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Research Paper

An Implementation of the AI-based Traffic Flow Prediction in The Resilience Control Scheme

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Abstract

Today, often a reliable and dynamic sensor system is found to be necessary to control intelligent transportation systems. While these dynamical sensor systems are often found to be useful for the ordinary situations, the resilience-control-related issues are not yet fully addressed in the literature. The traffic flow is an important resource, which if found to be disturbed by a malicious threat it may cause further insecurities, e.g. if the sensor data is not accessible due to a malicious sabotage of the on-the-road sensors. Furthermore, often centers for the data gathering and prediction are suffering from data-loss because of imperfections of the data gathering itself. To overcome the resulting difficulties, a prediction engine is required to estimate the traffic flow, with the ability to compensate for the lost sensors.

In this paper, a traffic flow prediction engine is proposed in which the artificial-intelligence-based methods are used to perform the optimization task. This method is implemented for the test in the real-world situation and its efficiency in traffic estimation is proved to be reliable. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is trained with the particle swarm optimization (PSO) algorithm and the Artificial Neural Network model (ANN) is used to predict the flow. In addition, The Principal Components Analysis (PCA) method is adopted to reduce the dimension of the features. The results show the method's efficiency in predicting the traffic flow. The MLP method is the method with the best performance. The MLP method's error is about 8.5 percent which is 12.2 for MLP-PCA which makes it the worse method to come by for this application, and 10.8 for NFN-PCA. This prediction engine can be practically implemented and used as a replacement for the sensors to predict the traffic flow.

Keywords: Intelligent Methods, traffic estimator engine, reliable sensor system, principal components analysis.

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1. Introduction

Transportation has always been one of the most important aspects of human civilization and is considered as a necessity for the human life. Due to the increase in demand and the number of vehicles, the industrialization of societies, and the expansion of cities, the phenomenon of traffic congestion has become an undeniable fact all over the world. This also is a major social and national challenge and a lot of human and national capital are designated for it, [Ramezani et al. 2012]. Nowadays, the advancement of new technologies has made suitable conditions for intelligent, targeted and coordinated management to enhance productivity and increase the efficiency of the transportation network.

In intelligent transportation systems, traffic flow prediction is one of the main issues and plays an important role in traffic control, stoplight control, travel time control, and so on. Traffic prediction is used for a wide range of purposes, from planning to designing and operating the highway network. On the other hand, traffic flow prediction can help the management and control of actual traffic time on the road or city, which increases the safety and efficiency of transportation systems. By using an appropriate algorithm for performing modeling operations, traffic flow prediction can be also used to predict all network traffic variables in the future based on real-time and past traffic measurements.

In [Torfehnejad and Jalali, 2018], authors tend to represent the traffic flow as a stochastic process and they try to model the stochastic variation of traffic condition and subsequently predict the traffic condition. The make use of autocorrelation of time series samples of density and flow which are collected from segments with predefined specification and tend to find the trend in traffic variation.

On the other hand, the problem of traffic estimation may be assumed as a major issue in urban areas if it is looked from the aspect of a strategic resource. Modern highway and intersection controller and monitoring systems are being fully autonomous and smart systems are taking the control of these systems. As these systems are becoming more complicated and advanced, the resilience issues become more important. The dynamical sensor systems which are crucial for the data gathering process, may happen to be sabotaged by malicious natures in terror attacks to the city. If the sensors are manipulated, or disconnected for example by cutting the related cables and inductive loop sensors, the high-importance parts of the highway may be losing their effectivity and be congested for several hours. The prediction engines must be capable of compensating for this outbreak of sensors, if it is necessary in emergency situations. On the other hand, the data gathering costs are often assumed to be high. Often based on the budgets of the governments in developing countries the quality of the gathered data is not as good as it must be, they often include a large amount of garbage data which is not labeled or preferable from the valid ones. The valid data is a useful asset for the traffic researchers or the high-level policy- or decision-makers. Therefore, the proposed estimation engine in this paper, tends to smooth the raw data and produce the valid traffic data based on AI-based algorithms by assuming the data loss in garbage data sectors.

Generally, traffic prediction is divided into two major groups: long-term prediction and short-term prediction. In this research, we develop tools for short-term traffic flow prediction. Traffic flow prediction has been studied extensively in the literature. [Hooshdar et al. 2004] use a neural network to predict the cars' queues for traffic control in highways, and the information is sent to the drivers using the Variable Message Sign

(VMS) system. [Li et al. 2013] employ a backward propagation neural network based on Particle Swarm Optimization (PSO) method to improve the accuracy of the chaotic series prediction.

Due to shortcomings of traffic sensors configuration, the wavelet neural network approach is used to predict short-term traffic flow. In this method, suitable sensors are selected using PSO algorithm by [Yu et al. 2015]. [Ma et al. 2016] use a predictive model based on a fast, online sequential Extreme Learning Machine (ELM) with a forgetting mechanism. A fuzzy rule-based system (FRBS) is presented by [Li et al. 2011] to predict traffic flows. [Hosseini et al. 2014] adopts Neural Network and Mutual Information (MI) theory to predict traffic flow.

In some methods, like [Hadiuzzaman, Karim, Rahman and Hasan, 2016] a practical tool is developed to assess the safety consequences of arterial roads in long-term urban transportation plans in Dhaka the capital of the Bangladesh. The generalized linear model approach is used to develop separate models to predict number of crashes for different levels of crash severity. The test is done in major arterial segments with the highest rate of crash.

[Ganin et al. 2019] it is mentioned that as many cities are adopting advanced Intelligent Transportation Systems (ITS), these systems are open to many vulnerabilities especially to cyber-attacks an efficient solution is needed to tackle the regarding problems. Currently, vulnerabilities are managed by common methods of traditional risk assessment that assesses potential failures of the system in response to specified threats such as cyber-attacks or physical terror-attacks. In this scheme resilience is defined as the ability of the system to recover and adapt to different threats. The resilience control scheme is therefore an emerging area that holds promise for assessing threats to ITS.

In other study [Zhang, 2020] a quantitative framework is proposed to assess the freeway traffic resilience for threats that is introduced to the road by accidents. The study aims to apply this to assessment of existing infrastructure of modern highways during the disruptive events.

In [Ferrara, Sacone, & Siri, 2018], the importance of the resilience control in modern highway systems is outlined as an approach that facilitates security in the data-based highway control scheme.

In [Biron, 2017)] a new resilient control approach is developed to secure cyber physical systems against cyber-attacks. The goal of the method is to prevent networks failures resulted from cyber-attacks to affect the connectivity of the systems. The main challenge for their work arises from unreliable communication network. This method is consisted of three main parts: ***Physical fault diagnostics***, ***Cyber-attack/failure resilient strategy***, ***Decision making algorithm***. The Physical fault diagnostics part makes sure that CPS works normally while there is no cyber-attacks or network failure in the communication network. The Cyber-attack/failure resilient strategy part consists of a resilient strategy for specific cyber-attacks to compensate for their malicious effects and at last the decision making algorithm identifies the specific existing cyber-attacks/ network failure in the system and deploys corresponding control strategy to minimize the effect of abnormality in the system performance.

In [Poor Arab Moghadam, Pahlavani & Naseralavi, 2016], an ANFIS-CART based model is used to predict the behaviors of following vehicles. The approach is categorized to handle the micro traffic flow simulation. In this paper, a var-following model is developed by the combination of the ANFIS and Classification And Regression Tree (CART) to simulate and predict future behavior of each Driver-Vehicle-Unit (DVU).

[Zhao et al. 2007] employ a TSK type self-organizing fuzzy neural network method for short-term traffic flow prediction. Moreover, methods such as Kalman filtering [Barimani et al. 2012], Moving Average (MA) and ARIMA Model [Williams et al. 1999] have been used to predict traffic flow. Nonparametric methods [Gong et al. 2003] and [Lam et al. 2006] and Markov chain model [Sun et al. 2004] are other approaches used to design the predictive model. Hybrid models including the combination of singular spectrum analysis and kernel extreme learning machine (SSA-KELM) [Shang et al. 2016], Neural-Genetic Models [Abdulhai et al. 2002], and Autoregressive Integrated Moving Average with Generalized Autoregressive Conditional Heteroscedasticity (ARIMA-GARCH) [Chen et al. 2011] have been used to improve the accuracy of traffic flow prediction.

For intelligent control of the traffic flow, a reliable sensor system is quintessential [López et al. 2018]. Due to the weak points of the sensor systems, such as data losses, the existing traffic control methods are not efficient. Therefore, traffic problems remain, and the traffic situation has not been sufficiently improved. For example, this situation may rise when someone cuts the sensor cables or in some accidents the cables or the distribution system is corrupted.

Also, in [Mamdoohi, Saffarzadeh, & Shojaat, 2015] tends to estimate the capacity drop. Their estimation method is based on a comparison between breakdown and queue discharge flow rates and also on the estimation of the capacity distribution function before and after breakdown. The traffic flow sensor breakdown is able to add to the issues of this estimation, therefore resilience scheme is needed to perform the task more robust.

(The main aim of this paper is to provide a prediction engine for traffic flow using artificial intelligence algorithms based on the optimization of detectors when the disconnection of the sensor system occurs. The resilience control scheme is chosen to tackle these problems as sensor cottage and system failures are quite often possible to happen in the emergent situations. The resilience control scheme is chosen as it is proven to be effective when it is used in other works. The main steps and contributions of this paper are listed as follows:

1. PCA is used to select the appropriate feature to obtain the best input structure for the prediction model and reduce computational complexity.
2. The prediction of the future traffic flow is investigated using Adaptive Neuro-Fuzzy Interface System (ANFIS) which is trained using particle swarm optimization. The Multi-Layer Perceptron Neural Network (MLP) is another method considered in this paper. To train this neural network, the Levenberg-Marquardt, the Scaled conjugate gradient, and the Gaussian-Newton algorithms are used.
3. When the sensors are disconnected and data is not accessible, among the output of the used prediction methods, the one with less prediction error is used.

In the proposed method, the ANFIS trained by PSO algorithm is used to predict short-term traffic flow. In order to evaluate the applicability and performance of the proposed method, the results are compared with that of Multi-Layer Perceptron Neural Network structure, which is a powerful tool for modeling and prediction of nonlinear systems. The traffic data used in the proposed prediction engine, as a case study, is related to one of Iran's main roads, Sorkheh-Aradan road. The Aradan-Semnan road is placed in the Iran’s west-to-east transit rout which is one of Iran’s main tracks. Since the road contains two different streams of traffic from southern part of Iran one from Qom – Garmsar highway and one from

Tehran - Semnan highway it is a perfect representative for the demand of transit to the east both from south and the west. This road has two separate lines for the east-west traffic and two other lines for the west-east traffic. An online inductive traffic count device does the traffic count job for 5 different classes of vehicles. The data are divided as hour time intervals. The data is represented to the algorithm by a rate of 1440 per hour. In the learning process the data related to the sensor cut-out is not used. The data is related to the passing traffic of 5 different classes of vehicles which is placed on the surface of the road by the national organization of transportation.

The resilience control is utilized in many methods of the literature to overcome same issues as the issue of this paper. For example, the resilience control scheme is used to tackle drawbacks of ITS in the time of cyber-security issues. Applying the resilience control method to overcome the same issue when the sensor or the data-gathering infrastructure of the roads is under attack is not yet addresses in the literature.

The outline of this study is as follows. In section 2, the structure of the proposed model is explained. Section 3 presents the proposed prediction method and provided details about the used data. In Section 4, the criteria for evaluating the performance of estimators are discussed. In addition, the proposed method is employed for the real data and simulation results are analyzed. Finally, the paper is concluded in section 5.

2. Prediction

In this paper, a multi-layer perceptron neural network (MLP) is used to predict the short-term traffic flow and its performance is compared with the ANFIS method trained with PSO. In addition, to reduce the computational complexity, the PCA method is used to select the appropriate feature and to obtain the best input structure for the prediction model. The structure of the proposed predictive engine and the overall simulation process for the prediction of the traffic flow are by following the block diagram of Figure 1.

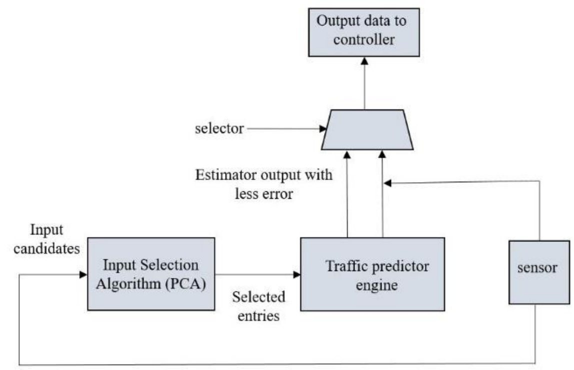

Figure 1. Traffic Flow Prediction Block Diagram

2.1 Artificial Neural Network (ANN)

ANN is a prevalent approach for prediction and various ANN structures are employed for different systems [Abdi et al. 2015], [Gupta et al. 2017] and [Divsalar et al. 2011]. The structure of the neural network which is used for this research has multiple input nodes. A neural network consists of different layers and weight components. In general, there are three types of neuron layers in neural networks:

1. ***Input layer:*** It gets raw data fed to the network. The dimension of input data is 12 and is 4 when we used PCA method to select the appropriate feature. In this paper, the prediction model only considers the time element in the prediction process. By applying forward-backward selection algorithm, the past intervals traffic flow data $p(t-1)$, p(t-2), p(t -3), p(t-4), p(t-24), p(t-48), p(t-72), p(t-96), p(t-168), p(t-336), p(t-504), p(t-672) are selected as the input variables for predicting the future interval of traffic flow p(t+1).

2. ***Hidden layers:*** There are five hidden layers between the input and output layers. The neurons in each hidden layer take in a set of weighted values and produce an output through an activation function, which is a ***Tansig*** function.
3. ***Output layer:*** The output layer is the last layer of neurons, and by using purelin activation function produces the output, which its dimension is one.

2.2 Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) has the ability of learning, optimizing, and balancing. A system that formulates a mapping of input to output using fuzzy logic is known as the Fuzzy Inference System (FIS). Fuzzy inference system is also called a rule-based system because these systems consist of several "if-then" phrases. A network structure that connects several nodes with several links, defines a comparative network. The nodes represent the processing units, and the links are the connections between those processing units. All nodes, or at least part of them, are consistent with nature, that is, the output of the system is constructed from the node parameters. Learning rules are adjusted so that they reduce the system error. Figure 2 shows the structure of an adaptive neuro-fuzzy system [Jang, 1993].

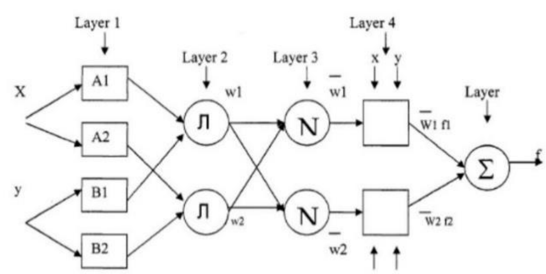

Figure 2. ANFIS structure

This Structure is implemented using the MATLAB ANFIS function which utilizes PSO algorithm to optimize the solution.

2.3 Principal Component Analysis (PCA)

This algorithm is one of the prevalent techniques for reducing dimensions [Daffertshofer, 2004]. This method is effective in compressing multivariate data. PCA helps to compress and reduce the dimension of the data while preserving the variation present in the dataset. This technique determines the directions in which the variance of the data is the highest value and displays the data set in a new and independent coordinate system. The direction in which larger variance is found is of greater importance to the algorithm.

3. Case Study

In this section, the proposed method is applied to the data obtained from Sorkhe-Aderan road. The obtained data is huge to evaluate and validate the method's ability to dealing with large data. The traffic data, which is used in this paper is mainly consisted of the number of passenger cars and is gathered during April and May 2011. This data is hourly traffic volume, and the goal is to predict the traffic flow for the next hour [Ramezani, 2012] and shows the statistical parameters of the used data in this paper.

By construction the covariance matrix and choosing the bigger elements, the most influence from the input is detected. In this paper the covariance matrix is constructed and the biggest values of the main diagonal were reported as 0.192, 01.83, 0.161, .0216 which are related the inputs from an hour earlier data from the day before, the same hour from the week before and the same hour from four weeks before. In this paper by using the PCA method we mean to choose these four inputs to reduce the dimensions of the input vector. Therefore, while the data of one day before, two days before and three days before have been chosen among 12 possible data, these data should be replaced by the data of one hour ago, one day before, two days before and three days before.

Table 1. Parameters of the used data.

Data	No. Samples	Parameters of the Data used			
		Mean	S. D	Min	Max
Traffic Flow	1440	373.72	135.76	44	827

3.1 Result Analysis

In order to evaluate the performance of estimation algorithms, the Root Mean Square Error (RMSE), the Scatter Index (SI), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) criteria are used. These criteria are defined as follows:

$$\mathbf{RMSE} = \sqrt{\frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{i=1}}^{\mathbf{N}}(\mathbf{Real\ \ Value} - \mathbf{Prediction\ \ Value})^{\mathbf{2}}} \quad (1)$$

$$\boldsymbol{MAE} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}}|\boldsymbol{Real\,Value} - \boldsymbol{Prediction\,Value}| \quad (2)$$

$$MAE = \frac{RMSE}{Mean\ Real\ Value} \quad (3)$$

$$MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\frac{|Real\,Value - Prediction\,Value|}{Real\,Value}\right) \times 100 \quad (4)$$

$$VAPE = Var\left(\frac{|Real\,Value - Prediction\,Value|}{Real\,Value}\right) \times 100 \quad (5)$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x}_i)(\hat{x}_i - \bar{\hat{x}}_i)}{\sum_{i=1}^{N}(x_i - \bar{x}_i)\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}}_i)} \quad (6)$$

where N is the total number of the data, x_i and $\hat{x}_i$ are actual and simulated traffic flow data, respectively The $\bar{x}_i$ is the mean of actual data and $\bar{\hat{x}}_i$ is the mean of predicted data.

In order to reduce the dimension of the data before the prediction phase, the PCA algorithm is used. ANFIS and MLP are adopted for the prediction, and PSO is used for training both of them.

3.2 Traffic Prediction using MLP with All Past Data

The Multilayer Perceptron neural network (MLP) with five hidden layers is considered for traffic prediction. To train this neural network, the Levenberg–Marquardt, the Scaled conjugate gradient, and the Gaussian Newton algorithms are used. Randomly 70%, 15%, and 15% of the data are selected for training, validation, and testing of the neural network respectively.

After the training phase, the acquired network is used for the test data which the results are given in Figure 3 Each of the figures represents the output of the neural network and the actual traffic flow data, the correlation coefficient, error, and error probabilistic distribution. In addition, to predict traffic flow, the data of one to four hours ago, one day to four days before the same hour and a week to four weeks ago of the same hour were used.

Table 2. Parameters of the used data.

Parameters	Value
Number of Repetition	**100**
Population Size	**200**
$\boldsymbol{c_1\ and\ c_2}$	**2.01**
$\boldsymbol{p_1\ and\ p}$	**Rand** $\in [\mathbf{0}, \mathbf{1}]$
Cos Function	**MAPE**

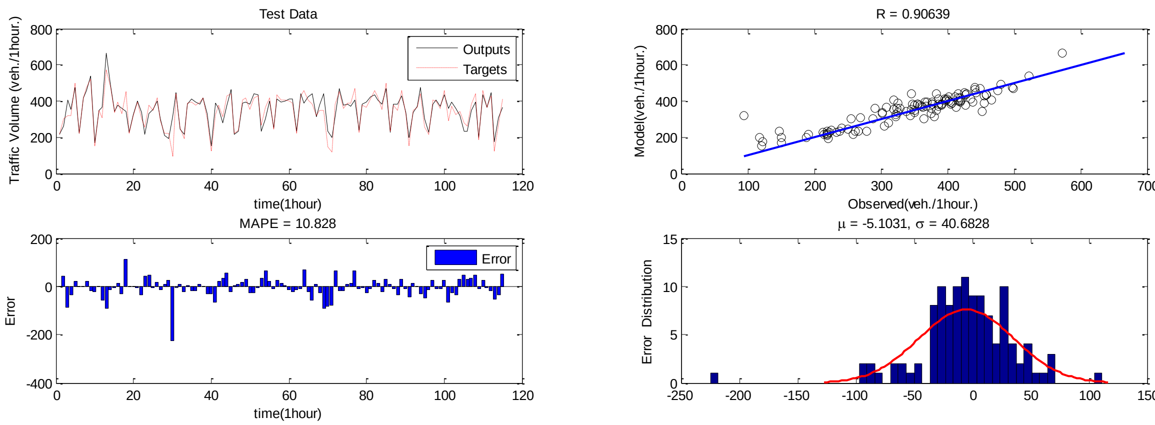

Figure 3. Traffic flow prediction using trained ANFIS by PSO using PCA-based features.

3.3 Traffic Flow Prediction using ANFIS

In this section, to predict the traffic flow, the ANFIS model, which is trained by the PSO method, is used. Randomly 70% of the data is selected for training and 30% is allocated for testing. The PSO parameters are presented in **Error! Reference source not found.**. The type of membership function used is the general bell-shaped, and there are four inputs in which each one has three membership functions. Inputs are selected using the PCA method. The data of one day before, two days before, and three days before have been chosen among 12 inputs. The results of this experiment are given in Figure 3. This figure represents the calculated values using ANFIS model and is in the opposite of the actual values, errors, and error probabilistic distribution. Furthermore, Figure 4 depicts the convergence of the related objective function.

3.4 Traffic Flow Prediction using MLP

In this section, using the PCA algorithm only 4 inputs from 12 inputs are selected as the best input, and the prediction has been performed using the MLP neural network. The number of hidden layers is 5. To train this neural network, Levenberg-Marquardt algorithm is adopted and 70% of the data is randomly selected for training. We also use 15% of data for validation, and the rest for testing.

The results of this neural network are shown in Figure 6. Each of the figures represents the output of the neural network versus the actual traffic flow data, the correlation coefficient, error, and error probabilistic distribution. In this section, data from one day to four days before the same hour has been used to predict the traffic flow.

By using PCA algorithm, the number of inputs for the prediction decreases. As a result, the volume of computation decreased significantly, and a compromise between the prediction error and the speed as well as the volume of the calculations is achieved.

4. Model Validation

In the proposed prediction engine, MLP neural network and ANFIS which are trained with PSO, are employed to predict the traffic flow hourly. Furthermore, we used the PCA method for feature selection. Although using PCA causes more

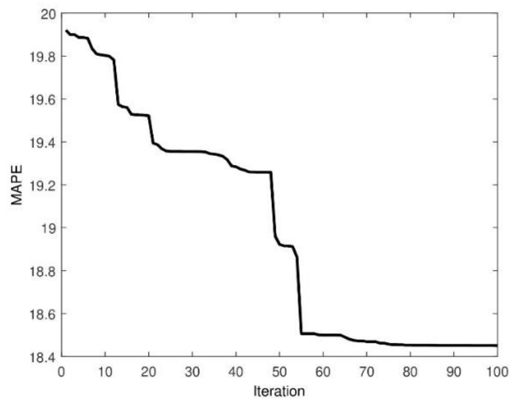

Figure 4. MAPE convergence process

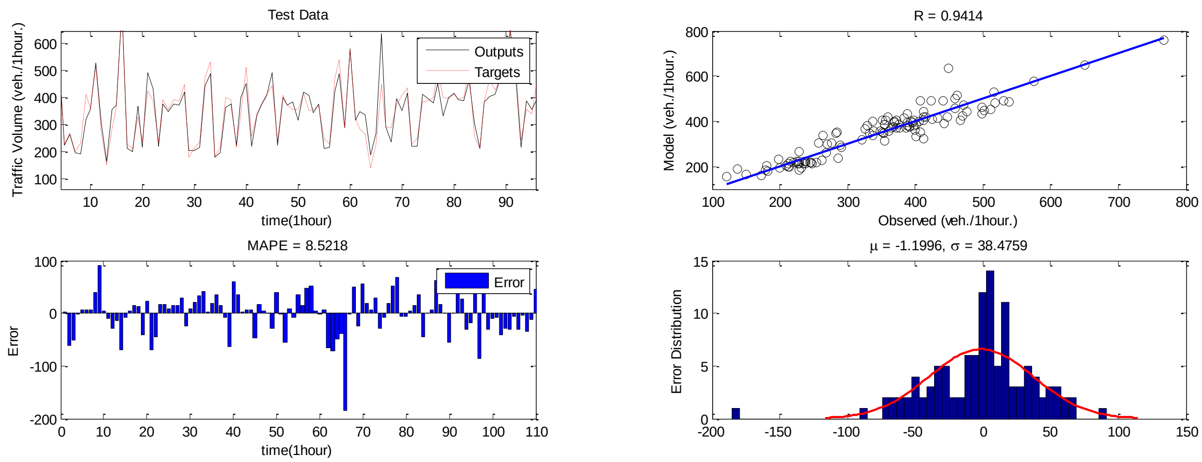

Figure 5. Traffic flow prediction using trained MLP Neural Network with Levenberg–Marquardt method using all data.

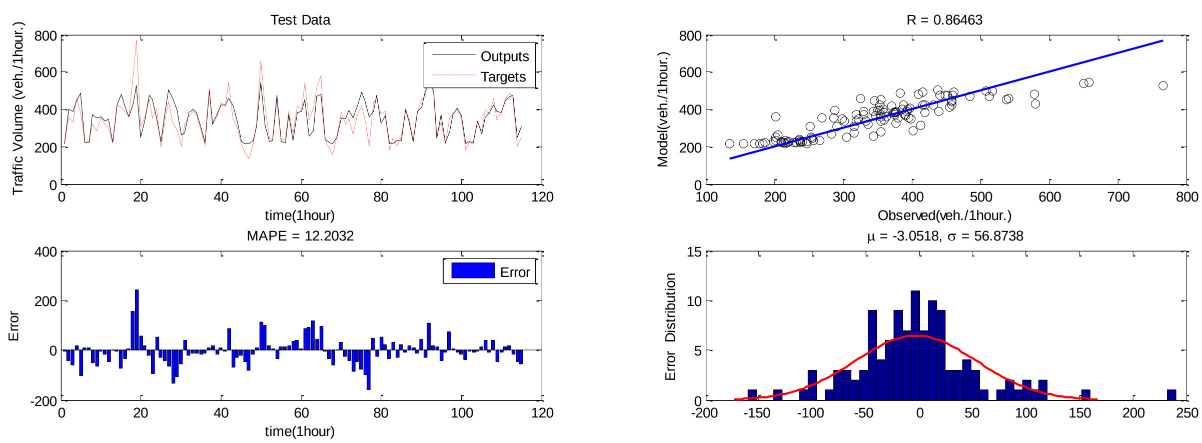

Figure 6. Traffic flow prediction using trained MLP with Levenberg-Marquardt method using PCA-based features.

Table 3. Simulation result comparison

Method	Trained NFN with PSO using PCA method.	Multi-layer Perceptron NN with PCA	Trained MLP Neural Network
MAPE	8.9289	15.401	8.5218
MAE	1.9533	48.627	32.290
VAPE	0.7417	0.0381	0.7801
SI	0.1270	0.2084	0.1148
R	0.9035	0.7765	0.9414

prediction error, the time and complexity of computations are reduced. Table 3 shows the comparison of different methods for predicting traffic flow.

The numerical results show that the proposed estimation methods have good performances in predicting traffic flow. Due to metaheuristic optimization algorithms ability in avoiding local minima, a well-tuned PSO algorithm can remarkably increase training performance in comparison with nonlinear programming optimization techniques [Esbati 2017].

The correlation factor (R) which is obtained from ANFIS trained by PSO is more than that of the trained MLP neural network models using PCA-based features. As it is depicted in the results of the Table 3, The results of the simulation with the use of ANFIS-only method shows a 38% decrease in the corresponding error while a 61% decrease in error is obtained with the use of ANFIS and PCA method together, with respect to the MLP method.

Furthermore, the results show that among the three different training methods, the performance of the Levenberg-Marquardt algorithm is the best. The minimum amount of MAPE obtained among these results corresponds to the results of the trained MLP neural network with Levenberg-Marquardt method optimization. On the other hand, the correlation factor (R) obtained by trained MLP Neural Network with Levenberg–Marquardt method is bigger than those of the trained MLP neural network with Scaled conjugate gradient and trained MLP with Gaussian Newton methods which means that the obtained results by this method are less scattered than the other two methods.

This method is also applied to the data provided for another segment of the same road which is called Aradan-Semnan. This road is adjacent to the sorkheh-Aradan section at the same corridor. Due to more data loss of this data, the trainig process was not performed perfect. Due to this zero data, the error in the results also is more than other simulation provided in this paper.

5. Conclusion

This paper proposes a traffic flow prediction method based on artificial intelligence to compensate for the sensor systems' limitations. These limitations could be due to the sensors' disconnection and the primary loss of their data stream. This field is often called resilient control, where the resilience of a sensor system is tending to be improved by different control methods. The multi-layer perceptron neural network method, Adaptive Neuro-Fuzzy System (ANFIS) and particle swarm optimization (PSO) algorithm are used to predict the traffic flow in the proposed predictor engine.

The precision of prediction depends on the data which is used as the input of the prediction engine. However, increasing the number of inputs will raise the complexity and computation time and even may lead to failure. In this paper, the Principal Component Analysis (PCA) method is used to compress and reduce the dimension of the input data without any further data loss. This technique calculates the directions in which the data variance has the highest value.

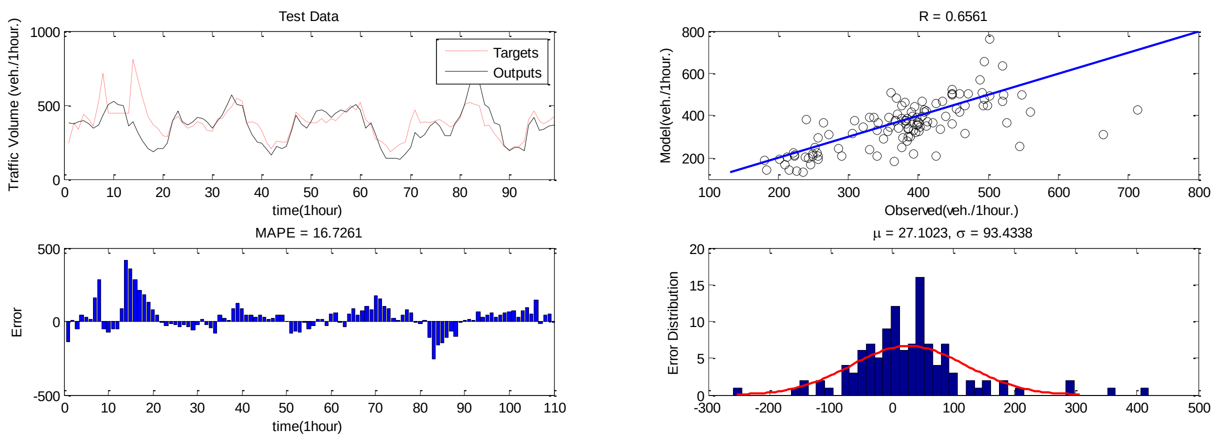

Figure 7. Traffic flow prediction using trained MLP Neural Network with Levenberg–Marquardt method using all data for Aradan-Semnan.

Therefore, the high precision prediction operation is performed for every one-hour interval. The prediction is applied to the data gathered from one of Iran's main roads. The resulting simulation data indicates that the proposed method compromises the time and complexity of computations and prediction error. In other words, with a slight increase in error, the complexity of computation significantly decreases.

Simulations conducted in this paper show that both the MLP and the NFN-PCA method are more prominent and efficient to conduct the traffic flow prediction by far in comparison to the other methods such as MLP-PCA. The MLP method is also applied to another data from different section of the road. These data are obtained at the same time; therefore, the results are comparable with each other. Thus the MLP is both performed on two different sections of the road and different methods are applied to certain section road and after all the MLP method is proven to be the most efficient. It can be concluded that this algorithm is effective to predict the traffic flow in high-volume networks. The proposed method also provides a reliable sensor system in the case of sensor disconnection.

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7. APPENDIX

6.1 Particle swarm optimization Algorithm

Particle Swarm Optimization (PSO) algorithm is an evolutionary population-based method that has many key benefits in comparison with other similar optimization methods. Fewer parameters to set, being computationally efficient and easy implementation for various problems could be named as some of the PSO's advantages. The primary version of the PSO algorithm has some weak points in its local search. More precisely, in PSO algorithm particles tend to quickly converge around an optimal global response, but local searches often take a long time to find the exact location of an optimal global point. Revisions, however, have been made in the new versions. In general, the PSO algorithm has the following steps:

1. ***Step 1:*** Create the initial population and evaluate it.
2. ***Step 2:*** Determine the personal experience as well as the best experience of the whole group (particles).
3. ***Step 3***: Update position and speed using equations below.

$$V_i^{k+1} = wv_i^k + c_1r_1\left(Pbest_i^k - x_i^k\right) + c_2r_2\left(Gbest^k - x_i^k\right) \quad (7)$$

$$X_i^{k+1} = x_i^k + v_i^{k+1} \quad (8)$$

Where c_1 and c_2 are two positive constants. r_1 and r_2 are two random numbers with a uniform distribution in the range of $0\ to\ 1$. W is the weighted weight chosen as in equation below:

$$W = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} * iter \quad (9)$$

Step 4: Determine the stop conditions according to the objective function and if the conditions are not met, go back to step 2 [Trelea 2003].

While the resilience control is being used to update the lagged information of the Sorkhe-Aradan and Tehran-Semnan road, in future a comparison will be done on the data from different roads of Iran to obtain their cross correlation. This will let us obtain the relationship between traffic flow of these roads which eventually leads to methods to decrease the error in traffic flow prediction. As reported in the figure, the results of the Tehran-Semnan road are not as precise as the data for Sorkhe-Aradan because the sensor cottage was of higher rank than the Sorkhe-Aradan road. From 1140 data point 189 was due to cottage. Due to this cottage, the results is of less quality which emphasizes on the role of the validity of the data being used for test and learning procedure.