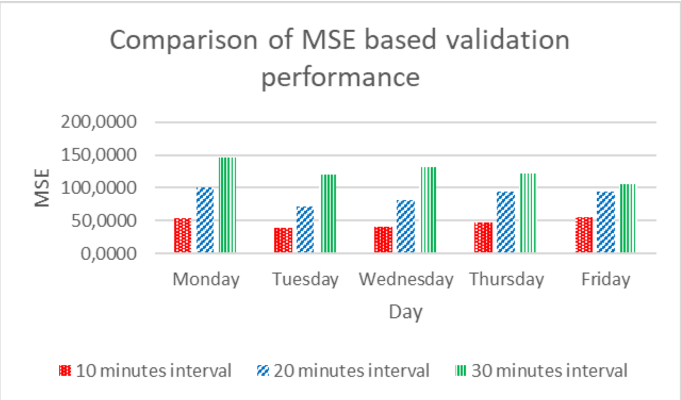


Figure 7. Comparison of validation performance when the model was determined based on the MSE

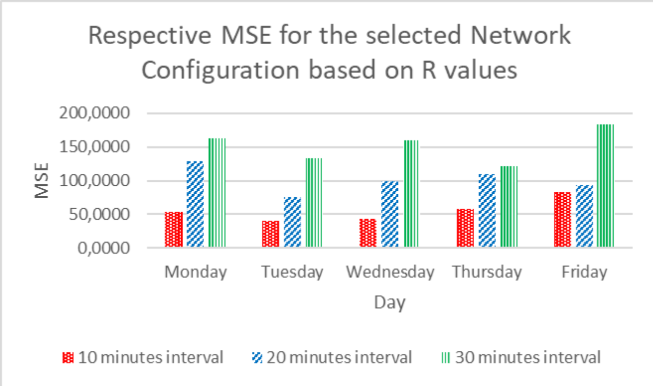


Figure 8. Comparison of MSE when the model was determined based on the best regression value R.

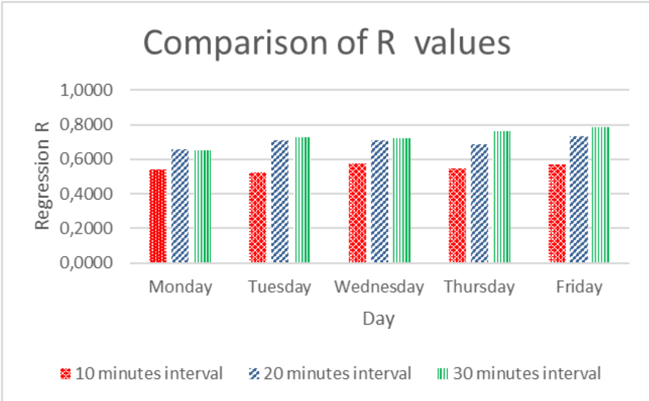


Figure 9. Comparison of validation performance when the model was determined based on the best regression value R.

The figures from Figure 10 to Figure 24 depict the training statistics for Wednesday with all three data sets. It is arbitrarily chosen as a specimen sample for depicting the training process. From the figures, it is obvious that there are a few outliers beyond the confidence bound for the training with 10 minutes of data, in error autocorrelation, and input error cross correlation. These outliers are reduced in 20 minutes data and 30 minutes data which would be due to the reduced number of zero data existing compared to the 10 minutes data set.

When the training performance plots of 10 minutes, 20 minutes, and 30 minutes data of Wednesday are considered as shown in Figure 10, Figure 15, and Figure 20, one can see that the tendency to overfit reduces as the training MSE becomes lower than the validation MSE. However, it can further be noticed that the MSE of the model increases with the period while R improves to 0.489, 0.659, and 0.639 for validation and 0.479, 0.559, and 0.707 for all as shown in Figure 11, Figure 16, and Figure 21. This observation would demand the solution developer negotiate the selection of performance indicators between MSE and R.

A comparison is available for error autocorrelation in Figure 12, Figure 17, and Figure 22 while the input cross-correlation is explained in Figure 13, Figure 18, and Figure 23 for all three different time-span data. These plots imply that the error autocorrelation and the input cross-correlation have less effect when the data is looked at a large time scale.

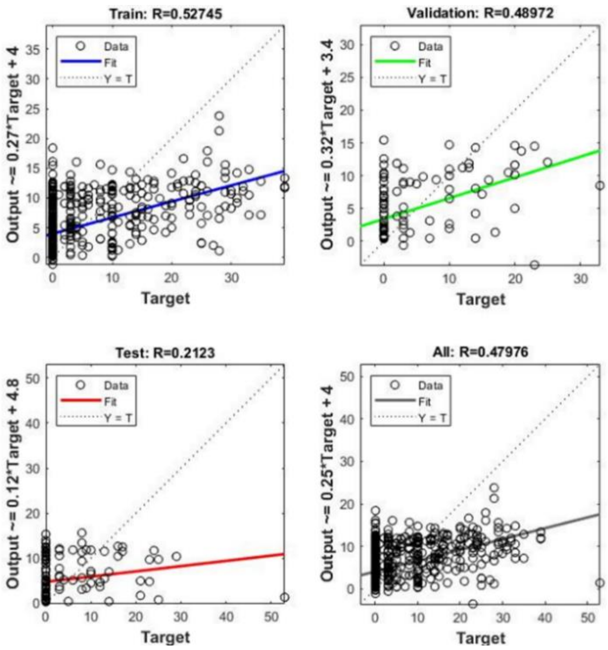
Furthermore, Figure 14, Figure 19, and Figure 24 provide a visual explanation of the prediction performance in terms of target data (real values), predicted values and the error. The performance is better when there are more similar data points available. The error seems higher for the data that are lying far away from the typical data distribution. That means, for a problem like traffic data which is more randomized, it is necessary to have a large data set to get the network prediction with great accuracy.

6. CONCLUSIONS

Short-term traffic occupancy prediction models for a particular road link in the UK are developed by adopting a deep learning technique called NARX neural network. Before developing models, the required traffic data are extracted from the huge raw data of the SCOOT system by designing a C++ Extractor program.

In this research, different scenarios of time intervals (10 minutes, 20 minutes, and 30 minutes) are considered for the study of prediction accuracy.

Based on The correlations of the developed models, it was found to be better for the scenario of 30 minutes intervals than for other scenarios of time intervals. The validation results show that the prediction models for the 30 minutes interval have very good accuracy in estimating future traffic occupancy. Therefore, the prediction models based on 30 minutes interval scenario can be applied for road links in the UK. It is possible to improve the model accuracy by extracting additional data representing the whole months in a year.



Training results for 10 minutes data of Wednesday

Figure 10. Regression plot of the selected NARX model for Wednesday with 10 minutes data

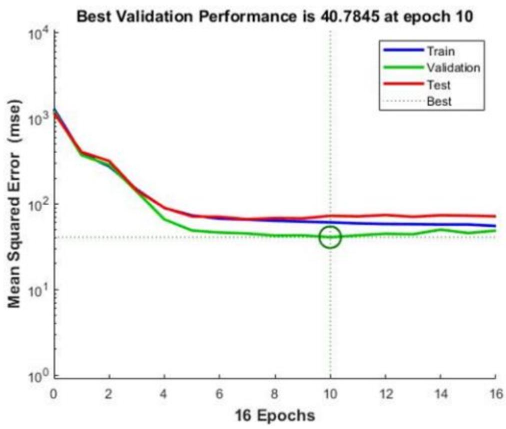


Figure 11. Performance of the selected NARX model for Wednesday with 10 minutes data

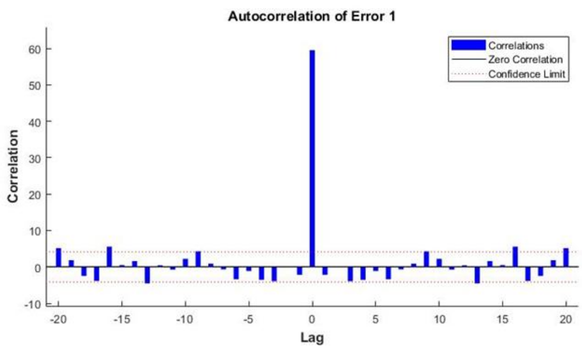


Figure 12. Error auto correlation of the selected NARX model for Wednesday with 10 minutes data

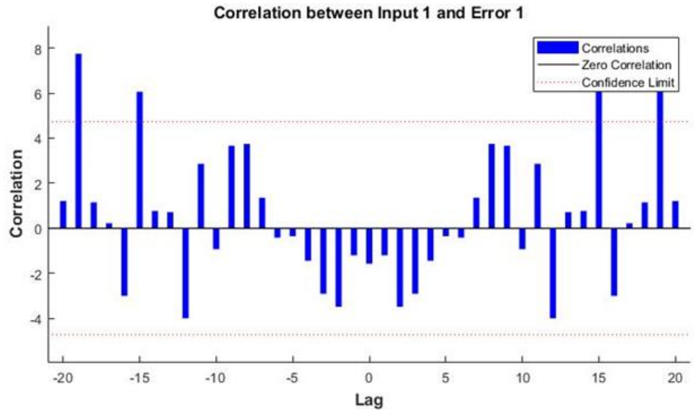


Figure 13. Input error cross correlation of the selected NARX model for Wednesday with 10 minutes data

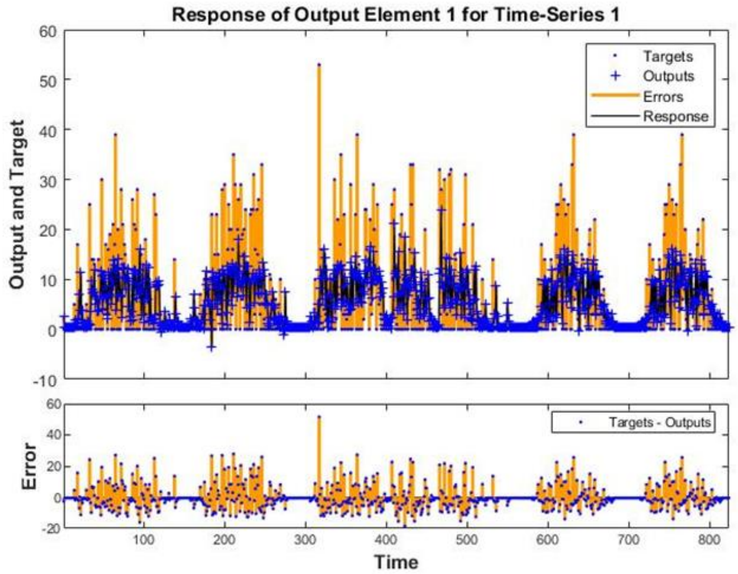
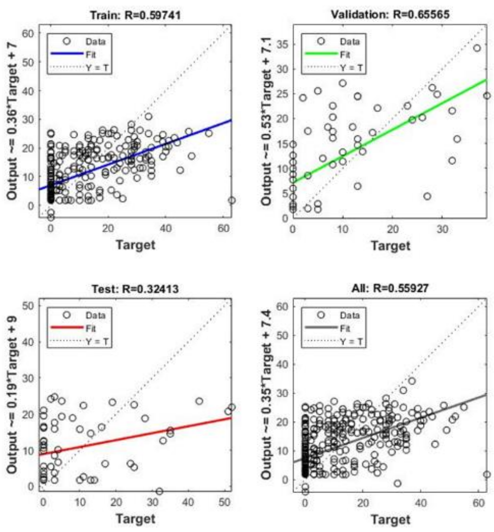


Figure 14. Time series response of the selected NARX model for Wednesday with 10 minutes data.



Training results for 20 minutes data of Wednesday

Figure 15. Regression plot of the selected NARX model for Wednesday with 20 minutes data

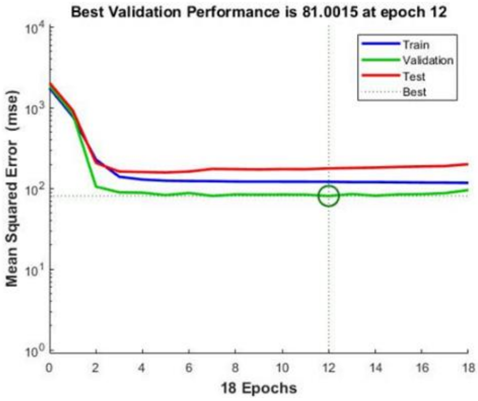


Figure 16. Performance of the selected NARX model for Wednesday with 20 minutes data.

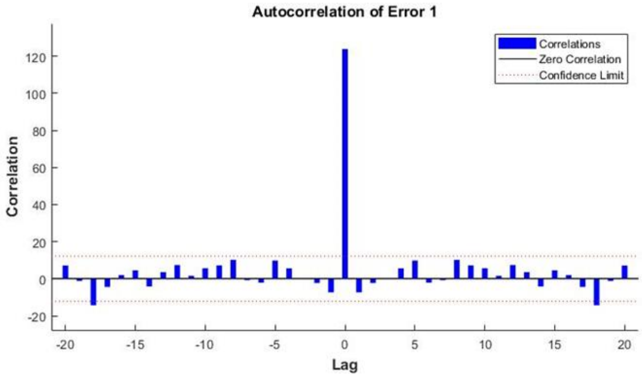


Figure 17. Error auto correlation of the selected NARX model for Wednesday with 20 minutes data

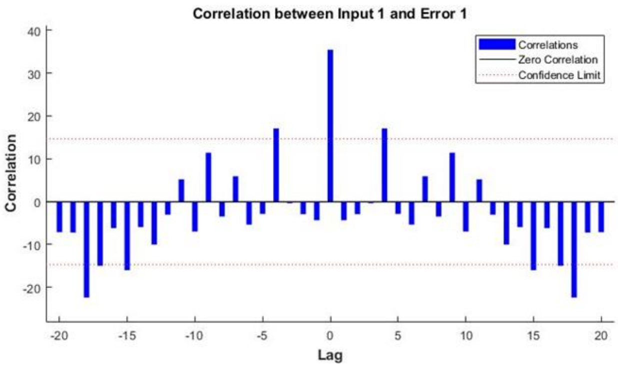


Figure 18. Input error cross correlation of the selected NARX model for Wednesday with 20 minutes data

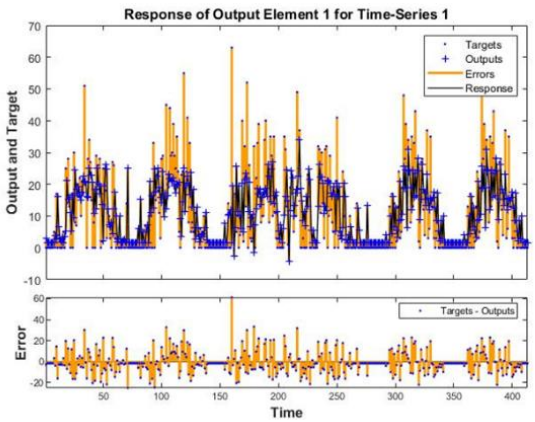
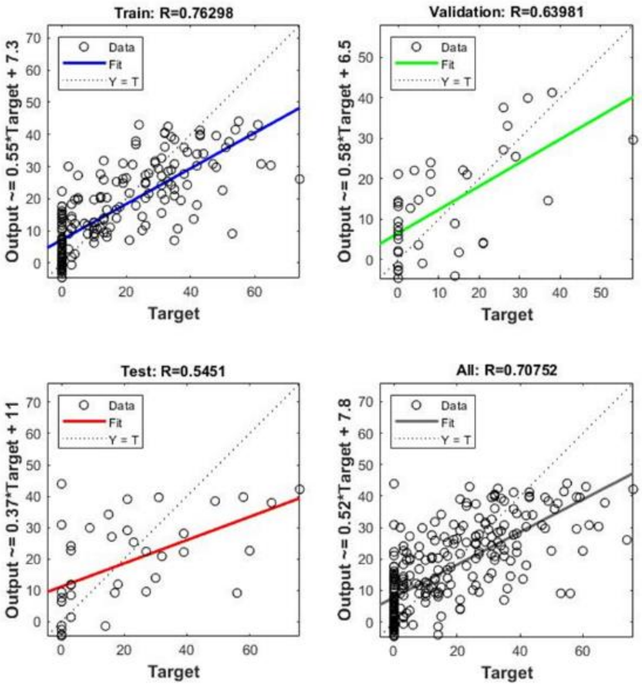


Figure 19. Time series response of the selected NARX model for Wednesday with 20 minutes data.



Training results for 30 minutes data of Wednesday

Figure 20. Regression plot of the selected NARX model for Wednesday with 30 minutes data.

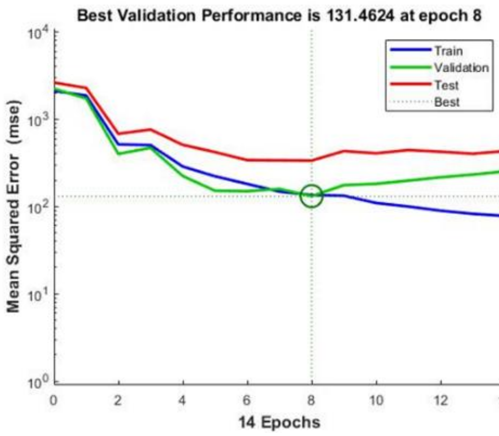


Figure 20. Performance of the selected NARX model for Wednesday with 30 minutes data

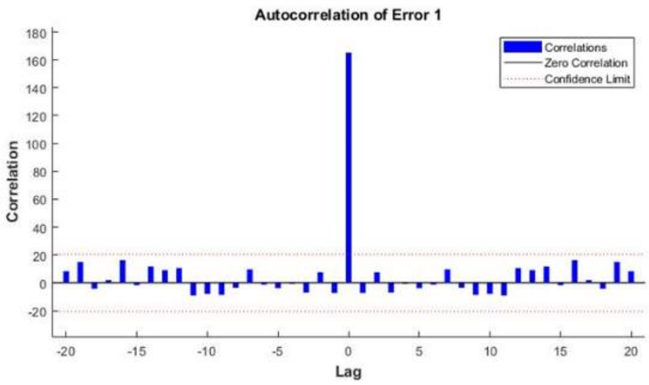


Figure 22. Error auto correlation of the selected NARX model for Wednesday with 30 minutes data.

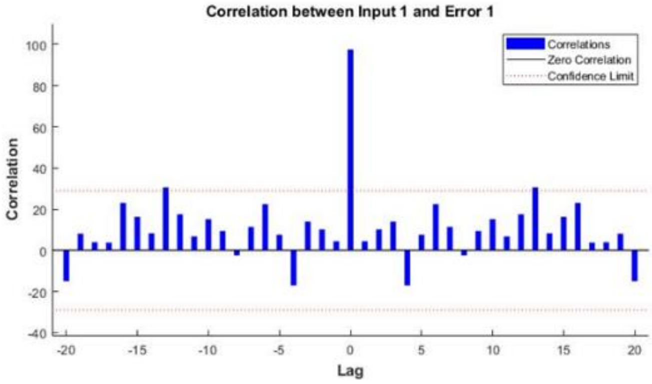


Figure 21. Input error cross correlation of the selected NARX model for Wednesday with 30 minutes data

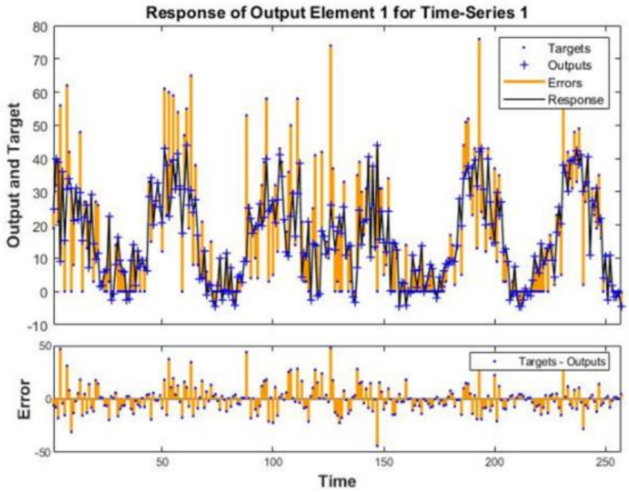


Figure 22. Time series response of the selected NARX model for Wednesday with 30 minutes data.

REFERENCES

[1] Bretherton RD. Scoot Urban Traffic Control System—Philosophy and Evaluation. IFAC Proc Vol [Internet]. 1990;23(2):237–9. Available from: doi.org/10.1016/S1474-6670(17)52676-2

[2] Figueiredo L, Jesus I, Tenreiro Machado JA, Rui Ferreira J, Martins De Carvalho JL. Towards the development of intelligent transportation systems. In: IEEE, editor. IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC [Internet]. Oakland, CA, USA; 2001. p. 1206–11. Available from: doi:10.1109/ITSC.2001.948835

[3] Vanajakshi L, Rilett LR. A comparison of the performance of artificial. neural networks and support vector machines for the prediction of traffic speed. In: IEEE Intelligent Vehicles Symposium, 2004 [Internet]. Parma, Italy: IEEE; 2004. p. 194–9. Available from: oi:10.1109/IVS.2004.1336380

[4] Hosseini SH, Moshiri B, Rahimi-Kian A, Araabi BN. Traffic speed prediction using mutual information. In: IEEE, editor. IEEE Canadian Conference on Electrical and Computer Engineering (CCECE) [Internet]. Montreal, Canada; 2012. p. 1–4. Available from: doi:10.1109/CCECE.2012.6334975

[5] Zeng D, Xu J, Gu J, Liu L, Xu G. Short term traffic flow prediction using hybrid ARIMA and ANN models. In: Workshop on Power Electronics and Intelligent Transportation System [Internet]. Workshop on Power Electronics and Intelligent Transportation System: IEEE; 2008. p. 621–5. Available from: doi:10.1109/PEITS.2008.135

[6] Li, K. L., Zhai, C. J., & Xu JM. Short-term Traffic Flow Prediction Using a Methodology Based on ARIMA and RBF-ANN. In: Chinese Automation Congress (CAC) [Internet]. Jinan, China: IEEE; 2017. p. 2804–7. Available from: doi:10.1109/CAC.2017.8243253

[7] Jadaan KS, Al-Fayyad M, Gammoh HF. Prediction of Road Traffic Accidents in Jordan using Artificial Neural Network (ANN). J Traffic Logist Eng [Internet]. 2014;2(2):92–4. Available from: doi:10.12720/jtle.2.2.92-94

[8] Innamaa S. Short-term prediction of traffic situation using mlp-neural networks. In: Proceedings of the 7th world congress on intelligent transport systems. Turin, Italy; 2000. p. 1–8.

[9] Dougherty MS, Cobbett MR. Short-term inter-urban traffic forecasts using neural networks. Int J Forecast. 1997 Mar;13(1):21–31. Available from: https://doi.org/10.1016/S0169-2070(96)00697-8

[10] Dia H. An object-oriented neural network approach to short-term traffic forecasting. Eur J Oper Res [Internet]. 2001;131(2):253±261. Available from: https://doi.org/10.1016/S0377-2217(00)00125-9
[11] Sharma B, Kumar Katiyar V, Kumar Gupta A. Fuzzy Logic Model for the Prediction of Traffic Volume in Week Days. Int J Comput Appl. 2014;107(17):1–6.
[12] Zhang Y, Ye Z. Short-term traffic flow forecasting using fuzzy logic system methods. J Intell Transp Syst Technol Planning, Oper [Internet]. 2008;12(3):102–12. Available from: https://doi.org/10.1080/15472450802262281
[13] Wang H, Zheng L, Meng X. Traffic accidents prediction model based on fuzzy logic. In: Advances in Information Technology and Education. Berlin, Heidelberg: Springer; 2011. p. 101–8.
[14] Li L, Lin WH, Liu H. Type-2 fuzzy logic approach for short-term traffic forecasting. IEE Proc Intell Transp Syst [Internet]. 2006;153(1):33–40. Available from: doi:10.1049/ip-its:20055009
[15] Yang S, Ma W, Pi X, Qian S. A deep learning approach to real-time parking occupancy prediction in transportation networks incorporating multiple spatio-temporal data sources. Transp Res Part C Emerg Technol [Internet]. 2019;107:248–65. Available from: https://doi.org/10.1016/j.trc.2019.08.010
[16] Quek C, Pasquier M, Lim BBS. Pop-traffic: A novel fuzzy neural approach to road traffic analysis and prediction. IEEE Trans Intell Transp Syst [Internet]. 2006;7(2):133–46. Available from: doi: 10.1109/TITS.2006.874712
[17] Khaleel N, Hartley J, Mahmood M. An Adaptive Neuro Fuzzy Inference System for Traffic Occupancy Prediction. Rev AUS [Internet]. 2019;26(2):281–8. Available from: doi:10.4206/aus.2019.n26.2.36
[18] Yang HF, Dillon TS, Chen YPP. Optimized Structure of the Traffic Flow Forecasting Model with a Deep Learning Approach. IEEE Trans Neural Networks Learn Syst [Internet]. 2017;28(10):2371–81. Available from: doi: 10.1109/TNNLS.2016.2574840
[19] Lv Z, Xu J, Zheng K, Yin H, Zhao P, Zhou X. LC-RNN: A deep learning model for traffic speed prediction. In: Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence (IJCAI-18) [Internet]. Stockholm: International Joint Conferences on Artificial Intelligence; 2018. p. 3470–6. Available from: https://doi.org/10.24963/ijcai.2018/482
[20] Gu Y, Lu W, Qin L, Li M, Shao Z. Short-term prediction of lane-level traffic speeds: A fusion deep learning model. Transp Res Part C Emerg Technol [Internet]. 2019;106:1–16. Available from: https://doi.org/10.1016/j.trc.2019.07.003
[21] Jia Y, Wu J, Du Y. Traffic speed prediction using deep learning method. In: IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC [Internet]. Rio de Janeiro, Brazil: IEEE; 2016. p. 1217–22. Available from: doi: 10.1109/ITSC.2016.7795712
[22] Miglani A, Kumar N. Deep learning models for traffic flow prediction in autonomous vehicles: A review, solutions, and challenges. Veh Commun [Internet]. 2019;20:1–36. Available from: https://doi.org/10.1016/j.vehcom.2019.100184
[23] Aqib M, Mehmood R, Alzahrani A, Katib I, Albeshri A. A Deep Learning Model to Predict Vehicles Occupancy on Freeways for Traffic Management. Int J Comput Sci Netw Secur. 2018;18(12):246–54.
[24] Yu R, Li Y, Shahabi C, Demiryurek U, Liu Y. Deep learning: A generic approach for extreme condition traffic forecasting. In: Proceedings of the 17th SIAM International Conference on Data Mining, SDM 2017 [Internet]. Houston, Texas, USA; 2017. p. 777–85. Available from: https://doi.org/10.1137/1.9781611974973.87
[25] Xu X, Zhang Y. Individual time series and composite forecasting of the Chinese stock index. Mach Learn with Appl. 2021;5(November 2020):100035.
[26] Xu X. Corn Cash Price Forecasting. Am J Agric Econ [Internet]. 2020;102(4):1297–320. Available from: doi:10.1002/ajae.12041
[27] Xu X. Contemporaneous and Granger causality among US corn cash and futures prices. Eur Rev Agric Econ [Internet]. 2019;46(4):663–95. Available from: doi:10.1093/erae/jby036
[28] Xu X. Price dynamics in corn cash and futures markets: cointegration, causality, and forecasting through a rolling window approach. Financ Mark Portf Manag [Internet]. 2019;33(2):155–81. Available from: doi:10.1007/s11408-019-00330-7
[29] Xu X. Using Local Information to Improve Short-Run Corn Price Forecasts. J Agric Food Ind Organ. 2018;16(1).
[30] Xu X. Short-run price forecast performance of individual and composite models for 496 corn cash markets. J Appl Stat. 2017;44(14):2593–620. Available from: doi: 10.1080/02664763.2016.1259399
[31] Xu, Xiaojie and YZ. Residential housing price index forecasting via neural networks. Neural Comput Appl [Internet]. 2022;1–14. Available from: doi: 10.1007/s00521-022-07309-y
[32] Xu, Xiaojie and YZ. Second-hand house price index forecasting with neural networks. J Prop Res [Internet]. 2021;1–22. Available from: https://doi.org/10.1080/09599916.2021.1996446
[33] Xiaojie Xu YZ. Contemporaneous causality among residential housing prices of ten major Chinese cities. Int J Hous Mark Anal [Internet]. 2022;ahead of p. Available from: https://doi.org/10.1108/IJHMA-03-2022-0039

[34] Xu X, Zhang Y. House price forecasting with neural networks. Intell Syst with Appl [Internet]. 2021;12:200052. Available from: https://doi.org/10.1016/j.iswa.2021.200052

[35] Xu X, Zhang Y. Soybean and Soybean Oil Price Forecasting through the Nonlinear Autoregressive Neural Network (NARNN) and NARNN with Exogenous Inputs (NARNN–X). Intell Syst with Appl [Internet]. 2022;13:200061. Available from: https://doi.org/10.1016/j.iswa.2022.200061

[36] Xu X, Zhang Y. Corn cash price forecasting with neural networks. Comput Electron Agric [Internet]. 2021;184(March):106120. Available from: https://doi.org/10.1016/j.compag.2021.106120

[37] Xu X, Zhang Y. Thermal coal price forecasting via the neural network. Intell Syst with Appl [Internet]. 2022;14:200084. Available from: https://doi.org/10.1016/j.iswa.2022.200084

[38] Xu, Xiaojie and YZ. Coking coal futures price index forecasting with the neural network. Miner Econ [Internet]. 2022;1–11. Available from: https://doi.org/10.1007/s13563-022-00311-9

[39] TRL. Advice Leaflet 1: The "SCOOT" Urban Traffic Control System SPLIT [Internet]. 1995. Available from: available at scootutc. com/documents/1_SCOOT-UTC. pdf.

[40] Agatonovic-Kustrin S, Beresford R. Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. J Pharm Biomed Anal [Internet]. 2000;22(5):717–27. Available from: https://doi.org/10.1016/S0731-7085(99)00272-1

[41] Attoh-okine NO. Analysis of learning rate and momentum term in backpropagation neural network algorithm trained to predict pavement performance. Adv Eng Softw [Internet]. 1999;30(4):291–302. Available from: https://doi.org/10.1016/S0965-9978(98)00071-4

[42] Eldin NN, Senouci AB. Use of Neural Networks for Condition Rating of Jointed Concrete Pavements. Adv Eng Softw. 1995 Jan;23(3):133–41. Available from: https://doi.org/10.1016/0965-9978(95)00077-1

[43] Jang JSR, Sun CT, Mizutani E. Neuro-Fuzzy and Soft Computing-A Computational Approach to Learning and Machine Intelligence [Book Review]. IEEE Trans Automat Contr [Internet]. 2005;42(10):1482–4. Available from: doi: 10.1109/TAC.1997.633847

[44] Cadenas E, Rivera W, Campos-Amezcua R, Heard C. Wind speed prediction using a univariate ARIMA model and a multivariate NARX model. Energies. 2016;9(2):1–15.

[45] Boussaada Z, Curea O, Remaci A, Camblong H, Bellaaj NM. A nonlinear autoregressive exogenous (NARX) neural network model for the prediction of the daily direct solar radiation. Energies [Internet]. 2018;11(3):1–21. Available from: https://doi.org/10.3390/en11030620

[46] Pisoni E, Farina M, Carnevale C, Piroddi L. Forecasting peak air pollution levels using NARX models. Eng Appl Artif Intell. 2009;22(4–5):593–602. Available from: https://doi.org/10.1016/j.engappai.2009.04.002

[47] Ruiz L, Cuéllar M, Calvo-Flores M, Jiménez M. An Application of Non-Linear Autoregressive Neural Networks to Predict Energy Consumption in Public Buildings. Energies [Internet]. 2016;9(9):1–21. Available from: https://doi.org/10.3390/en9090684

[48] Narendra KS, Parthasarathy K. Learning Automata Approach to Hierarchical Multiobjective Analysis. IEEE Trans Syst Man Cybern [Internet]. 1991;21(1):263–72. Available from: doi: 10.1109/21.101158