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Novel Hybrid Fuzzy-Evolutionary Algorithms for Optimization of a Fuzzy Expert System Applied to Dust Phenomenon Forecasting Problem

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Abstract

Forecasting the dust phenomenon before its occurrence helps to take precautionary steps to prevent its consequences. This paper presents novel hybrid Fuzzy-Evolutionary algorithms to predict the dust phenomenon. For this, first a fuzzy expert system was designed and then it was optimized using evolutionary algorithms like Genetic and Differential Evolutionary algorithms. To evaluate the proposed hybrid models a real dataset including 55 years of the dust phenomenon in Zanjan province in Iran was considered. Performance of these methods was investigated through an ROC curve analysis in combination with a 10-fold cross validation technique. The accuracy of the fuzzy expert system was 92.13% and after optimization through the Fuzzy-Genetic model and hybrid differential evolutionary model was reached to 93.5% and 97.30%, respectively. The results are promising for early forecasting of the dust phenomena and preventing its consequences.

Keywords: *Fuzzy Expert System, Differential Evolutionary Algorithm, Genetic Algorithm, ROC Curve Analysis, Dust Phenomenon Forecasting*

1. Introduction

The dust phenomenon is a set of fine dry particles and dust in the air spreads by wind and covers a vast area in the air which darkens the sky [1]. Vehicles and desertification, industrial pollution, forest fires, plowing in dry areas may cause this phenomenon [2]. Dust is a very destructive phenomenon which causes harm to the environment, roads, constructions and weather, water cycle and the ecosystem in the cities [12]. Dust is one of the phenomenons which results in soil erosion and is called wind erosion. One of the major causes for its creation and augmentation is human carelessness towards sustainable development. Dust causes increases in concentration of suspended particles [13]. Especially the particles that is smaller than 10 microns which are the remaining suspended dust from dust storms. This leads to the decrease in horizontal and vertical viewing and this even could cancel flights and endanger human health and worsen respiratory diseases [12]. The suspended particles with dust pose some problems in our country. This clear the need for solutions to address these essential problems.

The purpose of this study is to design a fuzzy logic inference model to predict dust phenomenon in Iranian cities and this could be achieved through going back to the patterns belonged to the years and months back. Fuzzy expert system is required for weather forecasters to manage uncertainties sources and the related causes. This prediction could be such a help for weather forecasters to monitor pollution progress trend and warn people to make precautionary steps. The advantages and strength of fuzzy systems like logic using linguistic expressions and manipulating uncertainties which is a reliable method in predicting and modeling, could be utilized and the system performance could be evaluated through combining fuzzy, differential evolution algorithm and genetic. In this system, the collected data from a meteorological organization gathered from the expert and it is based on the forecaster's observations from horizontal viewing of the phenomena.

The rest of paper is organized as follows: Section 2 presents an overview of the related works for forecasting dust phenomenon. The proposed fuzzy and hybrid evolutionary models are explained in Section 3 and 4.

2. Review of the Related Works

A study was conducted to assess that applies multiple regressions, ANFIS, and ANN models for predicting dust storm occurrences in Sanandaj, Iran. For this, average daily weather variables were used and a ground station in Sanandaj from 2009 to 2012. It was shown that the ANFIS outperforms the other presented methods when using the same data [5]. A method based on fuzzy clustering technique was presented to analyze the dust frequency in Iran. This was the first time to use time series and the frequency of dust storms on 122 weather stations. The C-means fuzzy algorithm in accordance with torque from the frequency of dust storms was used. This clustering based method shows that storms in the northwest and west of Iran mostly comes from Sub-Saharan Africa and the Arabian Desert [9]. This study predicts dust storms based on the combination of rare classification algorithm. In this study, monthly data based on dust storm observation in China has been used and it includes average wind speed, average monthly temperature, rainfall and average relative humidity from 1961 to 2005. The total accuracy of the hybrid predictor algorithm is %96.51 [9]. In this study a neural network training based on differential evolution algorithm was presented and compared with other architectural weather predictors. The dataset used in this study includes atmospheric pressure, wind speed, wind direction, humidity and rainfall. This model was applied to the data from 1951 to 2005 [10].

A model to predict wind parameters on the dust phenomenon using artificial neural network was proposed in [14]. The study was based on data and statistics in Yazd synoptic stations in the period of 1953 to 2005 based on a monthly basis. In the study, input data includes the extent and continuity of the wind, horizontal viewing, the fastest wind speed, the average wind speed, prevailing wind speed and also dust storm which has been considered as the output of the model. In this paper, the most appropriate method which is forward regression in neural network with RMSE equal to 0 [14]. A system to predict short-term particle pollution in Ahvaz with the help of neural networks were designed. In this study, using 10-micron particulate matter pollution maximum data that was provided using 24-hour time frames to predict air pollution levels of pollutants in the city of Ahvaz [15]. A time delayed network with LMS learning algorithm was trained and the design and concentration of emissions was predicted [15]. Another study was conducted titled as the analysis of dust and the evaluation of its predictability based on statistical methods and ANFIS model in Zabol station. Statistics used in this study belongs to the time period of 41 years. Dust prediction was done based on the ANFIS and 70 percent of the data set was used for training and the rest was to validate the model. This model could predict the dust by 93% reliability in Zabol [16]. Another study was presented for analysis and classification of dust storm abundance using Fuzzy Clustering Model (FCM) in Iran [17]. Parameters used are hourly data, annual mean and maximum wind speed and satellite images were from the MODIS. A method was proposed to predict dust storms using artificial neural networks. System inputs were considered as maximum wind speed, rainfall, occurrence or non-occurrence of dust storms during the day and the day before were selected and output is based on the chosen target. The results in the short term prediction showed more success, and the accuracy was lower for longer periods [18].

In study reported recently, an integer linear programming method was applied to accelerate dust storm simulation. For this the K-Means and Kernighan-Lin methods were combined with the heuristic algorithm. This model. The results in the Integer Linear Programming has the least total communication cost theoretically, K-Means and Kernighan-Lin provides the most balanced partitioning result [19]. In another recent method a 3D multi-thresholding algorithm for identifying dust storm features was presented. Parameters used for simulation were latitude, longitude, elevation, and time. A multi-threshold scheme was defined for the identification of dust storm features with different dust concentrations in [20].

3. The Proposed Intelligent Models for Predicting Dust Phenomenon

This section includes the proposed models for dust forecasting. The rest of this section explains the input and output variables then it follows by fuzzy inference model and the two evolutionary hybrid models applied for dust phenomenon forecasting.

The main inputs for forecasting the dust phenomenon are as follows:

- *Wind speed*: If wind speed is 0-5, then it's slow and it doesn't have any effect on the dust phenomenon. If the wind speed is 4-16, it has a small effect and finally for the numbers greater than 4, it is very likely to occur.
- *Wind direction*: it shows the direction has big impact on the issue and it could worsen it if the wind direction is from Iraq (i.e. when it's 180-360)
- *Air pressure*: it shows if the air pressure is high, stable state occur and there will be no rainfall, and the dust is likely to occur.
- *Horizontal viewing*: it shows that if the dust phenomenon occurs, and the larger concentration of the phenomenon leads to the lower viewing. Horizontal viewing could be obtained by recording the value. Therefore, whenever horizontal viewing is 10000, this phenomenon occurs.
- *Rainfall*: It's the process of condensing water vapor because of atmospheric conditions and it falls in the form of liquid. This input indicates how the daily precipitation is and it can help reduce dust.

The output of the system is the occurrence of dust phenomenon.

3.1 The Proposed Fuzzy Expert System for Dust Forecasting

Fuzzy sets are capable of reasoning in case of uncertainty. Zadeh was the first to bring up Fuzzy set theory in 1967. Fuzzy sets are capable of modeling uncertain concepts, variables and vague behaviors. This theory can formulate uncertainty and make the ground for logic, inference, controlling and decision making [9]. Fuzzy systems are parallel systems which are capable of approximate reasoning [11]. The architecture of a fuzzy system and the relationships amongst elements are illustrated in Figure 1.

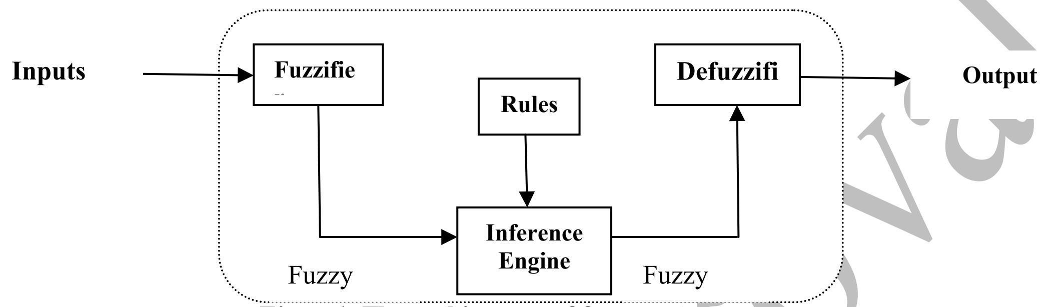

Figure1. The architecture of fuzzy expert system

As shown in Figure 1, the FIS architecture includes the following components:

- Fuzzy engine: The heart of fuzzy set is fuzzy inference engine which infers from the rules and inputs in form of linguistic expressions and fuzzy sets and the output is also a fuzzy set.
- Fuzzifier: it converts numeric inputs to fuzzy sets.
- Rules: fuzzy system contains some rules in form of IF-THEN.
- Defuzzifier: It takes the inputs in form of fuzzy sets, and the output of the fuzzy inference is a fuzzy set in form of a number.

Fuzzy expert system has different models that vary depending on the model rules as model systems. The overall process is designed fuzzy system for predicting dust phenomenon:

Step1: Collecting information and identifying needs in order to extract the actual data
Step2: Fuzzy system design using expert knowledge
Step3: Identify the problem and solve it with expert knowledge
Step4: Designing and defining membership functions and input and output system
Step5: Extraction rules using expert knowledge
Step6: Fuzzy system design, system evaluation with actual data and forecast results
Step7: The final performance evaluation using ROC curve analysis

3.2 The proposed hybrid Fuzzy-Genetic model

The performance of proposed fuzzy model depends on the parameters of membership functions. The main problem is how to design the parameters and rules of fuzzy expert system. It includes difficulties with access to expert knowledge in setting the parameters of membership functions of the fuzzy system, disagreements and different opinions of two experts on the same problem cause. Using a genetic algorithm, parameters of fuzzy system membership functions are optimized. Thus, fuzzy system is combined with Genetic algorithm to optimize membership function parameters. Figure 2 presents the overall process of the hybrid Fuzzy-Genetic model.

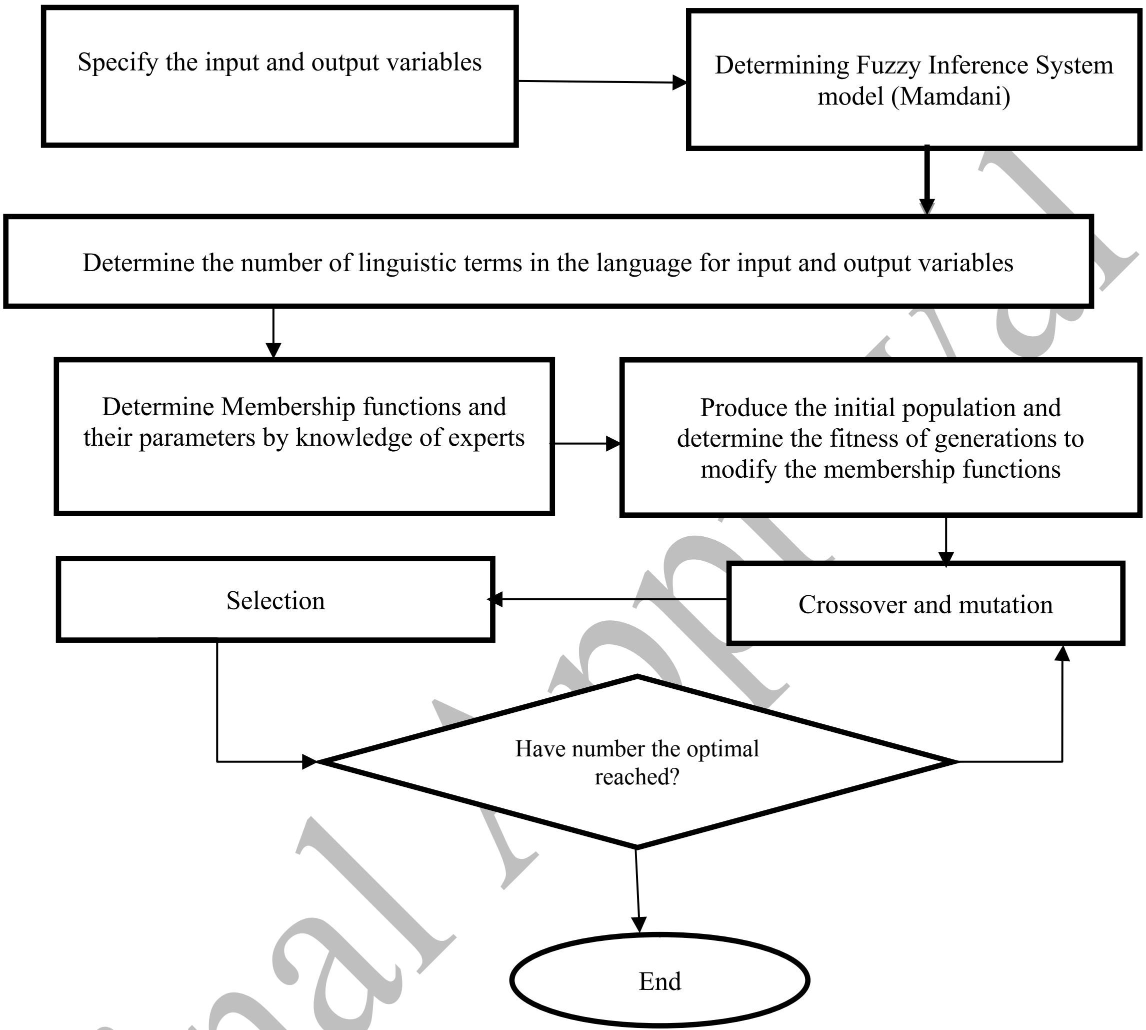

Figure2. Flowchart of Hybrid Fuzzy-Genetic Model

Figure2 represents the flowchart of hybrid fuzzy-genetic model designed to predict the dust phenomenon. After defining the input and output variables, the membership functions are determined using climate science. In other words the input to the space partitioning and extraction rules according to the nature of the problem and matched in the rules produced of membership functions using Genetic algorithms. The next step is to create an initial population and initialization. Decryption of each chromosome within a set of weights connection and to evaluate the merits of each chromosome can be done at this stage and Every generation produces offspring in each chromosome is carried out according to fitness function, Then apply the crossover and mutation operators in each chromosome and produce the next generation is done. After designing Hybrid Fuzzy-Genetic assessment of the actual data and forecast results. Then compare the model results with actual data after the design and square measure errors. Finally, in the last stage the final evaluation is performed using an ROC curve analysis system. The following parameters have been designed through the Fuzzy-GA method:

- *Crossover:* The combination allows two or more sections of a chromosome to other chromosomes combined So that the chromosomes of parts of chromosomes belonged to his father.
- *Mutation:* This allows you to randomly change the amount of genes within chromosomes. The location of the mutated genes is vital.
- *Selection:* The operator selects chromosomes that are better suited and combines them together to form the next generation.

3.3 Hybrid Fuzzy-Differential Evolution Algorithm

The combination of differential evolutionary algorithm with fuzzy models creates a system which is capable of deciding in uncertain conditions with a desirable performance. Fuzzy models are capable of managing uncertainties because of the fuzzy sets and fuzzy membership functions. Differential evolutionary algorithm is a search and optimization method which can improve the performance of the models. Once the search space is wide, due to the large number of parameters and tuning these fuzzy parameters is very complicated. In such cases, it is required to use optimization algorithms such as differential evolution algorithm to do the searching task and using the crossover, it can obtain such parameters and check all possible membership functions in the problem space, and find the optimized solution. Figure 3 shows the overall process of hybrid fuzzy-differential evolutionary algorithm.

According to Figure 3, the hybrid Fuzzy-Differential evolutionary model is as follows:

Step1. Specify the input and output variables according to the nature of the problem.

Step2. Determining fuzzy expert system model.

Step3. Define the definition of the problem parameters and algorithm and objective cost function, the number of unknown parameters or variables of decision making, the range is also variable. Algorithm parameters, including population size, and the probability of the cross-over.

Step4. Create initial population and determine the fit for generations to reform the membership functions.

Step5. The following steps are repeated until the termination condition is satisfied:

- For each member of the population, using mutation create a temporary response. The cross-over operator created and assessed.
- If the answer is better than the previous answer, it is replace, otherwise, the previous call is kept. In fact, the previous call is transferred to the next generation and is directly compared with its parent.

Step6. At the end, the best answer found so far, as output is returned.

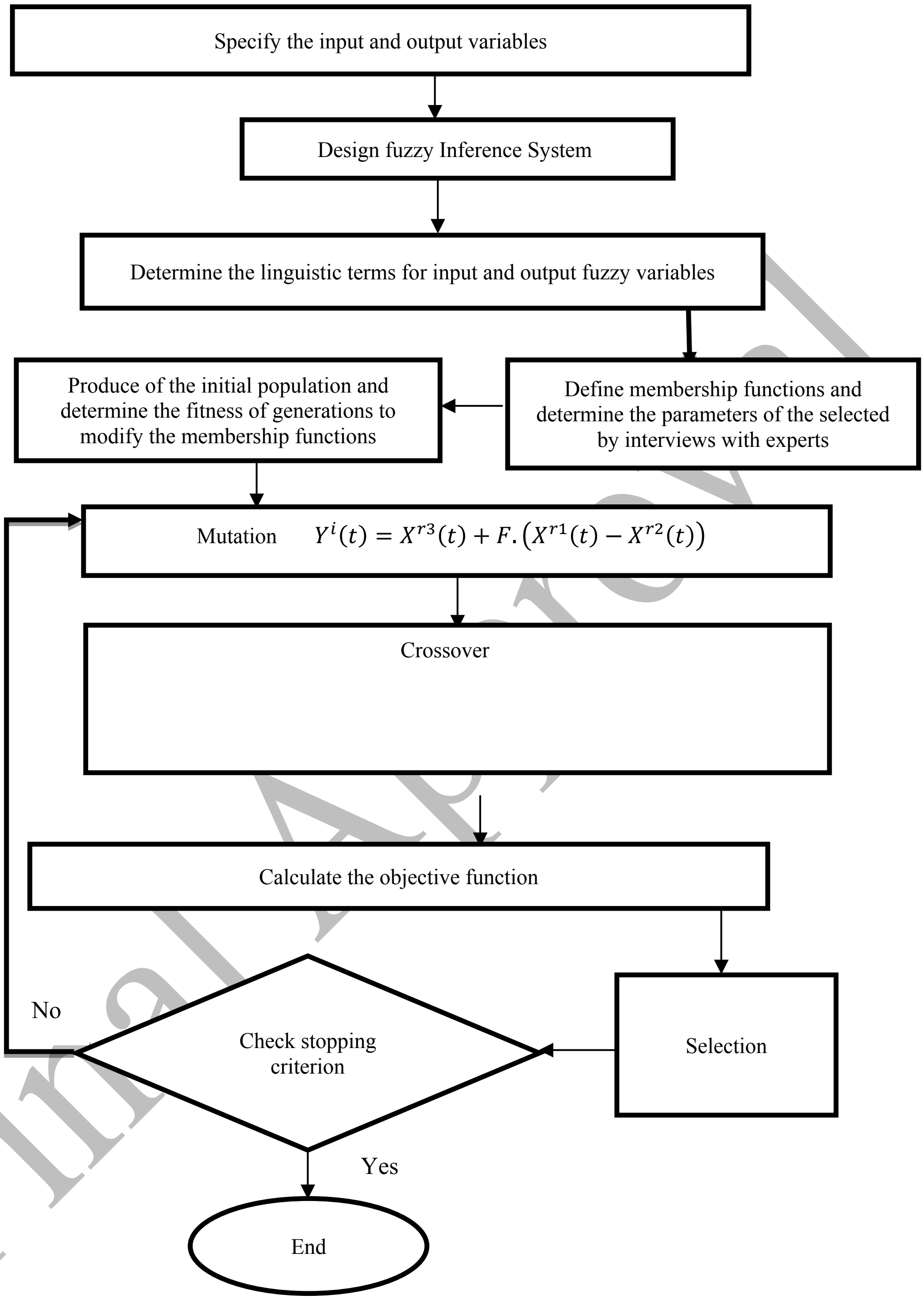

Figure3. Flowchart of Hybrid Fuzzy-Differential Evolutionary Algorithm

4. Experimental Results and Performance Evaluation

This section presents performance analysis and evaluation results of fuzzy expert system and comparison of the results. Membership functions of the fuzzy system and also input and output variables are shown in Figure 4. The membership function are all considered as Gaussian.

4.1 Evaluation of hybrid Fuzzy-Genetic Model

In this section, the result of applying the hybrid Fuzzy-Genetic model and its parameter specification are explained. Convergence of the hybrid Fuzzy-Genetic algorithm is shown in Figure 5. The proposed algorithm converged after 160 generations.

Table1. Analysis of the Genetic algorithm parameters

Percent of crossover	Percent of mutation	MSE
0.9	0.1	**0.0993**
0.7	0.3	**0.0921**
0.9	0.05	**0.0871**
0.5	0.03	**0.0765**
0.9	0.03	**0.0651**

Table1 shows the probability of crossover and mutation in various states the MSE result of the optimized system. As it can be seen in the results, the best result obtained is for the case with the crossover probability 0.03 and mutation probability 0.9

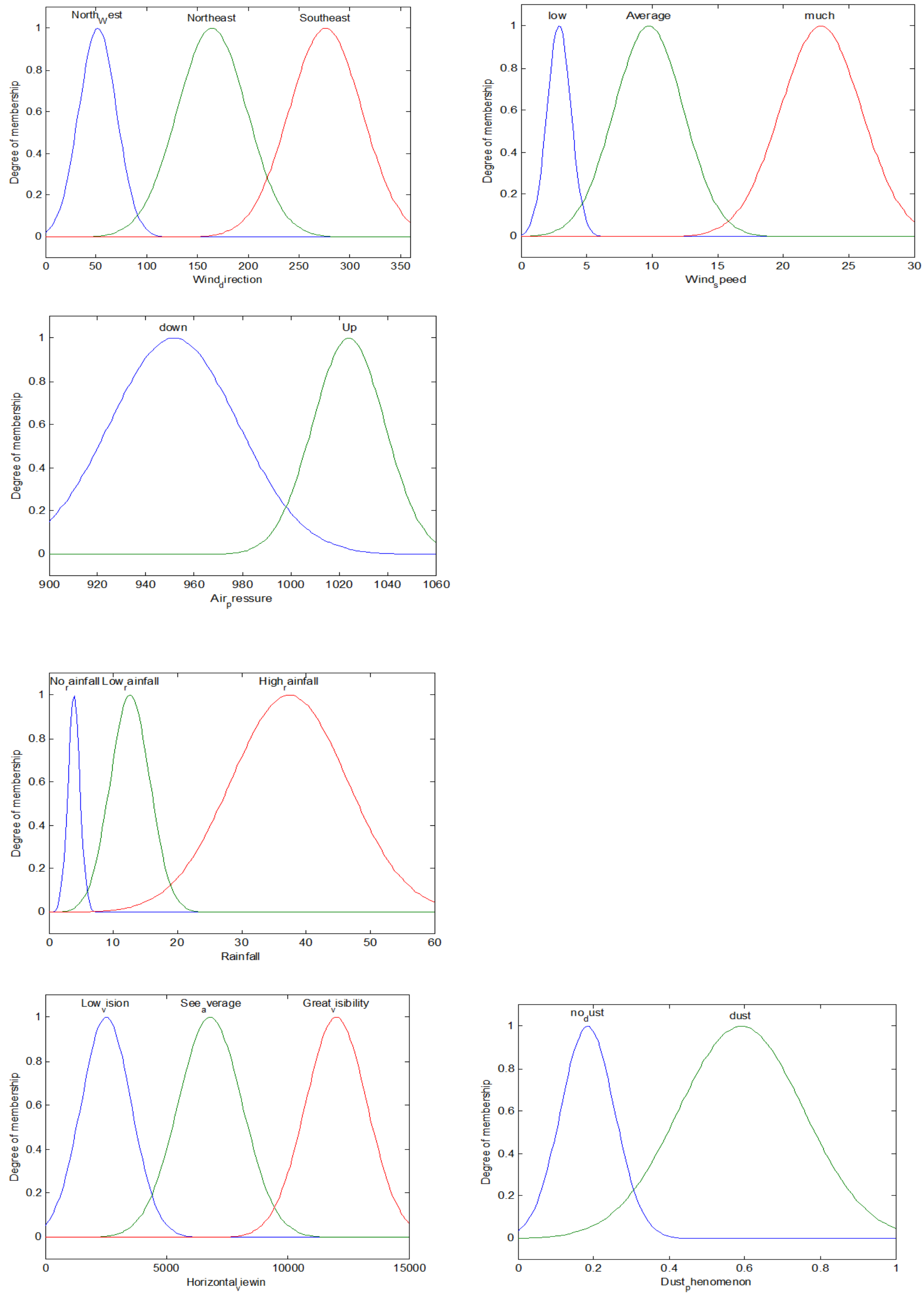

Figure 4. Membership functions of fuzzy expert system

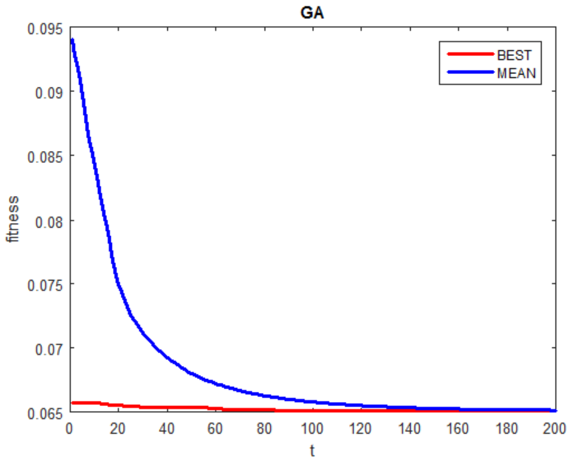

Figure5. Convergence of the hybrid Fuzzy-Genetic model

Figure 6 shows the membership functions of the optimized system using Fuzzy-Genetic algorithm. After optimization, the variance of the input rainfall and wind speed were increased.

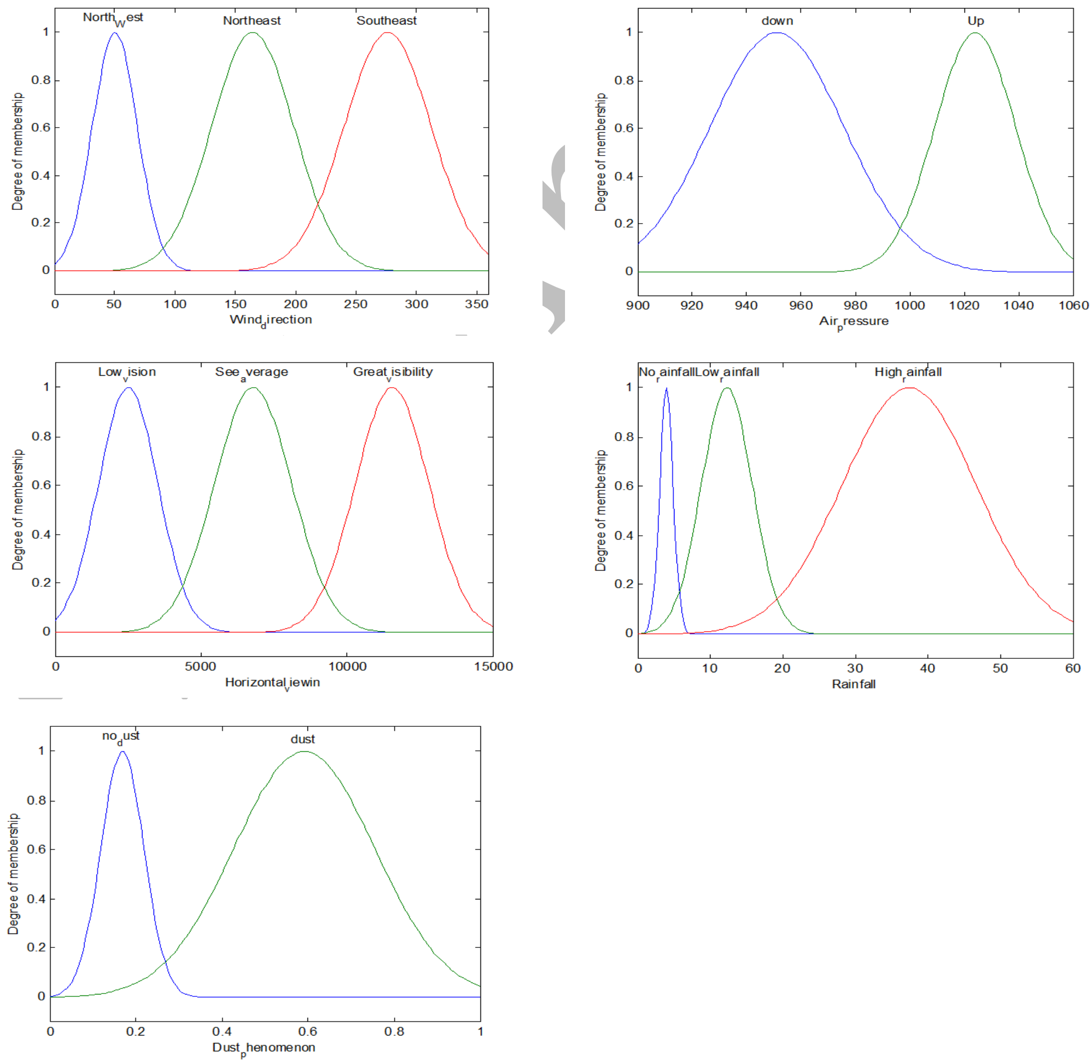

Figure6. Membership functions of hybrid Fuzzy-Genetic model

4.2 Evaluation of hybrid Fuzzy-Differential evolutionary algorithm

This section presents the experimental results of the fuzzy-differential evolutionary method including convergence model, the parameters of the system, and optimized membership functions. The convergancy of hybrid fuzzy-differential evolution is shown in Figure 7. This algorithm converges after 140 generations.

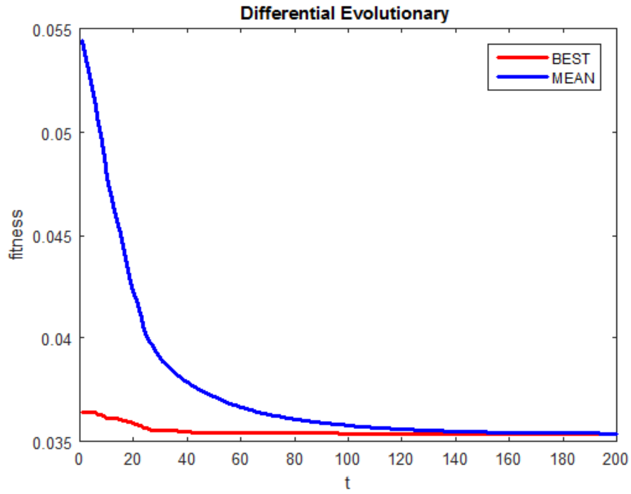

Figure7. Convergence of hybrid Fuzzy-Differential evolutionary algorithm

Table2. Analysis of the parameters of fuzzy-differential evolution algorithm

Crossover probability	Beta (Lower Bound)	Beta (Upper Bound)	MSE
0.02	0.1	0.9	**0.0719**
0.5	0.3	0.8	**0.0494**
0.3	0.5	0.8	**0.0467**
0.3	0.1	0.9	**0.0440e**
0.5	0.6	0.9	**0.0348**

In Table 2, the probability of crossover and mutation in different experiments using MSE are expressed. As it can be seen in the results, the best answer is for the case with the crossover probability 0.04. Mmembership functions of the optimized system using differential evolution algorithm are shown in Figure 8. After optimization, the variance of the input rainfall and air pressure have increased. The variance of the input wind speed and the output have decreased.

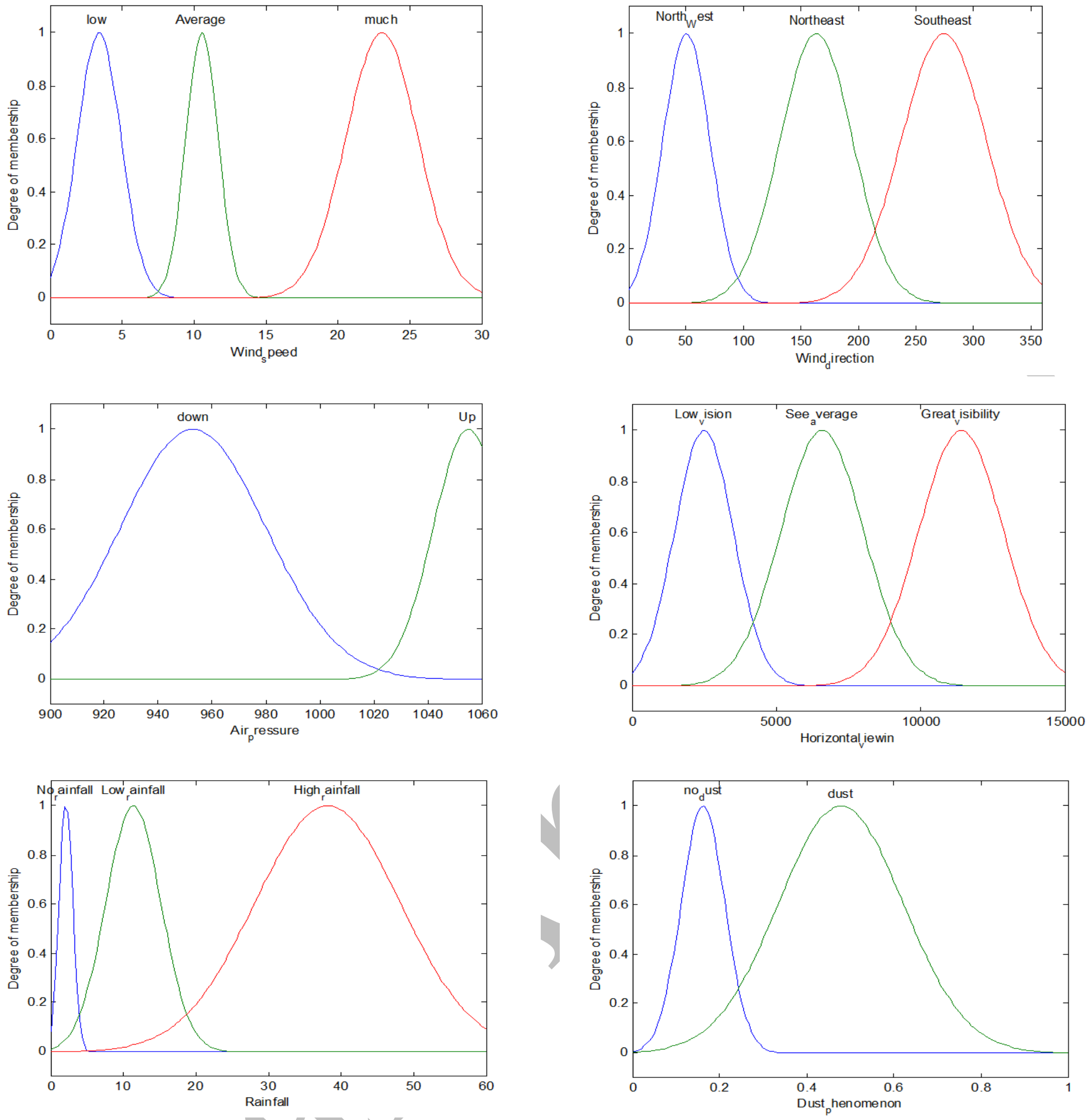

Figure8: Membership hybrid Fuzzy-differential evolution systems

5. Performance Evaluation of Proposed Models and Comparison Results

In this section, the results of the ROC curve analysis for the proposed models are presented. Furthermore, in order to have an unbiased view of the performance, a comparison of performance of the proposed methods after applying a 10-fold cross-validation technique is presented.

5.1 An ROC curve analysis of the proposed models

In Table3 performance of the proposed hybrid evolutionary models for Mamdani fuzzy expert system optimization after applying on the dataset including 6000 samples of the phenomenon of dust in Zanjan province in Iran has been evaluated using an ROC curve analysis and the results have been compared with each other.

Table3. Comparison results of the ROC curve analysis of the proposed models

Method	ROC (AUC)%	C.I% (AUC)	S.E	Sensitivity%	Specificity%
FIS	92.13	[90.80 93.45]	0.006	89.70	93.3
Fuzzy-GA	93.5	[91.80 94.31]	0.006	91.76	94.96
Fuzzy-DE	97.30	[96.49 98.10]	0.004	94.59	94.51

The hybrid Fuzzy-Differential evolution system with 97.30% accuracy outperforms the others. The hybrid Fuzzy-Genetic with 93.5% accuracy is better than the fuzzy system with an accuracy of 92.13%. Table 4 shows the confusion matrix results for the three systems which investigate fuzzy systems versus the Fuzzy evolutionary models.

Table4. Results of Confusion Matrix for the proposed models

Methods	TP	FP	TN	FN
Fuzzy-DE	4936	287	735	42
Fuzzy-GA	4960	263	713	64
Fuzzy	4859	364	697	80

In Table5, the comparison is amongst the results of the average 10-fold cross-validation method using hybrid Fuzzy-Differential evolution system for the training and test data are obtained 95.33% and 95.48%, respectively.

Table5. Compare results of the 10-fold cross-validation method of the proposed hybrid models

Methods	ROC (AUC)%		C.I% (AUC)		SE		Sensitivity%		Specificity%	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Fuzzy-GA	92.26	92.10	[90.88 96.48]	[87.93 94.87]	0.007	0.02	89.64	90.98	92.41	91.84
Fuzzy-DE	95.33	95.48	[94.01 97.41]	[92.11 98.84]	0.005	0.01	91.07	92.39	94.04	94.08

Performance of the three systems in order to predict the dust phenomenon can be seen in Figure 9.

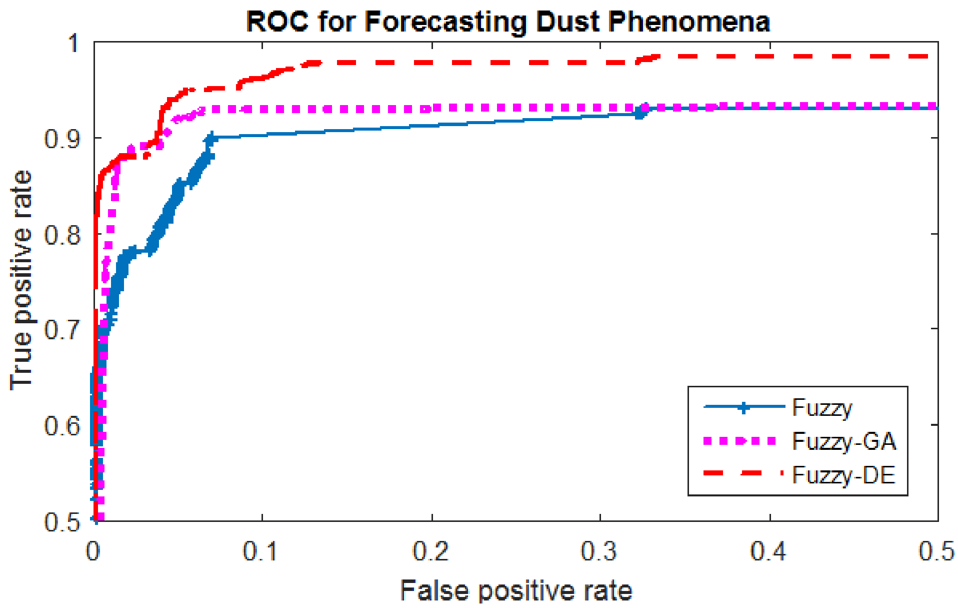

Figure9: ROC curve of the fuzzy- evolutionary algorithms

5.2 Comparison of the proposed models to other related methods

This section compares the fuzzy techniques and the proposed hybrid methods with some of important related works in Section 2. Table 6 shows the comparison of the proposed models to other related methods.

Table6. Comparison of the proposed models to other related methods

Method	**Advantages and Disadvantages**	**Accuracy**
ANFIS, and ANN models [5]	Satisfactory results in complex and uncertain.	83%.
Hybrid Neural Network Retrieval Model [1]	It can automatically provide real-time storm warning.	78.8%.
A Novel Combinational Forecasting Model using Classification Algorithm [9]	Predictive Ledger.	96.51%.
Fuzzy Expert System Model [This study]	The ability to model the sources of uncertainty.	92.13%.
Hybrid Fuzzy-Genetic Model [This study]	Using evolutionary algorithm and evaluation using a dataset from 55 years.	93.05%.
Hybrid Fuzzy-Differential Evolution Model [This study]	Using data from 55 years to examine the proposed model is used. Use of the vector difference between the solutions in the state space	97.30%.

As shown in Table 2, the proposed methods in this study competes with the previously reported works and the fuzzy-DE model outperforms the other methods with an accuracy of 97.30%. The main advantages of the proposed hybrid evolutionary models for forecasting the phenomenon of dust with the other models are:

1. Fuzzy expert system capabilities and understanding of the predictions and management under uncertainty.

2. Modeling knowledge base (set of rules) with the linguistic terms and if-then rules with high interpretability
3. Using suitable number of samples in the dataset to report reliable performance results
4. Using evolutionary techniques and combine them in search of the optimal model in large and complex state space
5. Using an ROC curve analysis to assess the balance between the cost and benefits of the proposed models
6. Using a 10-fold cross-validation method in the process system validation to have a robust and consistent view of the performance
7. The high accuracy of the proposed methods compared to other related work
8. The proposed Fuzzy-differential evolutionary model is superior to other methods because of its intelligence search behavior using the vector difference information of the solutions in the state space.

6. Conclusion

This paper presents the hybrid Fuzzy-Differential evolutionary and the Fuzzy-Genetic models in order to predict the dust phenomenon. In the present study, first a fuzzy expert system was designed and then it was optimized using the evolutionary algorithms like genetic algorithm and differential evolution. Evolutionary nature of these algorithms have been taken into account to optimize the system in the complex area of the dust phenomenon. The capabilities of fuzzy set theory was taken into account for predictions under uncertainty circumstances.To evaluate the fuzzy evolutionary models, a real dataset, including 55 years of the dust phenomenon in Zanjan province in Iran were considered. Performance evaluation was conducted through using an ROC curve analysis. The results revels that the accuracy of the fuzzy expert system was 92.13% and after optimization through the hybrid Fuzzy-Genetic and hybrid differential evolution models has reached to 93.5% and 97.30%, respectively. The superiority of the hybrid proposed models in this study came from combining the capability of fuzzy systems to cope with uncertainty in the input space in addition to evolutionary nature of optimization techniques applied to the fuzzy system in complex environment such as dust phenomenon forecasting problem. The results are promising for early prediction of the dust phenomena and preventing its side effects.

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