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Modeling the concentration of suspended particles by fuzzy inference system (FIS) and adaptive neuro-fuzzy inference system (ANFIS) techniques: A case study in the metro stations

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Abstract
Background: Today, the usage of artificial intelligence systems and computational intelligence is increasing. This study aimed to determine the fuzzy system algorithms to model and predict the amount of air pollution based on the measured data in subway stations.
Methods: In this study, first, the effective variables on the concentration of particulate matter were determined in metro stations. Then, $PM_{2.5}$, PM_{10}, and total size particle (TSP) concentrations were measured. Finally, the particles' concentration was modeled using fuzzy systems, including the fuzzy inference system (FIS) and adaptive neuro-fuzzy inference system (ANFIS).
Results: It was revealed that FIS with modes gradient segmentation (FIS-GS) could predict 76% and ANFIS-FCM with modes of clustering and post-diffusion training algorithm (CPDTA) could predict 85% of $PM_{2.5}$, PM_{10}, and TSP particle concentrations.
Conclusion: According to the results, among the models studied in this work, ANFIS-FCM-CPDTA, due to its better ability to extract knowledge and ambiguous rules of the fuzzy system, was considered a suitable model.
Keywords: Artificial intelligence, Railroads, Cluster analysis, Air pollution, Particulate matter
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Introduction

Today, the use of algorithms to predict phenomena in processes with a dynamic state and data with time series is increasing. Fuzzy systems and artificial intelligence are used to study the dynamic nature and ambiguous behaviors of data, and these techniques can be employed to model air pollution in terms of time. In recent years, air pollution has been known as one of the major environmental problems (1). The International Agency for Research on Cancer (IARC) has identified air pollution in general, and particulate matter (PM) in particular as carcinogenic (2). About 3.8 million deaths occurred due to indoor air pollution (3).

The subway is one of the places where people are exposed to polluted indoor air. The high concentration of air pollutants in subway stations will create critical and worrying effects because there are many travelers, passengers, and employees in this setting (4).

Various studies show that the concentration of air pollutants in the subway is higher than that in the outdoors. In a study conducted by Mousavi Fard et al, the average annual concentration of particulate matter with a diameter up to 2.5 µm ($PM_{2.5}$) and particulate matter with a diameter up to 10 µm (PM_{10}) in the subway was 1.5 and 1.7 times higher than that in the outdoor, respectively (5). In a study by Kwon et al, PM_{10} concentration in Seoul subway stations was two to three times higher than the outdoor (6). In a study by Aarnio et al, $PM_{2.5}$ concentration in the Helsinki underground metro stations was five to six times higher than in urban environments (7). Barmparesos et al showed that the PM concentration in Athen's subway system was reported to be 3 to 10 times higher than that in the outdoor environment (8). Contrasting results have been reported in several studies. In a review by Xu and Hao, the average number of particles in the ambient air and tunnel platforms was reported to be lower than the standard level (9). Also, in the Seoul subway station, the installation of a ventilation system reduced the PM concentration up to 80% (10). By identifying the factors affecting the increase in the concentration of particles in the subway air, its dangers can be prevented or reduced, as mentioned by Zhang et al in 2022 (11). In subways, high concentrations of pollutants can be due to the following factor: 1. The subway environment is relatively closed, so the inside air cannot circulate completely and mix with an adequate amount of fresh air. 2. The erosion of wheels and rails from train numerous brakes, air turbulence in the station and inside the tunnel, and poor monitoring and maintenance (12). Measurement and assessment of air pollutants, especially in closed environments such as subways, play an important role in determining ambient air conditions and control operations, but this monitoring requires many human resources and high cost (13). Also, there is uncertainty in most of the data and parameters affecting air pollution in the subway (13). The fuzzy system can analyze linguistic information and execute processes by displaying knowledge, reasoning, and taking into account uncertainty. One of the main components of a fuzzy inference system (FIS) is the knowledge base, which consists of "if-then" rules. The fuzzy system can provide decision-making and response using fuzzy inference rules (14). Designing and defining the appropriate form of these rules can play an effective role in determining the optimal system for the prediction of air pollution. In a study by Assimakopoulos et al on underground trains in Athens, the results showed that FIS can predict indoor air quality (15). In a study by Kim et al on the Korean metro system, a seasonal model was suggested for monitoring and forecasting indoor air quality (16). The modeling of air pollution is a useful and required issue, in particular in indoor environments. Therefore, the present study aimed to determine fuzzy system algorithms to model and predict the amount of air pollution based on the measured data (tunnel cleaning, station ventilation system, geographical location, season, airflow speed, tunnel length, ceiling height, *station height to ground level [*station depth*],* brake pad type, passenger density, relative humidity, days of the week, interval of train arrival at the station, type of train, and temperature) in metro stations. By predicting the particle concentration based on the factors affecting it in subway stations, it will save time and money.

Materials and Methods

This case study was conducted in the two seasons of autumn and spring 2021 on Tehran Metro Line 1. This line was chosen because Tehran Metro Line 1 has several stations with platforms of different heights and lengths, and it is also one of the longest lines of Tehran Metro, which is located from north to south of Tehran and has geographical diversity. Its different stations have different population densities (4). From 29 stations of Tehran Metro Line 1, 12 underground stations were selected. The criteria for selecting the stations include having different characteristics in terms of passenger density, platform height, geographical location, and being equipped with a mechanical ventilation system. The concentration of airborne particles was examined in different conditions.

The main steps of this study are presented below.

Determination of effective variables

The variables affecting the concentration of particles in metro stations were identified by a literature review (17-27), technical reports, and specialized interviews with experts in the health, safety, and environment (HSE) metro department, then, a list of these variables was prepared.

The initial list of variables was designed as a questionnaire based on Lawshe's method (28). The questionnaires were completed by 40 persons from experts and experienced employees in the HSE department in the metro, and content validity ratio (CVR), content validity index (CVI), and Cronbach's alpha coefficient were calculated to be 13.4, 0.8375, and 0.79, respectively.

After confirming the initial list of variables, the judgment matrix was ready and answered by 15 people with high experience in the occupation of the metro HSE department, to be weighted the variables. Then, to weigh the variables, the data were analyzed by Expert Choice software and the analytic hierarchy process (Table 1).

In the next step, the balanced scorecard (BSC) was

Table 1. Weighting the variables affecting the concentration of particles in the metro stations

Variable	Weight values	Measurement unit
Tunnel cleaning	0.115	Dry wash/wet wash
Station ventilation system	0.091	On/off
Geographical location	0.09	North/Center/South
Season	0.077	Spring/summer/fall/winter
Airflow speed	0.069	Meter per second) m/s (
The tunnel length	0.068	Meters (m)
Ceiling height	0.065	Meters (m)
station height to the ground level (station depth)	0.062	Meters (m)
Brake pad type	0.06	Ceramic, without organic asbestos, metallic without asbestos, metallic with asbestos
Passenger density	0.057	Number in a day (N)
Relative humidity	0.052	Percentage (%)
Days of the week	0.05	Early week/midweek/late week
Interval of train arrival at the station	0.05	Minutes (min)
Type of train	0.044	Alternating current (AC), direct current (DC)
Temperature	0.039	Centigrade (℃)

provided, and sub-variables were defined for each variable based on the literature review and similar studies (17-27,29). Then, the subgroups of each variable were approved by the same people. The final changes and corrections in the variables were made based on the opinions of experts. Eventually, BSC about the subgroups of each variable was determined by five people who had at least 20 years of experience in subway safety (Table 2).

Measurement of pollutants concentration

In this study, the particle concentration was measured in three sizes: the concentration of particulate matter less than 2.5 µg/m^3 in diameter ($PM_{2.5}$), total size particle (TSP), and the concentration of particulate matter less than 10 µg/m^3 in diameter (PM_{10}) during the two seasons of autumn and spring on every day of the week. Tehran Metro Line 1 is one of the busiest lines in Tehran Metro. This intercity line has 29 stations.

Among 29 stations, 7 and 22 stations are ground and underground, respectively. Ground stations do not have a mechanical ventilation system and operate on natural ventilation. In this study, having a mechanical ventilation system was considered as a criterion for station selection. Therefore, among 22 underground stations, 12 stations equipped with mechanical ventilation systems with different station heights to ground level (station depth) and geographical locations were randomly selected. In this study, the concentration of suspended particles was determined via direct reading, calibrated (the calibration was done in a comparative manner using the 7.851 calibration tower device with an error rate of ± 3% of the read dust concentration), and portable air monitor device (EPAM-5000 model, SKC Co, America) through OSHA CIM instructions. In this method, air is drawn by a vacuum pump through a membrane filter with a diameter of 47 mm, and the concentration of dust particles per second is detected. The sampling flow rate, working temperature, and humidity in this device were 1- 4.3 liters per minute (L/m), -10 to 50 °C, and 95%, respectively. Dust concentrations were immediately calculated and displayed on the LCD –SKC EPMA-5000. Also, the particle concentration in each station was measured at three points, the beginning, middle, and end of the platforms. At the end of each sampling period, measurement data was transferred to a computer for analysis (30).

Modeling the pollutants concentrations

The value of the three output variables was measured in µg/m^3 at each point ($PM_{2.5}$-PM_{10}-TSP) and the data of 15 input variables, which are obtained by multiplying the weight of each of them in the score of each variable (based on the scoring cards), was entered into Excel software. The entered data were finally normalized to be ready to enter the fuzzy system. Thus, to predict and model the concentration of the three types of fine dust studied,

Table 2. Balance score card (BSC) about the subgroups of each variable affecting the concentration of particles in metro stations

Variable (unit)	Subgroup	Score
Cards brake pad	Ceramic pads	1
	Pants without organic asbestos	0.75
	Semi-metallic pads	0.5
	Metallic pads without asbestos	0.25
	Metallic pads with asbestos	0
Type of train (AC, DC)	AC	1
	AC (70%), DC (30%)	0.75
	AC (50%), DC (50%)	0.5
	AC (30%), DC (70%)	0.25
	DC	0
Relative humidity (%)	60-80	1
	50-60	0.5
	40-50	0.25
	< 40 or > 80	0
Temperature (ċ)	18-22	1
	22.5-27	0.5
	27-37	0.25
	< 17.5 or > 40	0
Geographical location	South (Khayyam-Kahrizak)	1
	North (Tajrish-Mosalla of Imam Khomeini)	0.5
	Center (Beheshti-15 June)	0
Tunnel cleaning (dry wash/wet wash)	Wet wash, dry wash	1
	Wet wash	0.5
	Dry wash	0.25
	No washing	0
Interval of train arrival at the station (min)	10-20	1
	5-10	0.5
	3-5	0.25
	2-3	0
Air conditioning system (on/off)	On (moisturizing filtration)	1
	On (filtration)	0.75
	On (moisturizing)	0.5
	On (no moisturizing and filtration)	0.25
	Off	0
Passenger density (number in a day)	< 400	1
	400-1000	0.8
	1000-2000	0.6
	2000-4000	0.4
	4000-5000	0.2
	> 5000	0
Ceiling height (m)	> 4	1
	3-4	0.5
	2-3	0.25
	< 2	0

Table 2. Continued.

Variable (unit)	Subgroup	Score
Station height to ground level (station depth) (m)	0	1
	0-10	0.75
	10-20	0.5
	20-50	0.25
	>50	0
The length of the tunnel (m)	200	1
	200-500	0.75
	500-1000	0.5
	1000-1500	0.25
	>1500	0
Days of the week	Weekend: (Thursday-Friday)	1
	Mid-week: (Tuesday-Wednesday)	0.5
	Earlier in the week: (Saturday-Monday)	0
Airflow speed (m/s)	8-10	1
	6-8	0.8
	4-6	0.6
	2-4	0.4
	0.7-2	0.2
	<0.7	0
Season	Summer	1
	Spring	0.5
	Winter	0.25
	Autumn	0

AC: Alternating current, DC: Direct current.

modeling was done by FIS and adaptive neuro-fuzzy inference system (ANFIS) system. The two models used in this study are shown in Figure 1.

Training and design

The measured data were scattered, and to generalize the network to the whole data and obtain rules, 80% of the total data was used for training, 10% of the data was considered as check data and 10% for testing. In choosing the check and test data, considering that the data have different dimensions, and also, the direct effect of each parameter, the test and check data should be a good representative of the whole data. Also, since a large number of input variables reduces the transparency of the model and increases the complexity of the calculations, the effectiveness of the parameters was investigated. The results of the correlation matrix showed that for all three types of fine particles studied, the ventilation system (highest effect), cleaning of the station, days of the week, and passenger density are recognized as influential variables and entered into the model (15).

Evaluation of the proposed models

There were two ways to evaluate the proposed model: The rules generated at each station or area were evaluated statistically using test data from the same station or area. The accuracy of each station was assessed separately. The accuracy of predicting the pollutant concentration of all stations was evaluated simultaneously. Statistical tests such as RMSE (root-mean-square error), IA (index of agreement), FB (fractional bias), MBE (mean bias error), MAE (mean absolute error), AIC (Akaike information criterion), R (correlation coefficient), and R^2 (R-squared) were used for statistical analysis (13).

In the present research, considering that we were in a fuzzy set for accurate prediction of three types of airborne particles against the test and evaluator data, it depends on the measurement of a certain type of uncertainty. As a result, by epocing the modeling process 5000 times, the optimal point was determined and the uncertainty of the models was predicted.

Results

As shown in Table 3, the station, ventilation system, season, and geographical location were identified as the principal variables. Based on the analysis of variance (ANOVA) test, a statistically significant difference was observed between $PM_{2.5}$, PM_{10}, and TSP concentrations with station and ventilation system variables ($P<0.05$) (Table 3).

After entering the data into the software and selecting the check and test data for each parameter, the rules of fuzzy and fuzzy-neural inference systems were implemented in different cases. Then, the prediction modeling of the three types of fine dust was performed.

After specifying the fuzzy and fuzzy-neural laws, the prediction modeling of the three types of fine dust was done.

After entering the data into the software and selecting the check and test data for each of the parameters in different modes, the rules of the FIS were implemented. And after defining the fuzzy rules in the form of triangular fuzzy and trapezoidal models, the three types of micro-rounds were predicted. The characteristics of the designed systems (FIS and ANFIS) are given in Table 4. Figure 2 shows the rules used in model design.

In FIS-FCM, MBE test, with the highest strength compared to other tests, can predict 70%, 73%, and 76% concentrations of $PM_{2.5}$, PM_{10}, and TSP, respectively. In ANFIS-FCM (C-P.DTA), MAE test, with the highest strength compared to other tests, can predict 85%, 87%, and 85% concentrations of $PM_{2.5}$, PM_{10}, and TSP, respectively. The results from the accuracy of predicting the concentration of the pollutants for each designed system are shown in percent in Table 5.

According to Table 5, the closer the prediction accuracy to one, the higher the prediction rate of that model.

According to Table 6, the closer the uncertainty to zero, the higher the certainty of that model.

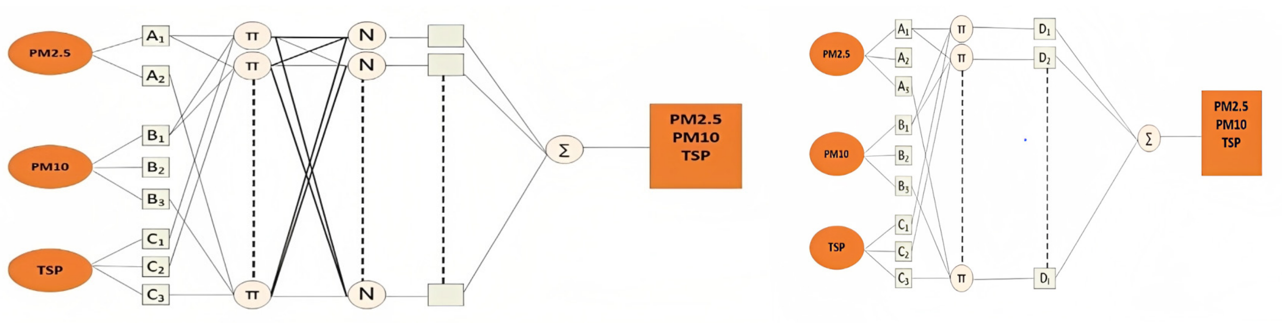

Figure 1. The architecture of FIS (a) and ANFIS (b)

Table 3. The effects of principal variables on the PM (μg/m³(concentration according to ANOVA test

Particulate Matter	Variable	*P* value
$PM_{2.5}$	Station	<0.001*
	Air conditioning system (ventilation system)	<0.001*
	Season	0.244
	Geographical location	0.085
PM_{10}	Station	<0.001*
	Air conditioning system (ventilation system)	<0.001*
	Season	0.218
	Geographical location	0.007*
TSP	Station	<0.001*
	Air conditioning system (ventilation system)	<0.001*
	Season	0.019*
	Geographical location	0.031*

* P<0.05.

Table 4. The features of designed systems (FIS and ANFIS)

Network type	Extraction of fuzzy basic rules	Input function operator	Network training algorithm	Output function operator	Non-fuzzy method
FIS	GS	AND	FI	OR	CGM
	FCM	AND	FI	OR	CGM
ANFIS	GS	AND	PD	OR	CGM
	GS	AND	C	OR	CGM
	FCM	AND	PD	OR	CGM
	FCM	AND	C	OR	CGM

FIS: Fuzzy inference system, ANFIS: Adaptive neuro-fuzzy inference system, GS: Grade segmentation, FCM: Fuzzy cognitive map, FI: Fuzzy inference, PD: Post diffusion, C: Compound, CGM: Center of gravity method.

Discussion

Indoor air pollution without proper ventilation has always been major safety and health challenges in these enclosed spaces. Today, with the rapid advancement of science and technology, artificial intelligence systems and computational intelligence, in general, have become increasingly important; computational intelligence tries to simulate and reconstructs the characteristics of intelligence such as learning and adapting it. Its main branches are fuzzy logic, neural networks, and evolutionary algorithms. Research in hybrid algorithms is one of the important topics in computational intelligence studies. By combining fuzzy logic and neural networks due to the complementary of these two systems, the advantages of both systems can be used together (31). The neural-fuzzy network gives us the ability to use the learning ability of the neural network to express the required knowledge about the desired phenomenon in the form of appropriate rules without the need for an expert. In this study, the factors affecting the concentration of airborne particles in Tehran metro stations were comprehensively studied and for the first time, the concentration of airborne particles in Tehran metro stations was predicted through the fuzzy system and the fuzzy-nervous system. There are few similar studies in the field of fuzzy modeling of airborne particle concentrations in subway stations around the world.

Modeling of the concentration of pollutants in the metro air, prediction and modeling of the concentration of pollutants using fuzzy rules (Sugno, Mamdani) were obtained in two forms: Mamdani FIS and ANFIS system. ANFIS was used to obtain the appropriate Sugeno rules, in which the FCM gradient segmentation and reduction-clustering methods were used to generate fuzzy basics using the available data. FCM and hybrid were used to create the Mamdani rules.

In these systems, the basic rules were extracted using data from the methods of segmentation of the input-output space and reduced clustering. In the first model, fuzzy rules (Mamdani) model training is considered based on knowledge discovery rules and prediction is done in two ways- gradient classification and FCM. Also, the weights that experts have given to the parameters affecting the level of metro pollution are considered. In the second proposed model, the data collected at each station are used to train the ANFIS network. To do this step, in each data model, the data were divided into three categories, educational data (80% of data), check data (10% of data), and test data (10% of data). The training data were then categorized using the FCM clustering method. Matlab software in a Linux environment was used to teach the network. This software provides a convenient environment for performing mathematical operations,

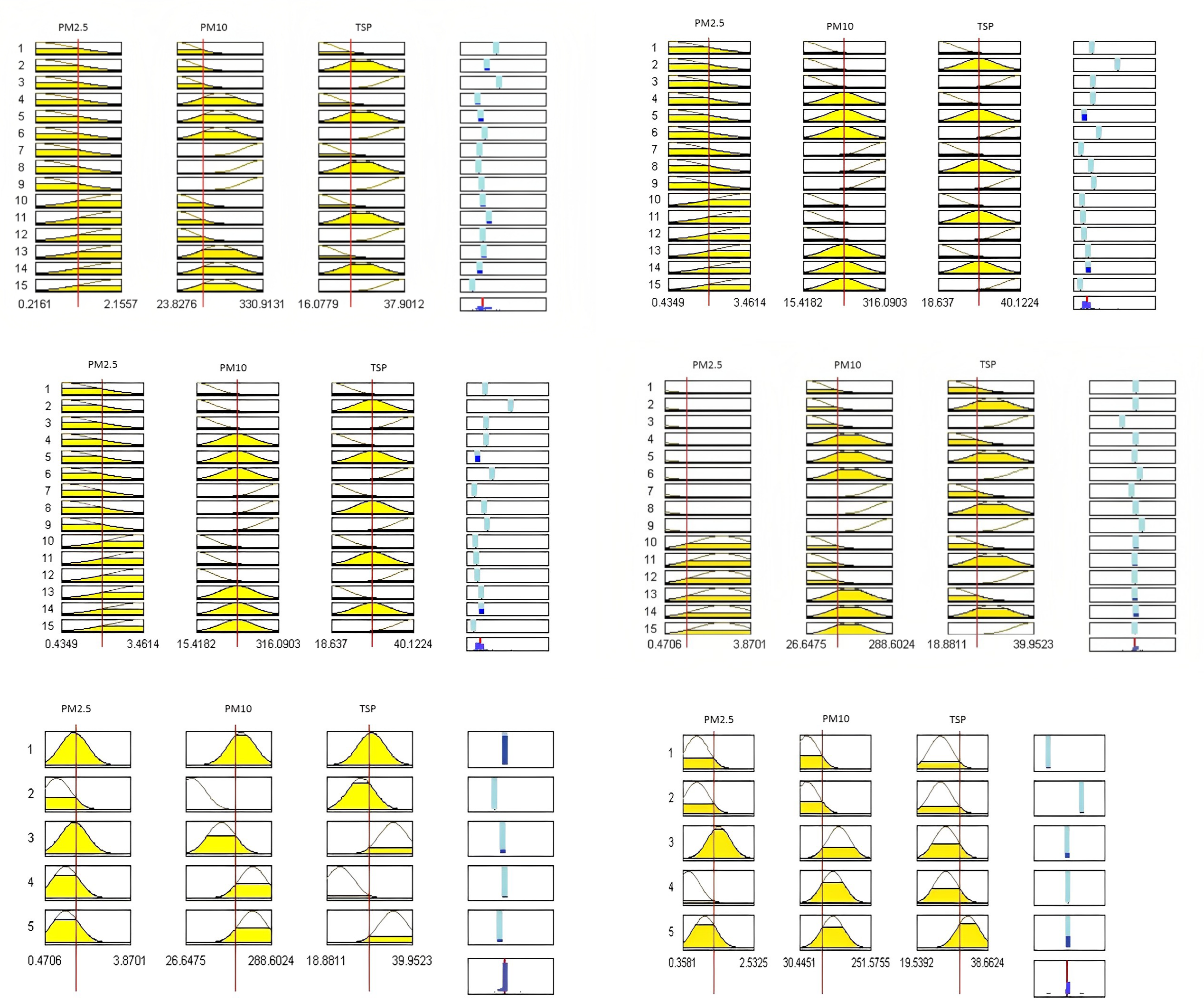

Figure 2. The rules of designed systems. FIS-GS (a), FIS-FCM (b), ANFIS-GC-PDTA (c), ANFIS-GS-HTA (d), ANFIS-FCM-CPDTA (e), and ANFIS-FCM-CCTA (f)

creating visual environments, and easy programming at the same time (13).

Based on the results of the present research model ANFIS system with FCM fuzzy clustering with the post-diffusion algorithm, with more than 85% prediction accuracy of the $PM_{2.5}$, PM_{10}, and TSP particle concentrations, with average error of 0.18, 0.21, and 0.24, respectively for $PM_{2.5}$, PM_{10}, TSP particles, among the various modes used in this research due to better capability of extracting knowledge and ambiguous rules of the fuzzy system, a better model was introduced. The results of a study by Asimakopoulos et al in Greece are consistent with the results of the present study on the quality of air inside subway trains. In their study, to determine the particle concentration of pollutants in metro stations, the variables of (total volatile organic compounds (TVOCs), PM_{10}, $PM_{2.5}$, and PM_1 have been investigated and a simple model of FIS for predicting particle concentration has been proposed (15).

This study examined fewer variables affecting airborne particle concentrations than the present study, and only a simple fuzzy model was investigated. While, in the present study, 15 variables affecting the particle concentration as well as two fuzzy and fuzzy-neural models in six modes were investigated. The results of the study are consistent with the results of the study of Park et al in Seoul metro stations, where the PM_{10} particle concentration was predicted using an artificial neural network (ANN) and could predict 67-80% PM_{10} in 6 metro stations (32). However, the prediction rate of airborne particle concentration in the present study was based on the model ANFIS system above 85%, which is higher than the prediction rate of the model ANN in this study. In a study by Ehsanzadeh et al on the air quality of Gholhak station in Tehran, the regression decision tree model was used to predict air quality, which is used as an efficient model with 99% predictive power for urban air quality (33). The percentage of prediction in this study is higher than that in the present study. Differences in the models used can be

Table 5. Evaluation of the predicted accuracy of the designed systems

			$PM_{2.5}$	PM_{10}	TSP
FIS	GS	RMSE	0.63	0.67	0.69
		IA	0.64	0.66	0.68
		FB	0.60	0.58	0.65
		MBE	0.64	0.63	0.67
		MAE	0.68	0.62	0.64
		AIC	0.65	0.66	0.69
		R	0.68	0.65	0.67
		R^2	0.69	0.68	0.69
	FCM	RMSE	0.69	0.70	0.73
		IA	0.66	0.70	0.69
		FB	0.64	0.65	0.80
		MBE	0.70	0.73	0.76
		MAE	0.73	0.69	0.78
		AIC	0.64	0.64	0.63
		R	0.65	0.63	0.67
		R^2	0.67	0.69	0.68
ANFIS	GC-PDTA	RMSE	0.62	0.68	0.70
		IA	0.73	0.76	0.78
		FB	0.70	0.69	0.71
		MBE	0.68	0.70	0.72
		MAE	0.70	0.70	0.74
		AIC	0.67	0.64	0.69
		R	0.68	0.66	0.67
		R^2	0.69	0.67	0.70
	GS HTA	RMSE	0.73	0.70	0.69
		IA	0.68	0.74	0.73
		FB	0.80	0.79	0.79
		MBE	0.78	0.80	0.81
		MAE	0.62	0.70	0.67
		AIC	0.65	0.66	0.69
		R	0.68	0.67	0.67
		R^2	0.69	0.68	0.70
	FCM-CPDTA	RMSE	0.84	0.82	0.85
		IA	0.82	0.83	0.85
		FB	0.83	0.88	0.85
		MBE	0.82	0.83	0.82
		MAE	0.85	0.87	0.85
		AIC	0.84	0.86	0.83
		R	0.87	0.85	0.86
		R^2	0.83	0.82	0.84
	FCM-CCTA	RMSE	0.80	0.83	0.82
		IA	0.79	0.80	0.78
		FB	0.82	0.79	0.78
		MBE	0.81	0.82	0.79
		MAE	0.76	0.79	0.78
		AIC	0.79	0.80	0.83
		R	0.83	0.85	0.84
		R^2	0.83	0.82	0.84

FIS: Fuzzy inference system, ANFIS: Adaptive neuro-fuzzy inference system, GS: Grade segmentation, FCM: Fuzzy cognitive map, PDTA: post-diffusion training algorithm, HTA: Hybrid training algorithm, CPDTA: Clustering and post-diffusion training algorithm, CCTA: Clustering and combined training algorithm, RMSE: Root means square error, IA: Index of agreement, FB: Fractional bias, MBE: Mean bias error, MAE: Mean absolute error, AIC: Akaike information criterion, R: Correlation coefficient, R^2: R-squared.

Table 6. Prediction uncertainty in FIS and ANFIS systems

		$PM_{2.5}$	PM_{10}	TSP
FIS	RMSE	0.29	0.31	0.36
	MBE	0.28	0.28	0.39
	MAE	0.34	0.31	0.37
ANFIS	RMSE	0.18	0.23	0.25
	MBE	0.19	0.21	0.24
	MAE	0.20	0.24	0.26

FIS: Fuzzy inference system, ANFIS: Adaptive neuro-fuzzy inference system, RMSE: Root means square error, MBE: Mean bias error, MAE: Mean absolute error.

a major factor. However, in this study, unlike the present study with 12 stations, only one station was studied and fewer variables affecting the particle concentration were considered. The most important feature of the present study was its novelty. In the field of modeling the factors affecting the concentration of airborne particles in Tehran metro stations, no study was conducted so far.

According to the study of Anitha et al (34) in India, which is consistent with the results of the present study, the ANFIS prediction model can determine the odor index with an average error of ± 0.32201 and the accuracy of the prediction model can be increased by giving more training samples. In the present study, limitations in these two models, because the number of available data is limited to a few metro stations, it can be said that it cannot be representative of all pollutants in all lines and metro stations. And because the data collection was done only in the two seasons of summer and autumn, the accuracy of the model for other subway lines will be less, and it is better to collect more data in different seasons and lines.

Suggestions for future studies include the use of other methods to create fuzzy constructs such as data mining methods, division of input and output space by tree or scattering method, and the use of the least squares algorithm to train neural-fuzzy network to optimize membership function parameters of Mamdani and Sugno rules and discovery of rules by genetic algorithm. Also, it is suggested to use other variables affecting air pollution to train neural-fuzzy networks. Given that one of the limitations of this study is the use of data in two chapters, for a comprehensive review, it is suggested to collect data in all chapters.

Conclusion

In conclusion, for operational work, if the real decision is to use fuzzy systems in the modeling and design of fuzzy pollutant warning system in the subway, it seems that the use of the fuzzy neural system with FCM clustering and post-release training algorithm is suitable for this. It should be noted, however, that the results of the present study were measured in only one subway line and for two seasons, and the conditions for generalizing the research findings may be different for all subway lines and for all seasons, in this case more data collection in subway lines in all seasons is required. In general, the most important result of this study can be considered a platform for developing intelligent systems for modeling air pollutants, in the type of fuzzy-neural system, based on the FIS. In metro stations, the FIS is limited. In the pollutant modeling section with fuzzy systems, to increase accuracy and precision, it is better to use more data and different dimensions so that the complex metro environment can be better modeled.

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Conceptualization: Hassan Asilian Mahabadi.
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Competing interests

The authors declare that there is not any conflict of interests regarding the publication of this manuscript.

Ethical issues

This study was approved by the Research Ethics Committee of the Tarbiat Modares University (Ethical code: IR.MODARES.REC.1397.259), and ethical considerations and principles from the study beginning to the work close were regarded.

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