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ORIGINAL RESEARCH PAPER

Traffic management via traffic parameters prediction by using machine learning algorithms

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ABSTRACT

BACKGROUND AND OBJECTIVES: One of the short-term strategies to manage the traffic and make a balance between travel supply and demand for the near future is the short-term prediction of traffic parameters and informing the passengers. Therefore passengers are more likely to avoid traveling during traffic peak hours. In this study, hourly average traffic speed and hourly traffic volume as two traffic parameters that indicate traffic state are predicted for Karaj-Chaloos road in Iran.
METHODS: Since traffic data have large volume, machine learning-based models have more suitable performance than traditional models. However, it is not merely possible to discover the cause and effect relationships and the importance of features. In this study, after using the artificial neural network and K-nearest neighbor models to predict traffic parameters, to analyze the sensitivity of the results, the importance of used features is investigated. Also, the effect of passing the time over the accuracy of predictions has been examined.
FINDINGS: According to the results, the highest accuracy of predicting hourly traffic volume and hourly average traffic speed is achieved by the K-nearest neighbor that is equal to 61% and 91%, respectively.
CONCLUSION: Compared to the historical average as a benchmark model, a significant improvement in the accuracy of predictions has been obtained by the artificial neural network and K-nearest neighbor models.

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INTRODUCTION

Nowadays, by facilitating travel and greater human need of movement, the demand for travel has increased dramatically, and it is considered a severe challenge to meet the high volume of travel demand (Ferguson, 2018). One of the essential goals in transportation planning is making a balance between travel supply and demand (Miller, 2017). This balance can be achieved through the management of travel supply or demand. Generally, the two concepts of planning and prediction are closely related (Ziebart *et al.,* 2009). In transportation planning, while trying to maintain this balance in current conditions, it is essential to make it for the future. The balance between travel supply and demand is made for two short-term and long-term futures. Long-term planning is known as 4-steps classical models (Rasaizadi and Askari, 2020), but in short-term planning, which is the purpose of this study, making balance is done for the near future through short-term prediction (Vlahogianni *et al*., 2004). For this purpose, some traffic parameters such as traffic volume (Song *et al.,* 2018; Wu *et al.,* 2016), average speed (Zhu *et al*., 2019), travel time (Zhao *et al.,* 2018; Azad *et al.,* 2019), traffic density (Raj *et al.,* 2016) and traffic state (Li *et al.,* 2020, Ren *et al.,* 2018) are predicted and provided to travelers via intelligent transportation systems. It is expected that traffic volume will be reduced during peak hours, and some travelers will shift their departure time to off-peak hours. In this study, the hourly traffic volume and hourly average traffic speed of Karaj-Chaloos road as a suburban road in Iran are predicted using big traffic data collected by loop detectors. By predicting these two traffic parameters for the next hours until next months, a more stable traffic state can be expected (Jia *et al.,* 2018). Traffic data of this road is collected in one-hour periods for several years, so the number of observations is very high. On the other hand, many features are extracted from the calendar and traffic state. Classical models such as ARIMA (Auto-Regressive Integrated Moving Average) (Makridakis and Hibon, 1997) are not compatible enough with big traffic data (Davenport *et al.,* 2012). Therefore, this study employs the artificial neural network (ANN) and K-nearest neighbor (K-NN) as two methods based on machine learning for short term prediction using big traffic data, and the prediction accuracies are compared with the historical average model (Campbell and Thompson, 2005) as a benchmark. However, one of the disadvantages of the ANN and K-NN models is the lack of sensitivity analysis (Chang, 2005). In these models, the importance of predictive parameters is not determined by estimating the coefficients (Elevitch and Johnson Jr., 2020), such as statistical models (Alsolami *et al.,* 2020). In the current study, to overcome this defect and determining the importance of the predictive features, the accuracy of the model is calculated and compared with and without each feature. Another sensitivity analysis that is discussed in this study is to determine the accuracy of short-term predictions over time. For this purpose, the test data is divided into ten days periods, and the accuracy of each of these periods has been investigated over time. By performing these two analyses, the lack of interpretability of the ANN and K-NN models, which is always considered one of the weaknesses of these models, is partially resolved. In the rest of this section, previous studies related to the short-term prediction of traffic parameters through machine learning methods are reviewed. Karlaftis and Vlahogianni (2011) have analyzed similarities and dissimilarities of statistical models versus ANN models in transportation studies; they concluded that however, researchers had applied machine learning models in transportation studies, but because of lacking explanatory power and interpretability, the machine learning methods are like a black-box. Also, this is approved by other studies (Ibrahim *et al.,* 2019; Moreira *et al.,* 2020). Lou *et al.,* (2019) proposed a spatiotemporal traffic flow prediction method combined with the K-NN algorithm, which their results exhibited the proposed model can achieve a better performance compared with ARIMA, SVR, and wavelet neural network models. Li *et al.,* (2020) proposed an algorithm based on partial least square to predict traffic state. This algorithm extracts dominant spatiotemporal features. Also, it captures day-to-day variations from collinear and correlated traffic data. Three case studies assess the performance of the proposed method. Do *et al.,* (2019) predict traffic flow by using a deep learning-based traffic flow predictor with STANN (Spatial and Temporal Attentions). They compare STANN's prediction with support vector regression, random forest regression, feed-forward neural network,

gated recurrent unit, long-short term memory, and basic sequence to sequence predictions. This comparison shows the superior performance of the proposed model. Wang *et al.,* (2019) predict traffic speed by using a path based deep learning approach. They determine critical paths. Then, each critical path is modelled using the bidirectional long short-term memory neural network. Under a series of scenarios, the proposed model performance is compared with benchmark methods in which the highest accuracy is achieved for the proposed method. Bai and Chen (2019) developed a deep architecture to predict the short-term traffic flow in an urban traffic network. A deep machine learning architecture consisting of three modules: a pre-training module, a classification module, and a fine-tuning module, have been proposed to predict the short-term traffic flow. With the comparison analysis over the existing approaches, the proposed model showed superiority in short-term traffic prediction, especially under incident conditions. To achieve a more accurate and robust traffic volume prediction model, Shen and Li (2013) analyzed the sensitivity of the WNNM (Wavelet Neural Network Model). They assessed different numbers of input neurons, different number of hidden neurons, and traffic volume for different time intervals. The test results show that the performance of WNNM depends heavily on network parameters and time intervals of traffic volume. Using machine learning algorithms to predict traffic parameters is not limited to these studies, and it is investigated in many studies (Tan *et al.*, 2016; Tang *et al.*, 2017; Wu *et al.*, 2018; Zhao *et al.*, 2019). Li *et al.*, (2019) predict day-ahead traffic flow by using an optimized deep belief network. Sharmila and Velaga (2020) predict travel time by SVM and ANN. Naderpour *et al.*, (2018) investigate on compressive strength prediction of environmentally friendly concrete by using ANN. Also, Singhal *et al.*, (2017) use machine learning techniques for text mining problems.

The current study aims to the short-term prediction of hourly traffic volume and hourly average in Karaj-Chaloos road; that could be a useful management data which can be used for making some decision and improve the traffic circumstance. This research has carried out in Tehran, Iran, in 2020.

Fig. 1: Map of Karaj-Chaloos road

Table 1: Description of the raw dataset

Name	Details
ID	Road identification code
Mehvar_id	Route identification code
Start_time	Starting date and time of periods
End_time	Ending date and time of periods
TotalCarCounter	Hourly traffic volume
AverageSpeed	Hourly average traffic speed

MATERIALS AND METHODS

Data

In this study, hourly average traffic speed and hourly traffic volume are predicted for Karaj-Chaloos road in Iran. Fig. 1 shows the map of Karaj-Chaloos

Table 2: Description of considered features

Symbol	Description
ssn	Season
m_sc	Month in the solar calendar
d_sc	Day in the solar calendar
m_lc	Month in the lunar calendar
d_lc	Day in the lunar calendar
wd	Weekday
hr	Hour in day
d_n	Is it day or night?
hl	Is it a holiday or not?
n_phl	Number of past consecutive holidays
n_3phl	Number of holidays in 3 past days
n_fhl	Number of future consecutive holidays
t_hl	Type of holiday including national, religious, new year and weekends

road, in the north of Iran. Chaloos is a tourist city that attracts many recreational trips on weekends and holidays. The length of this spectacular mountain road is about 170 kilometers. Chalous-Karaj Road is one of the most popular roads to the north of Iran, which has so many sightseeing areas. That is why the road is sometimes mobbed with passengers during holidays.

Table 1 presents the detail of raw data. This data is collected by loop detectors vehicle by vehicle and aggregated in 1 hour periods.

An important point is the possibility of extracting more features with pre-processing of the data. By matching the solar and lunar calendars with the traffic date, a clear relation between traffic data and holidays was observed. The traffic data is not solely dependent on the holidays; also, it depends on the type of holiday. So it is essential to consider the calendar-related feature to predict traffic parameters. Aiming to train ANN and K-NN models for predicting speed and volume of traffic for the mentioned road, data of two first years is used to train models, and data of six subsequent months is used to test the accuracy of models. Table 2 introduces the extracted features and their description.

Another effective feature is related to weather and climate changes, which is not considered in this study because of two reasons. First, weather and climate indices are measured for Karaj and Chaloos cities and not for the Karaj-Chaloos road, and the distance between the considered road section and cities is far. The second reason is that weather and climate indices are measured daily for these cities while the traffic parameters are collected hourly. However, season and months are reasonably suitable representatives for weather and climate changes. These features are examined in previous studies. For example, Dunne and Ghosh (2013) develop a weather adaptive traffic predicting model that considers the effects of rainfalls. In another study, Koesdwiady *et al.*, (2016) predict traffic flow with weather information in connected cars. The proposed method enhances the accuracy of traffic flow prediction.

Artificial neural network

ANNs are a machine learning model in which its function is similar to human brain function. One of the usages of these models is to predict time series data. Similar to the human brain, the ANN tries to identify the order and patterns of input data, learn from experiences, and provide new results based on prior knowledge. One of the widely used ANN for prediction is the multilayer perceptron. This model is characterized by a three-layered network consisting of input, hidden, and output layers. Neurons in different layers are known as processing elements. The steps that are used to calibrate an ANN model are as follows (Daniel, 2013):

Step 1: Data segmentation

To use the ANN for time series prediction, data are divided into two segments of training dataset and test dataset. The network is trained using the training dataset, and the test dataset is used to test the performance of the network. Data from March 21st, 2017 to March 20th, 2019 of Chaloos-Karaj road

used for training the ANN and data from March 21st, 2019 to September 22nd, 2019 of the same road is used for test and determining the accuracy of that network.

Step 2: Data pre-processing

Data preprocessing improves the learning process. Normalization is one of the most common methods of preprocessing data. In this method, the data are changed so that the range of data changes is in the range [L, H].

Step 3: Train

ANN training algorithms are diverse. Momentum, Levenberg-Marquardt (LM), and Conjugate Gradient (CG) algorithms are the most known algorithms for training ANNs. In this study, the conjugate gradient algorithm is used to train the ANN. In this algorithm, the parameters of the ANN model are corrected to achieve minimum prediction error by using second derivatives.

Step 4: Test

The goal of the test step is to ensure that the model can predict properly. So part of the data which is not included in the training phase is used for prediction. Using RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error), the accuracy of prediction can be calculated.

In the ANN model, the input of each neuron is as Eq. 1:

$$u_j = \sum_{i=1}^{n} w_{ij} x_i + \theta_i \tag{1}$$

Where w_{ij} is the corresponding vector of connection weights between neuron j and previously connected neurons, i. x_i is a vector of used features in the input layer and θ_i is a threshold.

By using the sigmoid function, the output of neurons (h_j) is as Eq. 2:

$$h_j = \frac{1}{1+\exp\left(-u_j\right)} \tag{2}$$

Eq.3 shows the weight error δ_K connected to neuron k in the output layer.

$$\delta_k = \left(c_k - h_k\right) h_k \left(1 - h_k\right) \tag{3}$$

Where, c_k is the sample expectation.

The weight error δ_j connected to neuron j in hidden layers is calculated as Eq. 4:

$$\delta_j = \sum_{k=1}^{q} \delta_j w_{jk} h_j \left(1 - h_j\right) \tag{4}$$

Connection weights are updated as Eq. 5.

$$w_{ij}\left(t+1\right) = w_{ij}\left(t\right) + \eta \delta_j x_i + \alpha \Delta w_{ij}\left(t\right) \tag{5}$$

Where η and α are the learning rate of the ANN.

K-nearest neighbor

K-NN algorithm is a data classification approach that is nonparametric and calculates the distance between observations. This algorithm predicts the class of test data set according to the class of nearest observations. The steps that are used to calibrate a K-NN model are as follows (Neath and Johnson, 2010):

Step 1: Data Segmentation

In the K-NN algorithm, data is separated to train data and test data, just like the ANN segmentation.

Step 2: K value

K value in K-NN is a parameter that indicates the number of nearest neighbors to include in the voting process.

Step 3: Test

After calibrating the K-NN model, predictions on test data were assessed. It is notable that the maximum accuracy refers to the optimum value of K.

This paper used Euclidean distance to calculates the distance between data points, p, and q (Eq. 6).

$$d\left(p,q\right) = \sqrt{\left(q_1 - p_1\right)^2 + \left(q_2 - p_2\right)^2 + \ldots + \left(q_n - p_n\right)^2} = \sqrt{\sum_{i=1}^{n}\left(q_i - p_i\right)^2} \tag{6}$$

Euclidean distance is a mathematical straight-line distance between two points in Euclidean space. It

would be zero for identical points and high for points that show little similarity. Euclidean distance is widely used for k-nearest neighbors because it measures the regular distance between two points in Euclidean space (Hossain and Abufardeh, 2019).

RESULTS AND DISCUSSION

In this section, the prediction of traffic speed and volume by using the ANN and the K-NN is evaluated. Also, the sensitivity analysis of the result is examined by showing the importance of features and accuracy changes during the time.

Prediction accuracy

The ANN and K-NN algorithms are trained to predict traffic parameters, and to measure the

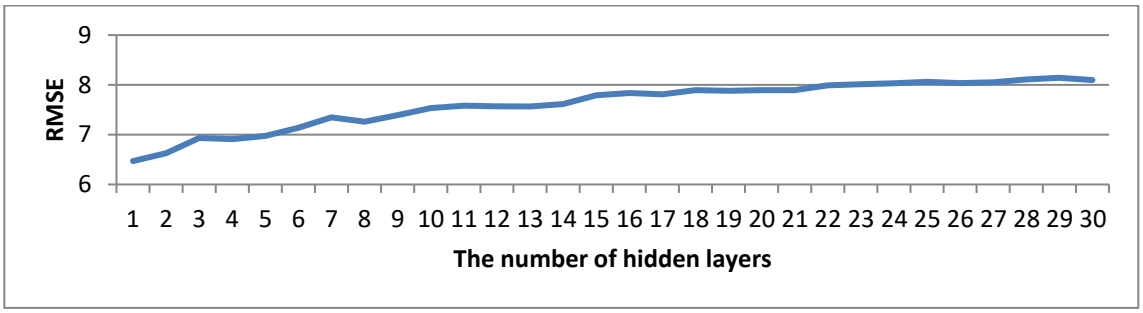

Fig. 2: Traffic speed prediction RMSE for different number of hidden layers

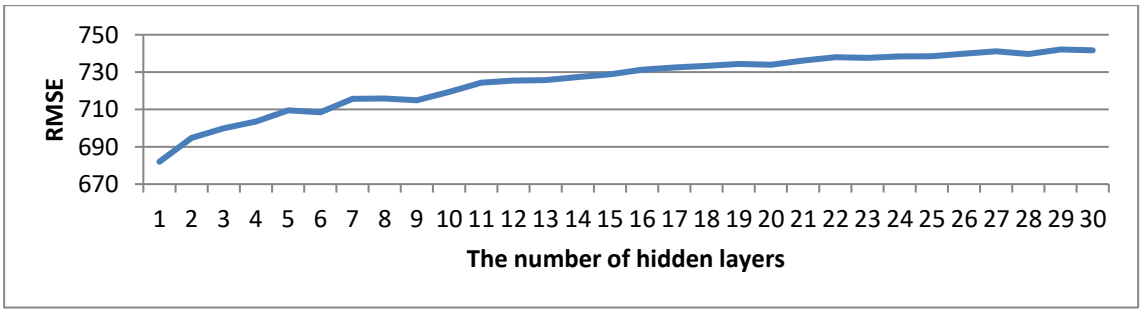

Fig. 3: Traffic volume prediction RMSE for different number of hidden layers

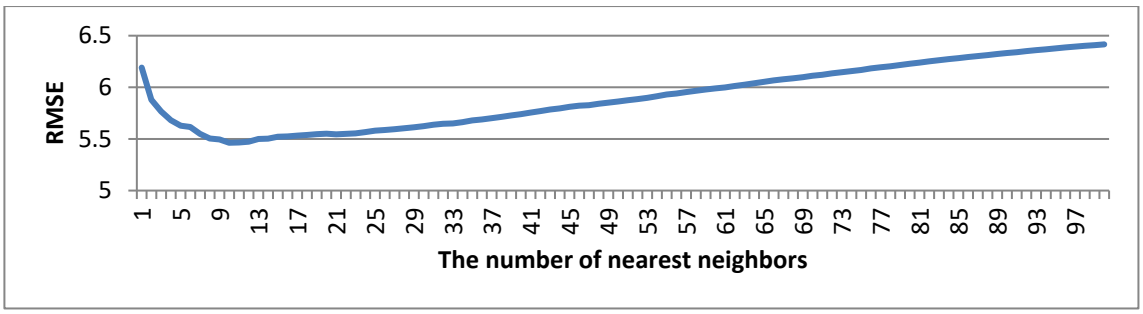

Fig. 4: Traffic speed prediction RMSE for different K

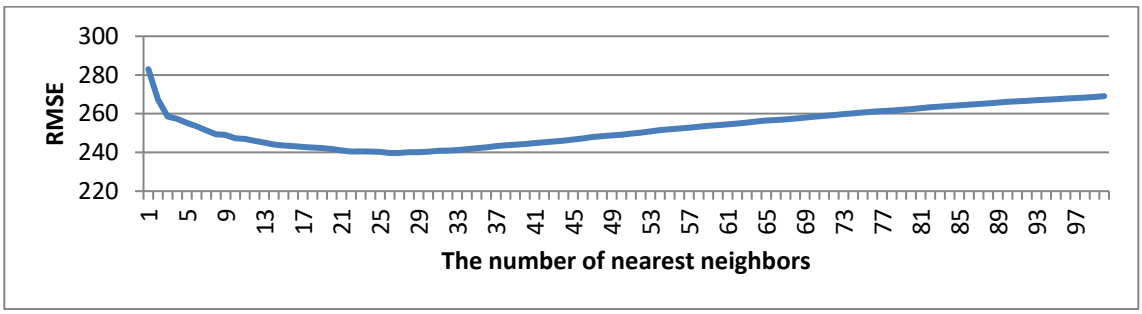

Fig. 5: Traffic volume prediction RMSE for different K

Table 3: ANN and K-NN prediction results in comparison to the HA

	K-NN		ANN		HA	
Predicted parameter	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Hourly volume	239.7	39%	682.0	75%	963.5	>100%
Hourly average speed	5.5	9%	6.4	11%	15.9	26%

Table 4: the importance of features for predicting the hourly volume and hourly average speed

Features	K-NN				ANN			
	Volume		Speed		Volume		Speed	
	RMSE	Change percentage	RMSE	Change percentage	RMSE	Change percentage	RMSE	Change percentage
ssn	306.00	0.26	7.29	0.00	713.90	4.68	6.46	0.16
m_sc	321.80	5.44	7.69	5.49	709.47	4.03	6.65	3.10
d_sc	284.88	-6.66	6.76	-7.27	712.69	4.50	6.45	0.00
m_lc	317.90	4.16	7.89	8.23	695.30	1.95	7.10	10.08
d_lc	285.60	-6.42	6.71	-7.96	715.90	4.97	6.47	0.31
wd	335.30	9.86	7.30	0.14	733.80	7.60	6.45	0.00
hr	344.30	12.81	8.18	12.21	723.30	6.06	7.62	18.14
d_n	305.70	0.16	7.30	0.14	705.40	3.43	6.50	0.78
hl	335.20	9.83	7.30	0.14	724.20	6.19	6.47	0.31
n_phl	308.55	1.10	7.42	1.78	714.90	4.82	6.69	3.72
n_3phl	305.30	0.03	7.30	0.14	711.73	4.36	6.47	0.31
n_fhl	331.40	8.58	7.29	0.00	727.20	6.63	6.46	0.16
t_hl	305.73	0.17	7.31	0.27	713.32	4.59	6.51	0.93
All	305.20	0.00	7.29	0.00	682.00	0.00	6.45	0.00

accuracy of the predictions, Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are calculated. Eq. 7 and Eq. 8 show RMSE and MAPE formulas.

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{7}$$

$$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{8}$$

To reach the maximum accuracy on the test dataset, it is essential to find the optimum value of K in the K-NN model and the number of hidden layers in the ANN model. Fig. 2 to Fig. 5 show the prediction error of each model based on a different value of parameters.

One hidden layer leads to the maximum accuracy of traffic volume and speed prediction by the ANN model. The optimum value of K in K-NN models for traffic volume and speed prediction is

equal to 27 and 10, respectively. Table 3 presents the results of final ANN and K-NN models besides the results of the historical average (HA) as a benchmark.

The presented results in Table 3 evinces that the K-NN model has a far better performance for hourly volume prediction in comparison with the ANN and the HA. Also, the K-NN model predicts hourly average speed more accurately compared to the ANN and the HA. The ANN outperforms the HA in terms of prediction error for both traffic volume and speed. In the next section, the effect of each considered feature on prediction accuracy is analyzed.

The importance of features

To find out the effect of each feature on prediction accuracy, the final K-NN and ANN models are trained with all the features except that considered feature. Table 4 exhibits the results of sensitivity analysis for all the available features in terms of RMSE.

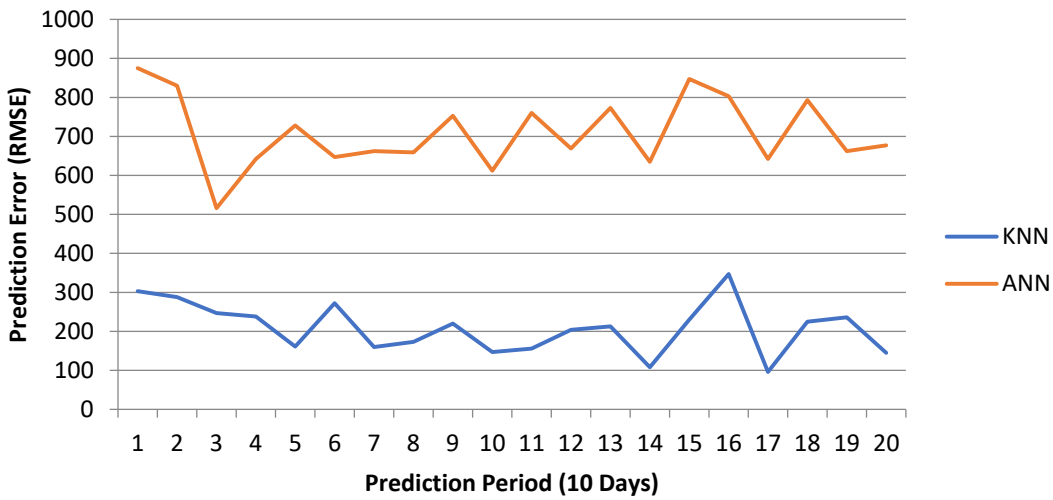

Fig. 6: Prediction error for the hourly traffic volume over the test dataset

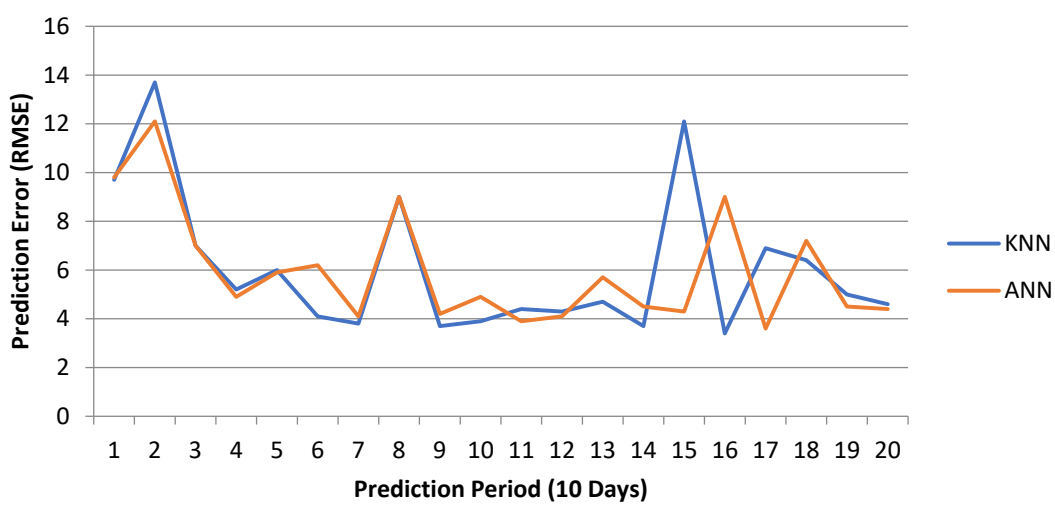

Fig. 7: Prediction error for the hourly average traffic speed over the test dataset

The ANN model, with all features, has the lowest prediction error for both traffic volume and speed. Although, in the K-NN model, removing d_sc and d_lc leads to achieving less traffic volume and speed prediction error compared to the K-NN model with all features. Based on the sensitivity analysis for the K-NN model, six features, including m_sc, m_lc, wd, hr, hl, and n_fhl have the most considerable effect on the accuracy of hourly volume prediction. If the trained K-NN for predicting traffic volume does not involve m_sc, m_lc, wd, hr, hl, and n_fhl, RMSE of the model would be 5.44, 4.16, 9.86, 12.81, 9.83, and 8.58 percent higher than the model with all features, respectively. For predicting traffic speed by K-NN, compared to the model with all features, eliminating m_sc, m_lc, and hr increases the RMSE by 5.49, 8.23, and 12.21 percent, respectively. For the ANN model, adding all of the features decreases the traffic volume prediction error. m-sc, m_lc, and hr are the essential features for traffic speed prediction by ANN, which ignoring them increase the RMSE, 3.1, 10.08, and 18.14 percent (Bratsas *et al*., 2020).

Accuracy changes during the time

Another critical point is the validation of predictions during the time. As this type of prediction is known as short-term prediction, it is essential to answer this question, how the accuracy of predictions varies over time and in different situations? Another sensitive analysis is done based on this question. Fig. 6 shows the hourly traffic volume prediction error in terms of RMSE within the six following months, which is separated in 10 days intervals. At the first interval of the diagram (first ten days of the test dataset), it could be seen that the calculated error is the maximum, and that is because of the new year's holidays in Iran and the occurrence of flood at that moment. This period generates an abnormal pattern of traffic in this case study. Then, in the next few months, prediction error significantly dropped due to getting back the trips to the routine. In June and July in Iran, there are many holidays, and this causes to increase the error of prediction. Lastly, by analyzing the summer results, it could be seen that the prediction error is getting stabilized, and the prediction error slightly oscillates. Besides, axiomatically is evident that the prediction error for the K-NN is significantly less than the error for the ANN in the short-term prediction of hourly volume in this case study.

Fig. 7 exhibits the hourly average traffic speed prediction error in terms of RMSE within the test dataset. Because of New Year's holidays in Iran and the occurrence of flood at that moment, the prediction error at the first interval is the maximum. By scrutinizing Fig. 7, it could be seen that significant changes in the eighth and fifteenth-period interval, and that is because of heavy rains in those mentioned days, which directly affect traffic speed (Hogema, 1996). Finally, on the other days that have neither precipitation nor a special holiday, the prediction is moderately fluctuating.

In previous studies, the MAPE of speed and volume prediction varied between 5-30% and 15-50% (Tan *et al.,* 2016; Tang *et al.,* 2017; Wu *et al.,* 2018; Zhao *et al.,* 2019). The calculated MAPEs in this study seem to be acceptable compared to these ranges.

CONCLUSION

In transportation studies, short-term predictions aim to make a balance between supply and demand. In this paper, ANN and K-NN models have predicted the hourly traffic volume of and hourly average traffic speed in Chaloos-Karaj road, which is one of the most critical roads of Iran. For training the ANN and the K-NN models, traffic data of the two years (March 2017 - March 2019) have been used, and for determining the precision of models, traffic data of the six subsequent months (March 2019 - September 2019) have assessed. To find the importance of each feature in the prediction of the traffic volume and speed, sensitivity analysis is done, and results show that wd, hr, hl, and n_fhl have the most significant impact on traffic volume and m_sc, m_lc, hr, and n_phl have the most significant effect on traffic speed prediction accuracies. Analyzing graphs of the prediction error over the whole six months period exhibits that by increasing the number of holidays, error of prediction will escalate in abnormal conditions. Results show that the lowest RMSE and MAPE for hourly volume prediction are achieved by the K-NN model, which is equal to 239.7 veh/hr and 39%, respectively. These two metrics for hourly average speed prediction are 5.5 veh/hr and 9%. As a suggestion for future studies, to reduce the prediction error using deep machine

learning methods and compare the results to the ANN and K-NN could be helpful.

AUTHOR CONTRIBUTIONS

S. Seyedabrishami commenced the process by conceptualizing and formulating the research idea. A. Ardestani implemented the ANN training and investigated the importance of features. Data preprocessing and cleaning, K-NN implementation, analyzing the accuracy changes during the time, reviewing the literature, results interpretation and discussion, and preparing the manuscript is done by A. Rasaizadi.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy has been completely observed by authors.

ABBREVIATIONS

ANN	Artificial neural network
K-NN	K-nearest neighbor
HA	Historical average
RMSE	Root mean square error
MAPE	Mean absolute percentage error
ARIMA	Autoregressive integrated moving average
STANN	Spatial and temporal attentions
WNNM	wavelet neural network model
ssn	Season
m_sc	Month in the solar calendar
d_sc	Day in the solar calendar
m_lc	Month in the lunar calendar
d_lc	Day in the lunar calendar
wd	Weekday
hr	Hour in day
d_n	Day or night
hl	Holiday or not
n_phl	Number of past consecutive holidays
n_3phl	Number of holidays in 3 past days
n_fhl	Number of future consecutive holidays
t_hl	Type of holiday
w1	One-way road
w_b	Impeded way
w_ob	Impeded opposite way
w_pb	Impeded parallel way

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