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Midterm Air Pollution Monitoring and Prediction Based on Adaptive Neural Fuzzy Inference System

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***Abstract:** The prediction air pollutants plays a decisive role in taking preventive measures in the community. In this paper, using the data received from the measurement centers of the air pollutants in different regions of Tehran and with the help of the intelligent approach of the adaptive networks-fuzzy inference systems, a scheme is designed that can automatically Forecast the amount of air pollutants in a few hours in future. For this purpose, two common pollutants of Sulfur dioxide and particulate matters have been selected. Therefore, in short-term and mid-term phases, the proposed algorithm is studied and the simulation results are analyzed in each phase. Simulation results indicate high accuracy in the short term forecast as well as acceptable accuracy in the mid-term forecast.*

***Keywords:** Air Pollution Prediction, Adaptive Neural-Fuzzy Inference Systems, Neural Network.*

I. INTRODUCTION

Air pollution prediction has become an important task in environmental modelling. In the prediction area, different methods have been applied. Some studies exploited neural networks in the prediction[1-5]. Different neural network structures have been employed and the results were also investigated for different air pollutant and particles. Classification techniques such as support vector machines and pattern recognition algorithms have been also applied on the prediction problem [6]. Machine learning models along with kernel models are among the other techniques applied in this context[7-9]. Some authors have been applied Markov models (HMM) to prediction[10-13]. Basically, we can divide these models into two categories. Some models exploit deterministic approaches[14-16] and some others use stochastic models[17]. As an example, in [17], a Bayesian network classifier can be used to estimate the probability of an air pollutant overcoming a certain threshold. By designing a multi-level classifier and learn it, the authors have improved the accuracy of the prediction system. Prediction of particulate matter in Taiwan has been proposed in {Soh, 2017 #835} by Dynamic Time Warping approach. The mentioned study discussed the distribution of PM and its cyclicality. In the context of smart cities and by developing internet of things (IoT) communication, {İ, 2017 #831} tried to use deep learning of big data in the air pollution concept. The authors in {Xi, 2015 #834}, have implemented the air pollution prediction system in 74 cities in China using the machine learning algorithm to enhance the system accuracy. In [12], based on the air quality data from Beijing, Tianjin and Shijiazhuang from 2001 to 2010, the dependency between the air pollution index (API) and climatological factors were investigated exploiting correlation analysis and principal component regression. In [8], according to the 2001–2010 data of air quality of Jinan City in Shandong province, the GM(1,1) model was formed based on gray system theory to estimate the ambient air pollution level in the next five years.

To exploit advantages of both methods, i.e., deterministic and stochastic methods, we adopted Takagi-Sugeno-Kangneural-fuzzy inference system to predict both short-term and mid-term air quality. We consider extra variables as system inputs such as humidity and wind speed to improve the previous studies in order to be used for citizens in smart city healthcare systems.

II. SYSTEM MODEL

In this section, Takagi-Sugeno-Kang inference system briefly described. This is a popular fuzzy logic system. The rules is as follows.

$$\begin{aligned}&\text{Rule } i: \text{ if } z_1 \text{ is } A_1^{i,k_1}, z_2 \text{ is } A_2^{i,k_2}, \cdots, \text{and } z_m \text{ is } A_m^{i,k_m}\\ &\quad \text{then } y^i = a_1^i x_1 + a_2^i x_2 + \cdots + a_q^i x_q \\ &\quad i = 1,2,\cdots,R.\ k_j = 1,2,\cdots,r_j.\end{aligned} \tag{1}$$

In which R is the number of rules in the system. z_j $(j = 1,2,\cdots,m)$ is the j-th characteristic variable that reflects different operating system status. x_l*(l =1, 2, ..., q)* is the l-th input and y^i is the output for the i-th rule. For the i-th rule, $A_j^{i,kj}$ is the fuzzy set of Z_j. The output is:

$$y = \sum_{i=1}^{R} \mu^i y^i \Big/ \sum_{i=1}^{R} \mu^i \tag{2}$$

In which μ^i is:

$$\mu^i = \bigwedge_{j=1}^{m} A_j^{i,k_j}\left(z_{j0}\right)$$

(3)

Finally, the output can be written as:

$$y = \left(\sum_{i=1}^{R} \mu^i a_1^i x_1 + \cdots + \sum_{i=1}^{R} \mu^i a_q^i x_q\right) \Big/ \sum_{i=1}^{R} \mu^i \tag{4}$$

Adaptive fuzzy-neural inference system is an intelligent method based on data deriving from expert system

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which exploit both the advantages of fuzzy and neural network systems. The structure of such system is depicted in Fig.1

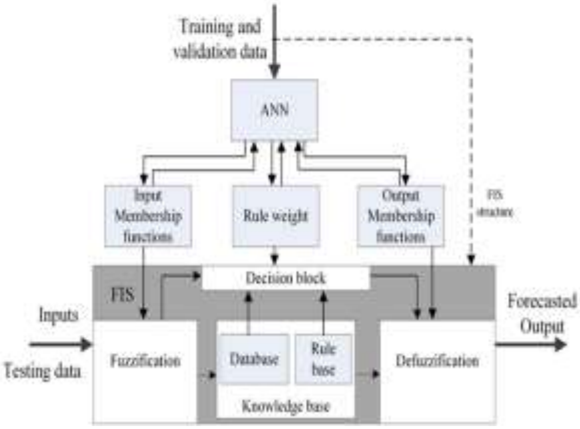

Fig. 1. Fuzzy-Neural Inference System Structure

III. PREDICTING POLLUTANTS

As we know, the first step in predicting air pollution is the prediction of the amount of particulates in the air. By obtaining the information from sensors, it can be specified whether the air is polluted or not. Different factors in the air are CO, O_3, NO_2, $SO_2$and so on. If the intensity of each factor in the air becomes more than a predefined threshold, it is said that the air is polluted. The structure of the predictive system is illustrated in Fig. 2. The main goal is to predict the value of particulates in the next hour by having those for the last three hours. To improve the system performance, we have used three factors of temperature, humidity and wind speed.

Fig. 2. Prediction System Structure

The data related to the past two days of each factor is depicted in Fig. 3. As depicted in Fig. 2, the proposed system has 8 inputs. These inputs have to be fuzzified. For each input, two membership triangular functions have been considered. These membership functions are shown in Fig. 4.

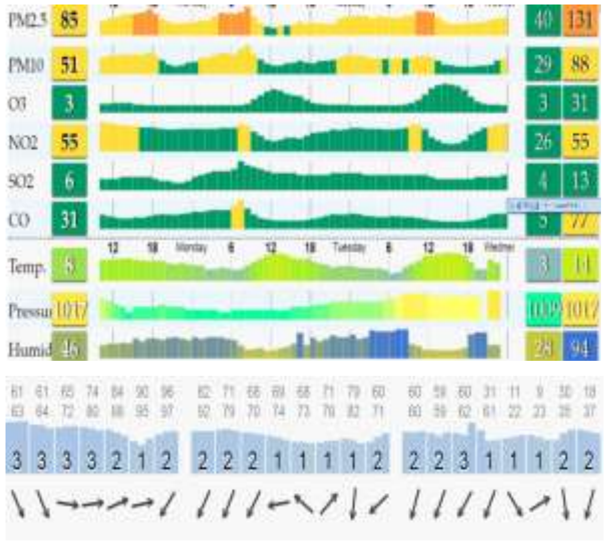

Fig. 3. Data from Different Factors Related to the Last 2 Days

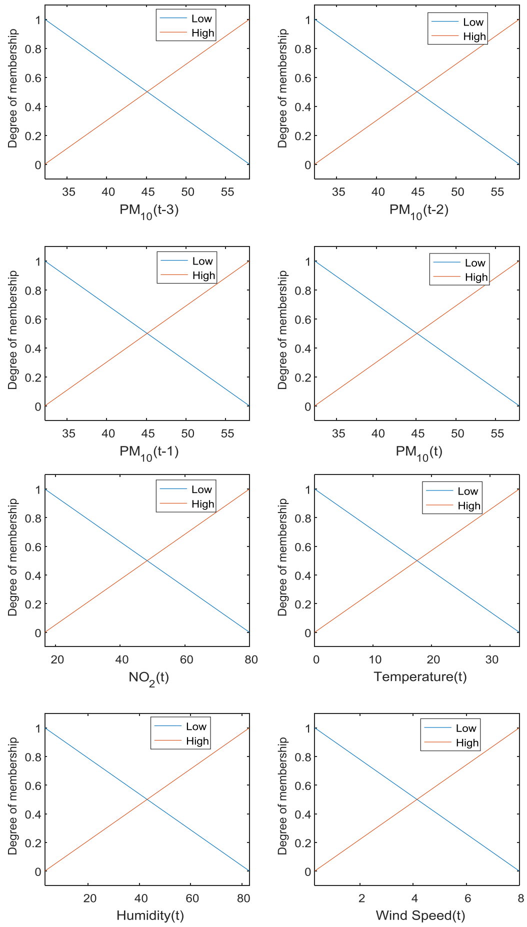

Fig. 4. Membership Functions Related to 8 Inputs

The sampled data for these 8 inputs are shown in Fig. 5.

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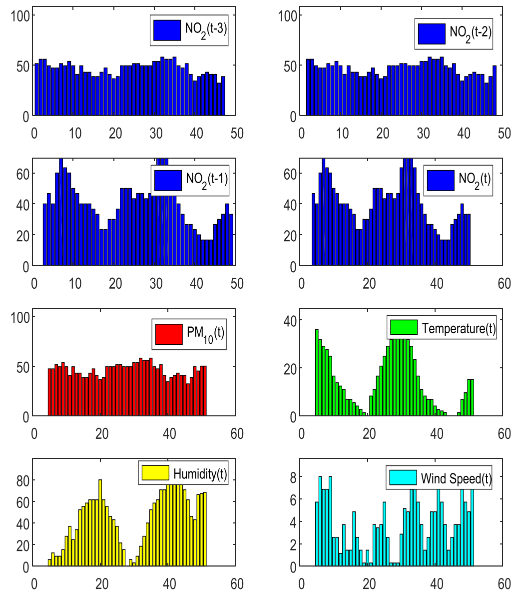

Fig. 5. Sampled Data Related to 8 Inputs

IV. SIMULATION RESULTS

In this section, the simulation results for the fuzzy-neural inference prediction system in given and discussed. Two scenarios are simulated. In the first, the next hour prediction system is designed by exploiting the last 48-hour data. In the second scenario, the amount of particulates for the next 6 hours is predicted by the past 48-hour observed data. The results are then compared with the real values. By applying 75% of the whole sampled data as training data to the proposed system, the output of the system which predicts the short-term amount of particulates is given in Fig. 6. Furthermore, the prediction error is also provided.

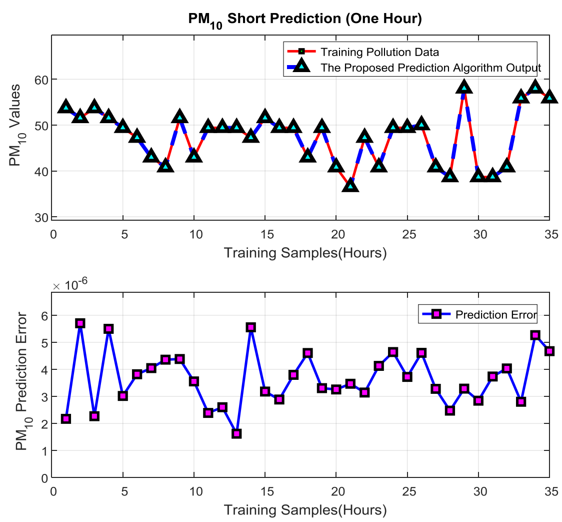

Fig. 6. System Output and Error for Short-Term Prediction

The remaining 15% of data is reserved for test and the 10% of the last is used for validating the system. Fig. 7 shows the system results as well as the performance error when applying test data.

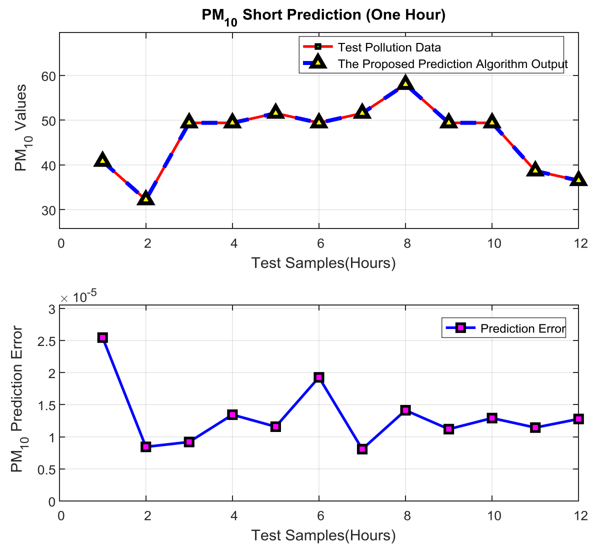

Fig. 7. System Output and Error for Short-Term Prediction of Test Data

Fig. 8 shows the system results as well as the performance error when applying validation data. As can be seen, the proposed system has high performance.

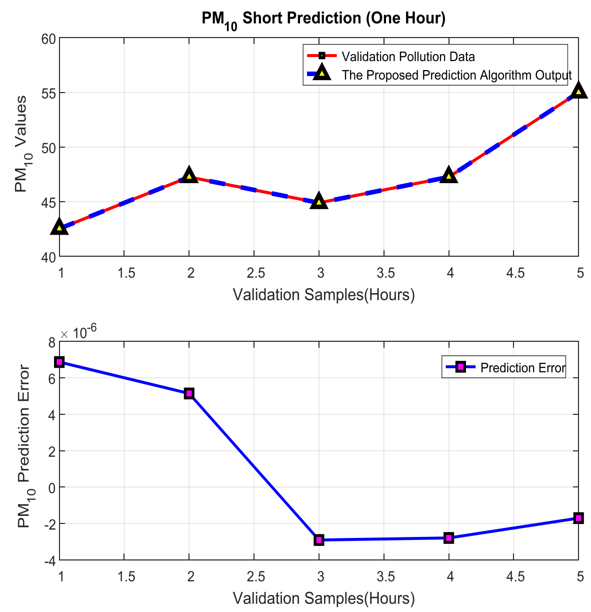

Fig. 8. System Output and Error for Short-Term Prediction of Validation Data

In the case of mid-term prediction, the next 6-hour amount of the pollutants are predicted. For the test data, the system output and error is depicted in Fig. 9.

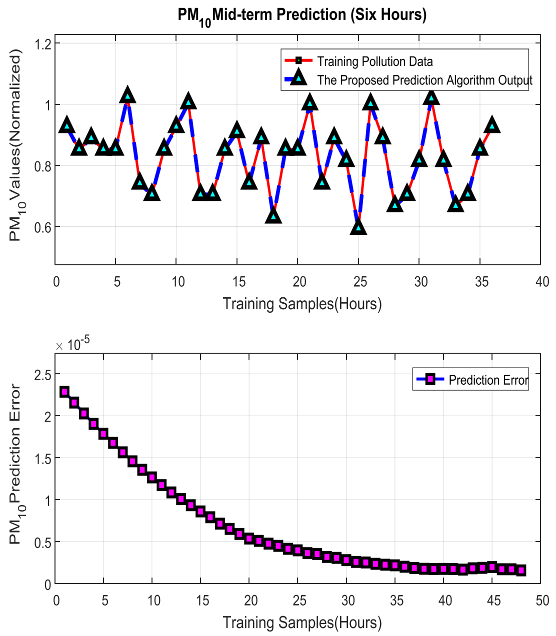

Fig. 9. System Output and Error for Mid-Term Prediction

Fig. 10 shows the system results as well as the performance error when applying test data on mid-term prediction. As can be seen, the proposed system has high performance.

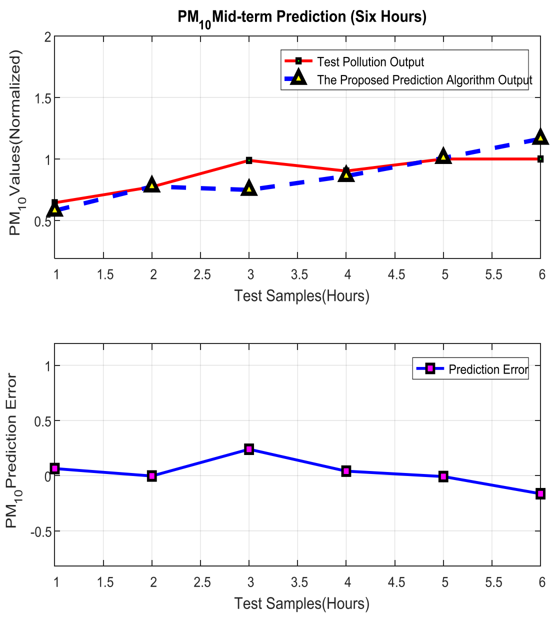

Fig. 10. System Output and Error for Mid-Term Prediction of Test Data

Fig. 11 shows the system results as well as the performance error when applying validation data on mid-term prediction. As can be seen, the proposed system has high performance.

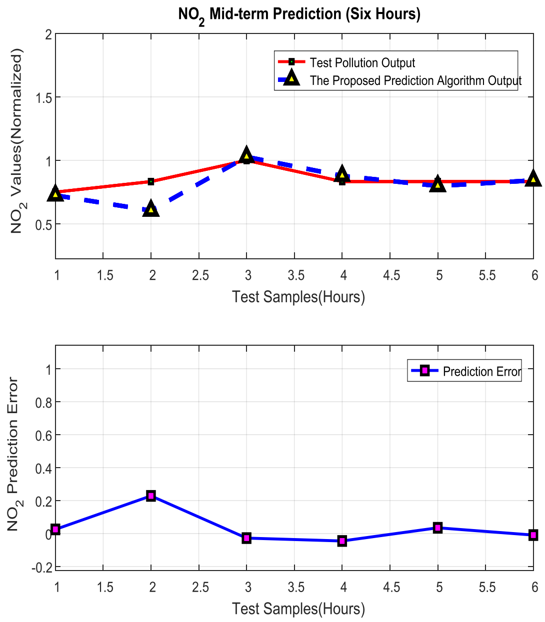

Fig. 11. System Output and Error for Mid-Term Prediction of Validation Data

V. CONCLUSIONS

In this paper, we proposed adaptive fuzzy-neural inference system in which air pollution is predicted both for mid-term and short-term scenarios. Besides popular inputs, we considered temperature, humidity and wind speed to improve the accuracy of the prediction. The simulation results show that the performance of the predictor is high compared to other systems.

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