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Assessment of Spatiotemporal Traffic Flow Patterns Before and During the COVID-19 Pandemic using Non-Linear Auto-Regressive with External Input in Tehran

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ABSTRACT

One of the main challenges for the transportation decision-makers of megacities is to understand, model, and predict the spatiotemporal variations in a traffic flow that has changed during the COVID-19 outbreak. These fluctuations in the transportation field are related to many factors, with the most important ones attributed to the variations in using public transportation facilities. This paper evaluates the spatiotemporal trend of public transportation facilities and traffic flow before and during the COVID-19 outbreak. The main contributions of our research are: to accurately predict urban traffic congestion based on the historical traffic data using our proposed non-linear auto-regressive with external input (NARX) artificial neural networks (ANNs) model and to identify its main spatial governing factors. The proposed model is validated based on time series data of traffic flow in Tehran, the capital of Iran in October, November, and December of 2020. According to the R and RMSE values, it has been detected that there are no significant relations between the residential land use, main streets, and distance to taxi stations for the change in traffic flow before and during COVID-19. Results demonstrated that the designed time series ANN model could accurately predict spatiotemporal traffic levels. The minimum value obtained in the results for recall, precision, and F-score is less than 0.72. The maximum quantity of RMSE is 0.235, which is the correct value for the defined process.

KEYWORDS

Epidemical Diseases,
Artificial Intelligence,
Spatiotemporal Modelling,
Time series

1. Introduction

Given that COVID-19 has posed many challenges in our lives, it is necessary to provide an interdisciplinary view of the current crisis through global governance, technology, and risk relationship perspectives (Ashcroft et al., 2021; Mele & Magazzino, 2021; Shepherd et al., 2021; Zhang & Shaw, 2020). In Iran, similar to many other countries, COVID-19 public health measures have influenced traffic flow. These measures include restrictions on night travel in big cities of Iran (after 9 pm, all non-essential trips have been forbidden), changes in urban traffic plan time intervals, and

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the usage of private cars instead of public facilities. At the same time, the changes in the traffic flow can be related to other spatial factors, such as road characteristics, land use, and the locations of bus, taxi, and metro stations (Muley et al., 2021). Therefore, monitoring and assessment of traffic patterns during the COVID-19 restrictions are necessary for understanding crashes, fuel consumption, air pollution, and trip safety in the cities (Han et al., 2021; Hasnain et al., 2020). In this context, this study aims to investigate the spatiotemporal changes in the traffic flow due to the COVID-19 pandemic in seven primary streets of Tehran, the capital of Iran. The main contribution is the application of non-linear auto-regressive with external input artificial neural networks (ANNs) to model the spatiotemporal times series of traffic flow before and during the COVID-19 outbreak (from October to December 2019 and the same time in 2020).

1.1. Highlights

- This paper evaluates the spatiotemporal trend of the traffic flow before and during the COVID-19 outbreak.
- The main contribution is the usage of non-linear auto-regressive with external input (NARX) artificial neural networks (ANNs) to model the spatiotemporal time series of traffic flow.
- This proposed model can predict the traffic level based on historical traffic level data.

2. Literature Review

Various studies have been performed to evaluate the traffic patterns and the decline in mobility patterns caused by the COVID-19 pandemic. An evaluation of the impact of the COVID-19 outbreak on the changes in traffic levels between 2019 and 2020 in South Korea, showed that the traffic increased by 17.3%%. Also in the following weeks, the decrease in traffic flow stayed at about 23%–26% (Lee et al., 2021). In addition, the country witnessed an upward trend in traffic levels in March due to the decline in the number of COVID-19 cases. In Spain, the impact of nationwide restrictions on traffic flow was evaluated by comparing traffic statistics from six weeks before to six weeks after when the country imposed nationwide restriction rules. (Aloi et al., 2020) Studies on traffic patterns have shown that during the morning and afternoon rush hour periods the traffic flow decreased more compared to the other periods. (Hudda et al., 2020) in Somerville reported that from March 27 to May 14, 2020, the truck and car traffic levels declined by 71% and 46 % respectively due to the closure of commercial activities. This decrease in traffic resulted in a 60%–68% decline in levels of (particulate matter) $PM_{2.5}$ and PM_{10} and a 22%–46% decline in carbon levels compared to pre-pandemic. (Beck & Hensher, 2020) assessed the impact of the COVID-19 outbreaks on travel activities in Australia. Their findings show that Australians have followed the government's strict social distancing guidelines, which has resulted in the flattening of the COVID-19 curve in the country. (Parr et al., 2020) compared the Florida Freeway traffic data in 2020 to 2019, and their results showed that since March 22, 2020, traffic flow has decreased by 47.5% in Florida. During the early stages of the COVID-19 pandemic, South Florida residents were more active. However, traffic levels in and out of South Florida declined dramatically after school closures. Additionally, their findings suggested that traffic in urban areas decreased earlier than traffic in rural areas. (Cruz & Sarmento, 2021) studied evaluated the effects of COVID-19 on road traffic from a highway operator's perspective. According to this study, the first response to short-term effects is the operator management response including the health, and safety of core jobs, and general financial impression. The focus of road operators has been to prevent service disruptions by prioritizing the safety of employees and their customers . COVID-19 has had different effects depending on the amount of traffic the type of vehicles, and the location of the roads. (Shilling & Waetjen, 2020) the study evaluated traffic safety during 22 days in California after the restrictions were imposed using a dual t-test. Specifically, the rate of traffic flow on freeways has decreased by 20 to 55 percent. One of the results of this study indicates an increase in normal speeds, between 1 and 4 miles per hour, on some roads. (Oum & Wang, 2020) used appropriate lockdown restrictions for COVID–19 pandemic on trips with the financial method of traffic flow in urban communities. According to the researchers of this study, policymakers should interfere with implementing this kind of lockdown. (Oguzoglu, 2020) assessed traffic safety in Turkey based on lockdown restrictions during March and April 2020 based on urban information which indicated a significant decrease in injuries and deaths.

(Arellana et al., 2020) evaluated several policies implemented by the Colombian administrations which demonstrated a significant change in aircraft and trip behaviors. The demand for motorized travel was condensed through the country, succeeding in an exceeding reduction in traffic. (Li et al., 2022) investigated the effect of COVID-19 on domestic on-air transportation in China. (Shabani et al., 2022) estimated the users' satisfaction of public transportation based on multi-criteria decision-making approaches. Although various investigations have been conducted in assessing traffic flow patterns, the use of time-series ANNs for spatiotemporal statistics monitoring has not been addressed adequately. In addition, the effect of spatial factors on traffic density after the COVID-19 outbreak has not been studied, yet.

3. Methodology

The main idea of this paper is the assessment of traffic pattern changes during the COVID-19 outbreak and the specification of its main contributing spatial factors. Three main steps have been taken (Figure 1): data preparation, spatiotemporal analysis using NARX time-series analysis, and estimating the governing spatial factors.

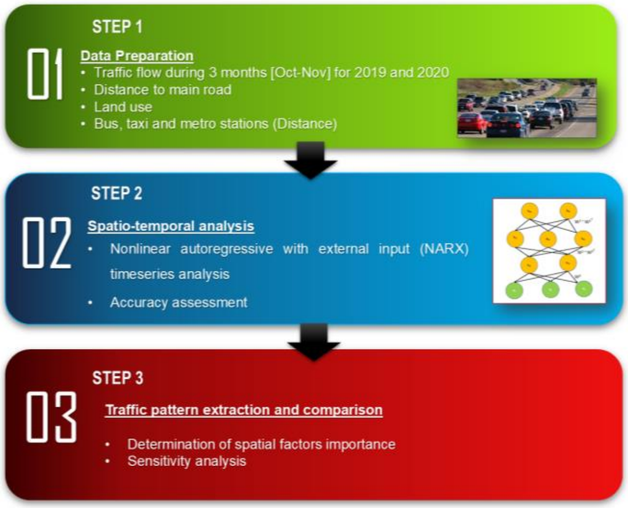

Figure 1. The flowchart of the proposed method

3.1. NARX Algorithm

An ANN is an assortment of linked components named artificial neurons, which roughly model the neurons in the biotic brain. Each connection, similar to the synapses, can spread an indication to further neurons (Hagan et al., 1997; Hagan & Menhaj, 1994).

Data is managed by some interconnected neurons that appear as synaptic contacts from the input nodes over a hidden layer attached to the output neurons. Each hidden neuron and input is produced from numerical weights and adopts the precise parameters that are shifted by a system via net training events (MacKay, 1992). Amongst neurons, the synaptic connections that activate throughout the network structure are protected with these weights. This method of computation can act on a parallel basis, similar to the person's nervous system. The ANNs could model non-linear problems and provide a beneficial substitute method to a quantity of both theoretic and real-world difficulties (Ding et al., 2015; Ruiz et al., 2016; Ticknor, 2013). In this paper, a time series predicting tool based on an ANN is applied to predict the traffic level based on the historical traffic levels data, road types, land use, and access to bus, taxi, and metro stations after the COVID-19 outbreak. The NARX procedure is a type of discrete-time and non-linear algorithm that can be formulated through Eq. (1) (Wang & He, 2020):

$$y(m+1)=f[y(m),\ldots,(y(m-d_y+1);$$
$$x(m-k),x[u-k+1,\ldots,x(m-d_u-k+1); \quad (1)$$

In which x(m) shows the input and y(m) shows the output of the method at discrete-time stage ‘‘m”; dy $\geq d_x$, and $d_x \geq 1$ is the input and $d_y \geq 1$ is the output memory instructions; k ($k \geq 0$) is a postponement item, recognized as the procedure dead-time (Ding et al., 2015). As k = 0, the NARX method can be shortened as Eq.(2) (Wang & He, 2020). Figure 2, is the NARX network topology.

$$x(m),\ldots,x(m-d_u+1);$$
$$y(m+1)=f[y(m),\ldots,(y(m-d_y+1); \quad (2)$$

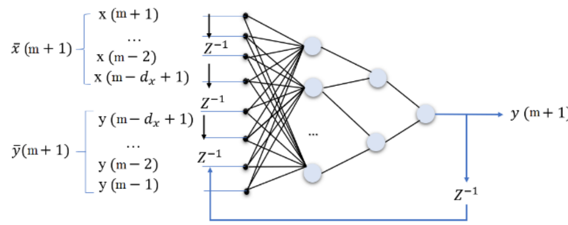

Figure 2. NARX structure (Z^{-1}: the measured time lag) (Parente et al., 2021).

The Levenberg-Marquardt backpropagation method (LMBP) is the final public learning instruction for the NARX algorithm (Alwakeel & Shaaban, 2010). The LMBP procedure was developed to estimate the second-order derivation to calculate the Hessian matrix. The Bayesian Regularization (BR) of ANNs is the other alternative training. These are more robust than regular backpropagation networks, and these might scale back or omit the need for wide cross-validation events. The BR may be considered a scientific method that adopts a non-linear regression into a well-posed arithmetical solution within the ridge regression method. This method specifically needs extra time to train but has a positive impact on good generalization for noisy data sets. The BR improves added items to Eq. (3).

$$F=\beta E_D+\alpha E_{Dw} \quad (3)$$

where, F shows the objective function, E_D is the summation of square errors, E_w is the summation of the square of the net weights, α and β are the objective perform parameters. In the BR network, the weights are measured based on random variable values, and so their density function is developed as the Baye’s rules, as indicated in Eq. (4) {Formatting Citation}:

$$P(w|D,\alpha,\beta,M)=\frac{P(D|w,\beta,M)P(w|\alpha,M)}{P(w|D,\alpha,\beta,M)} \quad (4)$$

P (D| W, β, M) : the likelihood function, which is the data growth possibility, given the weights (*W*).
P (W| α, M): the former density, which shows the learning of the weights before any data is gathered.
D: is the data set.
M: is the specific neural network model applied.
W: the vector of network weights.
P (D| a, b, M): a normalization factor, which assurances that the total probability equals 1.

(Foresee & Hagan, 1997) considered that the primary noise of the data was Gaussian so, they could control the probability weights’ density function. An ANN enhances the potential of overfitting upsurges intensely via other hidden layer neurons (Halley et al., 2008). The activation function is considered as Sigmoid. The procedure’s efficiency is computed based on the coefficient of determination (R2) and the mean-square error (MSE). Eq. (5) defines the MSE:

$$RMSE=\frac{\sum_{i=1}^{n}(\hat{y}_i-y_i)^2}{n} \quad (5)$$

in which $\hat{y}_i$ is the projected outcome, and y_i is the real target data.

3.2. Study Area

District 6 of Tehran Municipality is one of the urban areas of Tehran, which is located in the center of the city. Fig. 3, shows the study area and roads that are investigated in this paper. This area is limited from the north to Hemmat Highway, from the west to Chamran Highway, from the east to Modares Highway, and from the south to Enghelab Street. This region, with an area of 21,458 hectares, covers about 2.3% of the city of Tehran. As this area is a crowded district of the city, usually the main streets have a relatively high degree of traffic. Therefore, seven main roads were considered to assess the prevalence of Corona on the traffic flow trend (Javanbakht et al., 2021).

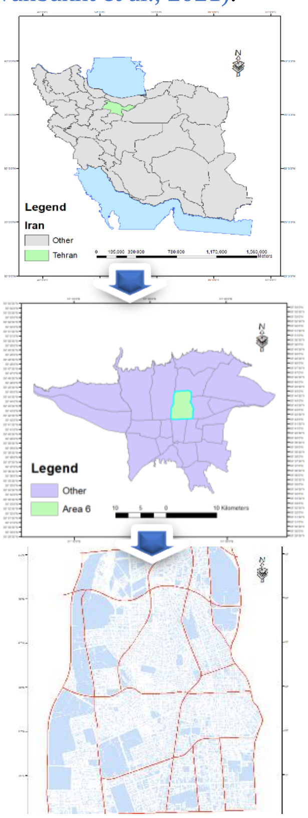

Figure 3. Maps of the study area and roads

4. Implementation

Execution includes data preparation, developing and running the NARX-ANN model, and sensitivity analysis which will be described as follows:

4.1. Data Preparation

The daily traffic flow has been derived from 'https: //map.tehran.ir/' and 'https: //www.google.com/maps' by extracting the traffic levels via their color (gray levels). The dataset consists of 6 main data categories including traffic data for seven main roads. For each day, the maximum level of traffic is considered for comparison. Figure 4, shows the traffic diagrams for each road from October to November 2019 and 2020.

4.2. Production of Criteria Maps by Spatial Analysis

The criteria maps are produced according to three spatial analyses: (1) Raster to vector conversion analysis with the aim to generate land-use maps, (2) Euclidean distance analysis with the aim to generate accessibility maps, and (3) Kernel density analysis with the aim to generate a density map (Figure 5). All the maps including roads, land use of urban parcels, metro stations, bus stations, and taxi stations as the input data of spatial analysis have been produced by NCC with a 1:2000 scale.

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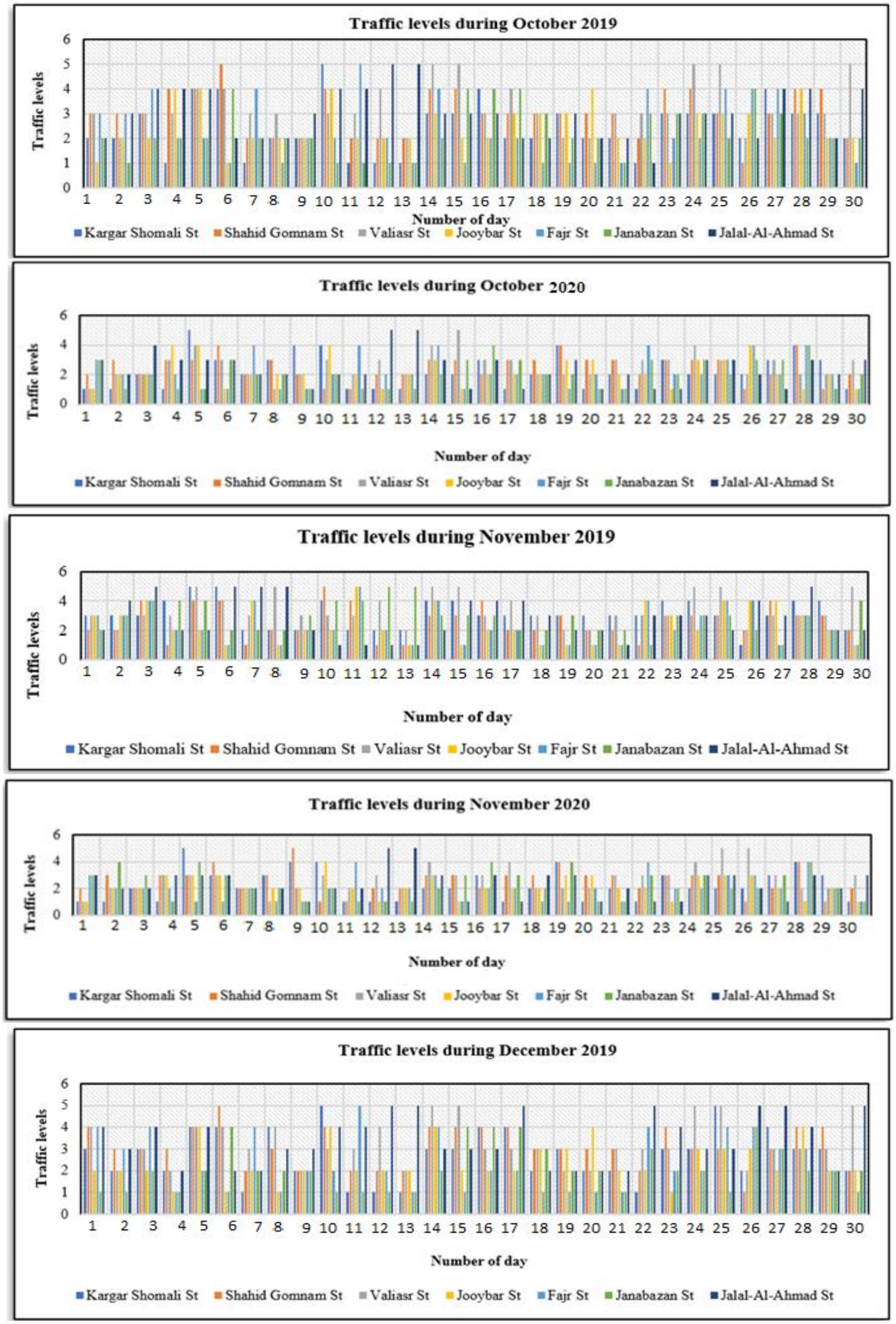

Traffic levels during October 2019
Traffic levels during October 2020
Traffic levels during November 2019
Traffic levels during November 2020
Traffic levels during December 2019
Traffic levels
Number of day
Kargar Shomali St
Shahid Gomnam St
Valiasr St
Jooybar St
Fajr St
Janabazan St
Jalal-Al-Ahmad St

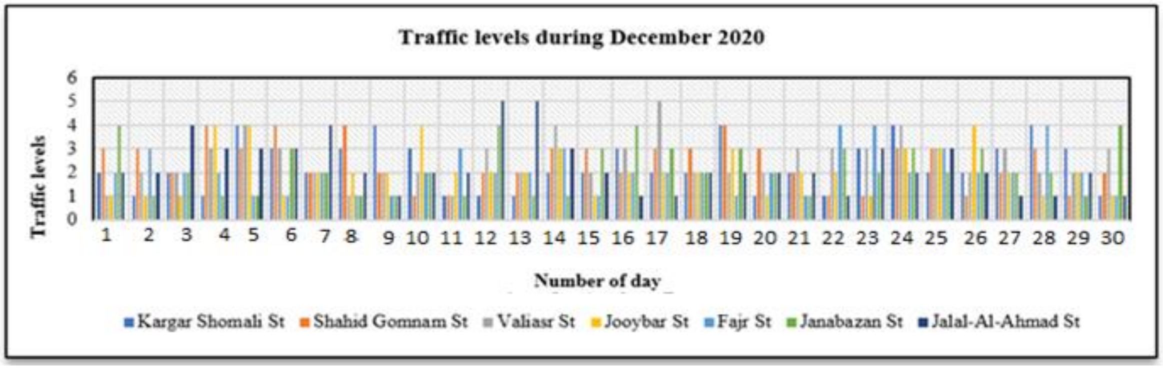
(a)

(b)

(c)

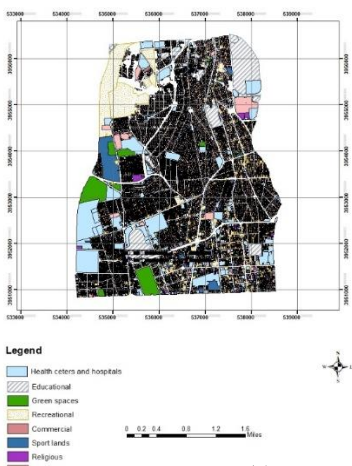
(d)

(e)

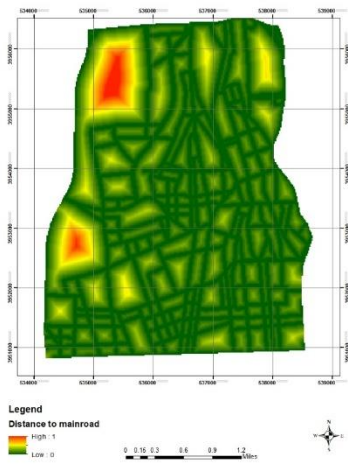


(f)

Figure 4. Traffic levels during COVID-19 for seven main streets of the study area: (a) October 2019, (b) October 2020, (c) November 2019, (d) November 2020, (e) December 2019, and (f) December 2020. ((a), (c), (e): before COVID-19 and (b), (d), (f): after COVID-19)



(a)



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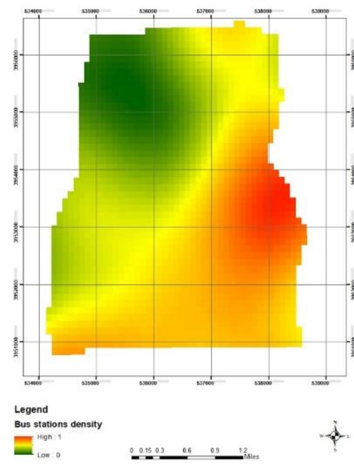
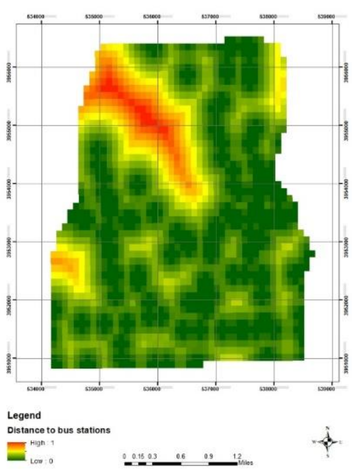
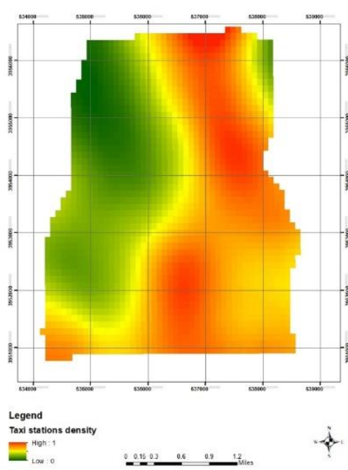


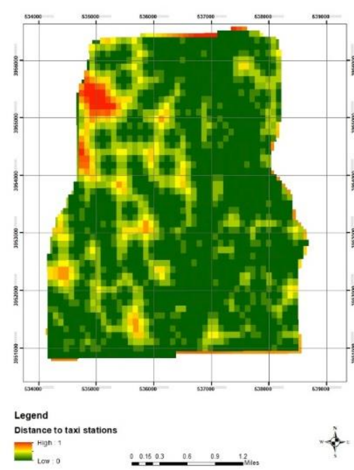
(c)



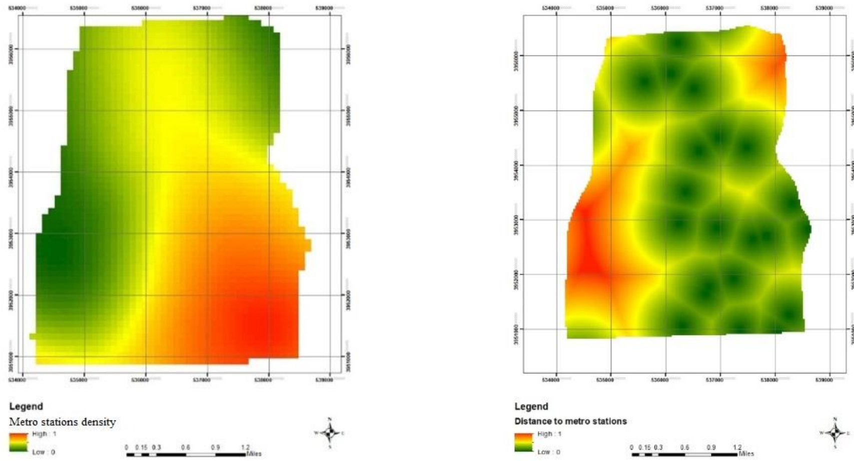
(d)



(e)



(f)



(g) (h)

Figure 5. Normalized criteria maps: (a) Land use, (b) Distance to the main road, (c) Bus stations density, d) Distance to bus stations, (e) Taxi stations density, (f) Distance to metro stations, (g) Metro stations density, and (h) Distance to metro stations

4.3. Normalization of Criteria Maps

The criteria have different units because they are related to various data sources. For criteria to be converted to suitability maps, they must be converted into comparable units (Shorabeh et al., 2020). Eqs. (6), (7), are used to normalize the data.

$$\mathrm{vmax}_{ij}=\frac{X_{ij}-X_{imin}}{X_{jmax}-X_{jmin}} \quad (6)$$

$$\mathrm{vmin}_{ij}=\frac{X_{jmax}-X_{ij}}{X_{jmax}-X_{jmin}} \quad (7)$$

Where, X_{ij} is the actual value for the location i, X_{jmax} shows the maximum value of the indicator, j, vmin_{ij} and $\mathrm{vmax}_{ij}$are the normalized values for the minimized criterion and maximized criterion respectively. X_{imin} is the minimum value for indicator j (Alizadeh et al., 2021).

5. Results

To evaluate the relation in the traffic flow before and after the COVID-19 pandemic, the traffic level has been assessed in the dual time (same day for 2019 and 2020). Also, the effects of road type, land use, and access to buses, taxi, and metro stations on the traffic flow have been analyzed. Road types have been classified into main streets and highways, whereas land use is classified into commercial, residential, educational, religious, sport, administrative and recreational factors. Distance factor includes distance to the bus stations, taxi stations, and metro stations, as well as the distance to facilities within 500 meters of the roads. For each month (October, November, December) and each route, an input/output matrix has been generated. Figure 6-10 shows the learning diagrams of the proposed network for one sample location – Kargar Shomali Street.

As seen, significant changes of traffic behavior have been detected after COVID-19 outbreak, especially in October. The overall trend shows the increasing traffic flow during the prevalence.

5.1. Accuracy Estimate

To measure the accuracy of the suggested technique, four communal standard measures were used .We estimated the common assessment criteria, including recall, precision, F-score, and RMSE, to test the predictions. Eqs. (8) to (11), formulated these criteria:

$$\mathrm{RMSE}=\sqrt{\frac{\sum (Y_i-\hat{Y}_i)^2}{n}} \quad (8)$$

where Y ̂ and Y are the predicted and extracted landmarks. Eq. (9) formulated Precision which equals to specified thought the values of true-positives (T-positives) and false-positives (F-positives), where F-positives indicate irrelevant landmarks and true negatives represent relevant landmarks that were determined.

Precision= (T-Positives) \ [(T-Positives) + (F-Positives)] (9)

Eq. (10) calculated recall, where the false negatives indicate relevant landmarks and true positives are the linked landmarks that were not determined.

Recall= (T-Positives) \ [(F-Negatives)+(T-Positives)] (10)

Eq. (11) formulated the F-score metric applied to get a fit composition of both recalls, and precision.

F-score= [(2×Precision×Recall) \ (Precision + Recall)] (11)

Table 1 shows the minimum, maximum and mean values for the RMSE, recall, precision, and F-score.

Table 1. The accuracy of our model according to RMSE, recall, precision, and F-score

	Max	Min	Mean
F-Score	0.90	0.69	0.79
Recall	0.89	0.72	0.81
Precision	0.92	0.67	0.78
RMSE	0.235	0.102	0.164

According to Table 1, the minimum values for recall, precision, and F-score are less than 0.72. Furthermore, the extreme amount of RMSE is 0.235; indicating a precise estimation for the specified scenario (the higher the recall, precision, and F-score, the more accurate the results and the lower the value of RMSE). The results support the overall effectiveness of the proposed method in the study region. The accuracy of the designed ANN construction highlighted with the minimum value of RMSE and the maximum quantities of the recall, precision, and F-score.

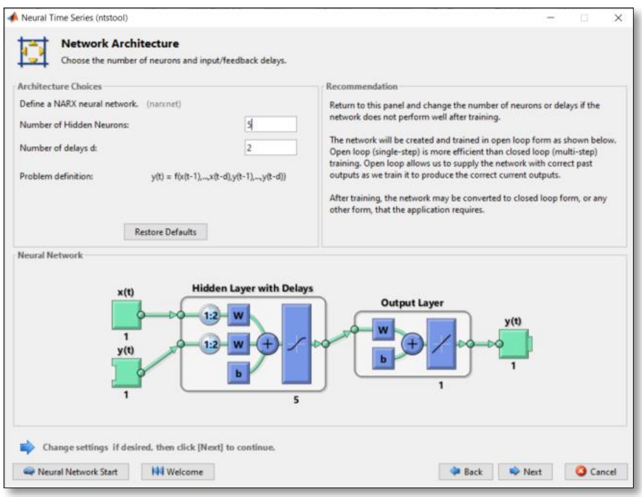


Figure 6. The NARX architecture with 5 hidden layer

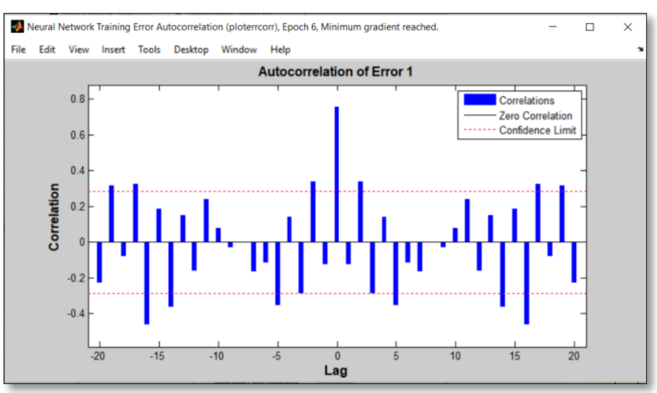


Figure 7. The Autocorrelation diagram (Oct)

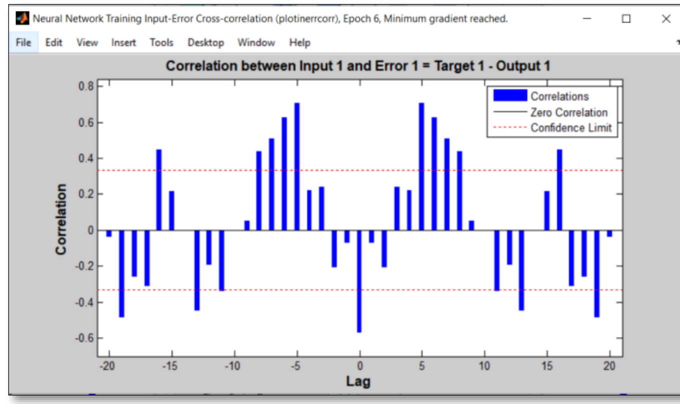


Figure 8. The Autocorrelation diagram (Nov)

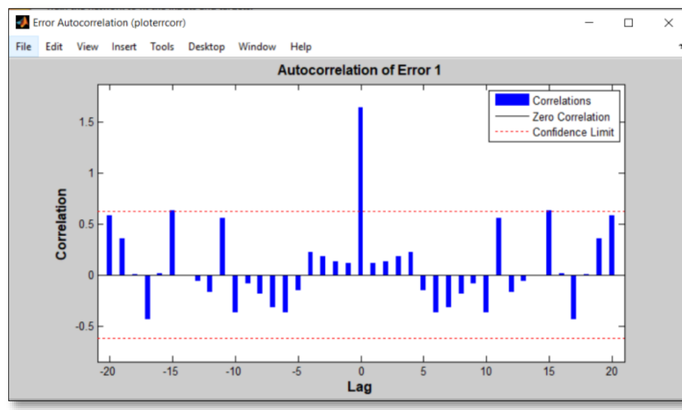
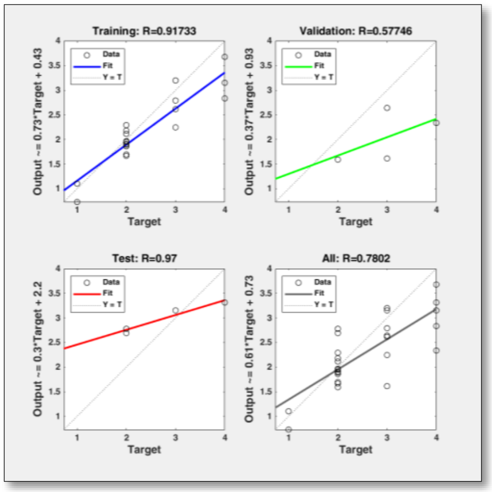
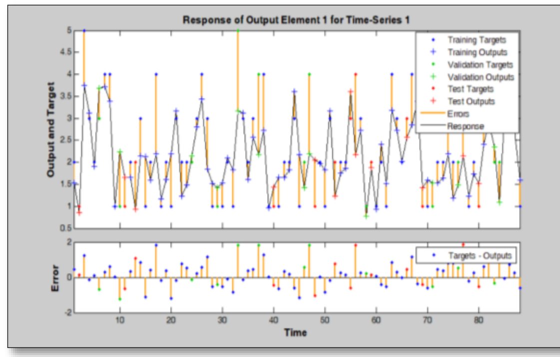
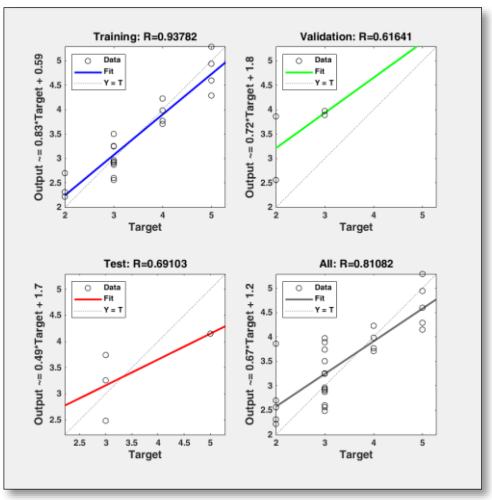


Figure 9. The Autocorrelation diagram (Dec)

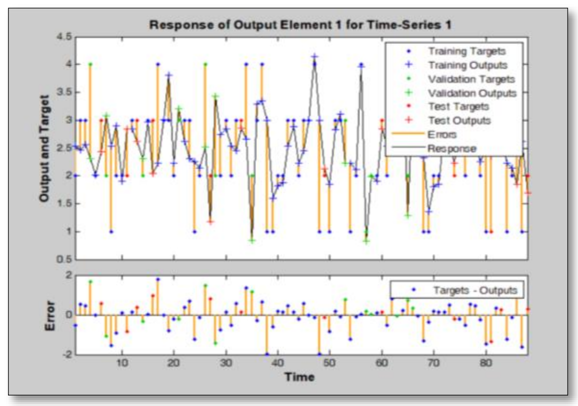


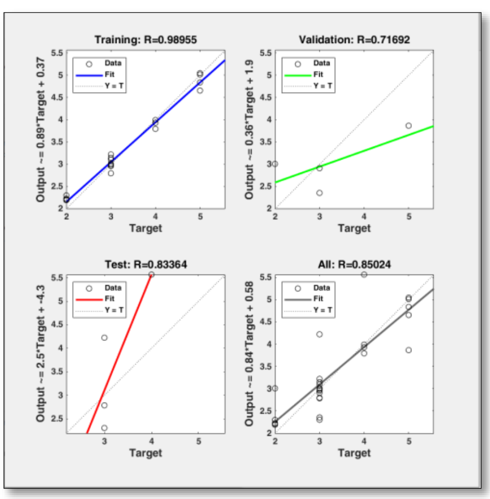
(a) October





(b) November





(c) December

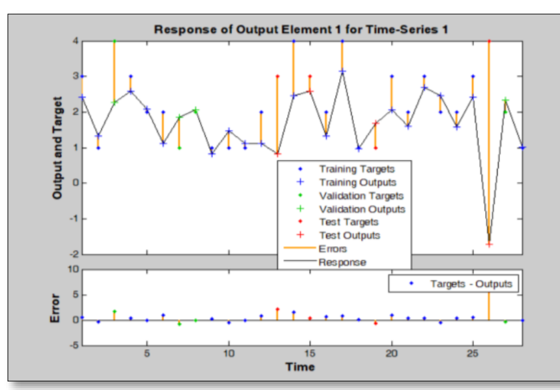


Figure 10. The time series of the trained NARX-ANN model

5.2. Sensitivity Analysis

The effect of each input parameter on the output is determined by sensitivity analysis. The sensitivity analysis indicates the influence of uncertainty sources (input and model) on the output uncertainty (Javanbakht et al., 2021; Qureshi et al., 2021). In each stage, one of the factors is omitted, and the R-value has been computed as it has been depicted in Figure 11. As seen, the most important factors for decreasing traffic flow are the commercial and educational land uses, and the efficient criterion for increasing traffic flow is the closeness to metro stations. According to the achieved R and RMSE, there are no significant relations between the residential land use, main streets, and distance to taxi stations for changing the traffic flow before and after COVID-19.

6. Discussions

Public transportation has an important role in daily urban life. The first key contribution of this study is proposing a guideline for comparing the traffic peak flow on main streets and highways, which could lead to new insights into changes in crashes and safety after the COVID-19 outbreak. As a continuation of this stage, the minimum and average traffics could be considered to assess beside maximum value. The latter property of the suggested method is evaluating the effect of spatial factors on traffic flow after the COVID-19 outbreak that confirmed the role of closing commercial and educational land uses on decreasing traffic flow and closeness to metro stations on increasing traffic flow. However, there are no significant relations between the residential land use, main streets, and distance to taxi stations for changing the traffic flow before and after COVID-19 was detected. The key contribution of this study is the application of the NARX-ANN method with the sigmoid activation function, as it can discover the non-linear relationships between the risk factors and traffic flow. The comparison of the results with (Dellicour et al., 2021; Shakibaei et al., 2021). showed that the traffic congestion during COVID-19 due to the spatial criteria has not been assessed yet.

According to the achieved results, the minimum values for recall, precision, and F-score are less than 0.72. Also, the risky amount of RMSE is 0.235; representing a precise estimation for the specified scenario (the higher the recall, precision and F-score, the more accurate the results and the lower the value of RMSE). The consequences support the overall effectiveness of the proposed method in the study region. The accuracy of the designed NARX high points with the minimum value of RMSE and the maximum amounts of the recall, precision, and F-score. Furthermore, conferring to the sensitivity analysis of the proposed method, there are no significant relations between the residential land use, main streets, and distance to taxi stations for changing the traffic flow before and after COVID-19.

7. Conclusion

This paper aimed to evaluate the spatiotemporal changes in transportation facilities and traffic flow in the seven main streets of District 6 of the Iranian capital, Tehran. The main contribution is the use of non-linear auto-regressive with external input ANN to model the spatiotemporal time series of traffic flow before, and during the COVID-19 outbreak from October to December 2019 and 2020.

The proposed method can predict the traffic level based on the historical traffic levels data, road types, land use, and access to bus, taxi, and metro stations. Results demonstrated that the designed time series ANN model could accurately predict spatiotemporal traffic levels. The minimum value obtained in the results for recall, precision, and F-score is less than 0.72. The maximum quantity of RMSE is 0.235, which is the correct value for the defined process. Also, the performance of the proposed method in the study area is determined by the average value of the criteria. Also, the lowest quantity of RMSE and the highest quantity of recall, precision, and F-score further determine the accuracy of the designed ANN structure. According to the results, the most important factors in reducing traffic flow are commercial and educational uses, and the adequate criterion for increasing traffic flow is proximity to metro stations. However, according to the results, there is no specific relationship between residential land use, main streets, and the distance to taxi stations to change the flow of traffic.

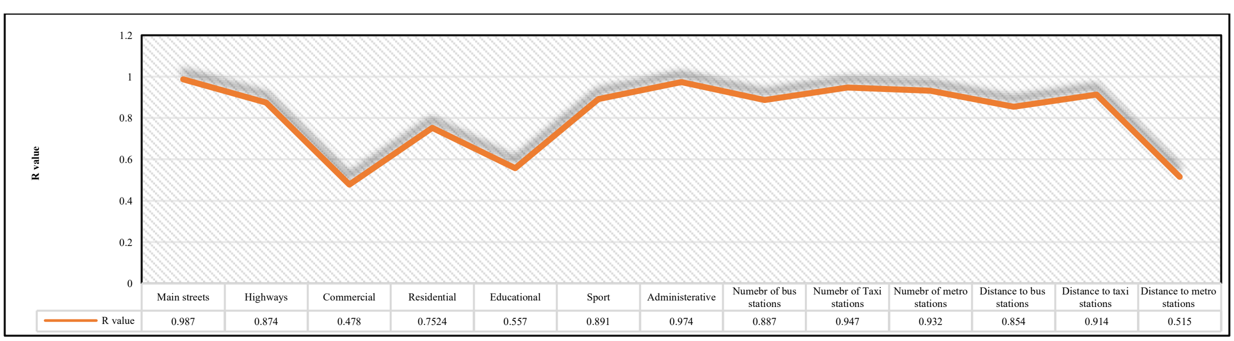


Figure 11. The sensitivity analysis diagram of involving factors

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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