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Sustainable Storm Water Management by Predicting Climate Change Using Fuzzy Neural Network and GIS

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A B S T R A C T

Analysis of urban climate changing is the basis for the implementation of storm water management measurements. Climate tensions such as changing precipitation patterns, fluctuations in temperature, and extreme events are already affecting water resources. For instance, precipitation pattern will be changed due to more water vapor in the atmosphere. Hence, it will not be evenly distributed. Some places will see more rain, others will get less snow. However, climate changes, such as the amount, timing, and intensity of rain events, in combination with land development, can significantly affect the amount of storm water runoff that needs to be managed. Firstly, this essay will be discussed about the prediction of climate change using a fuzzy neural network (FNN) and it shows the accuracy of this method for anticipating storm water. Secondly, based on the results of the first phase, it determines the critical area for preparing storm water systems with the application of GIS tools and technology.

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INTRODUCTION

Climate change represents the principal challenge that humans will have to face in this century. This awareness is rapidly migrating from the scientific world and environmentalists to the highest level of the institutions. According to IPCC report, the world has experienced warming effects [1, 2]. Observed changes in the climate due to increasing greenhouse-gas concentrations have made it essential to investigate these changes.

A violent disturbance of atmosphere with strong wind and usually rain, thunder or snow is called storm. Storm water is a term used to describe water that originates during heavy precipitation events. It may also be used to apply to water that originates with snow melt or runoff water from overwatering that enters the storm water system. Storm water that does not soak into the ground becomes surface runoff, which either flows directly into surface waterways or is channeled into storm sewers, which eventually discharge to surface waters such as river. It has been recognized that urban storm water pollution can be a large contributor to the water quality problems of many receiving waters, as runoff transports a wide spectrum of pollutants to local receiving waters and their cumulative magnitude is large [3, 4]. Together with population growth and increased water demands, future climate change is adding uncertainty to water resource planning and management. Global climate changes may alter the quantity and timing of local and regional precipitation that will affect the water supply, water quality and flood management. These effects should be understood the maximum amount as potential for guiding future planning of water resource management. Major recent water-related disasters including both floods, landslides and extensive droughts are reminders of both the destructive power of water and the tragic consequences associated to the lack of it in many regions of the World. These extreme events are only the final consequences of changes in land use and management that are affecting the water resources, under very different climate conditions. In some cases these effects may be linked, at least partially, to global climate changes.

The previewed climate changes may also affect water availability, because there is a strong link among storm water, climate change and water resources [5, 6]. The predictions are more runoff from rain, hotter and drier summers, and leading to more flooding and more frequent droughts [7, 8]. Changes in population, both in total number and distribution, are also strongly affecting the quality and quantity of the available freshwater, and sustainable water management. Water resources must be managed not only to satisfy people direct needs, but also for nature conservancy.

In recent years, the application of artificial and fuzzy neural networks (ANNs and FNNs) have been published in many papers, and neural networks models are useful tools in solving many problems in various fields such as classification

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in engineering, industry, control, prediction, meteorology, and environmental sciences [9-18].

ANN and multivariate statistics (MST) was applied for climate change modeling in New Zealand. The study declared that the climate change impact assessment needs data at the spatial and also the temporal resolution at which impacts occur [19].

Several authors reported on how to forecast precipitation and causes of storm water. However, only limited works applied artificial intelligent tool such as adaptive neuro-fuzzy inference system (ANFIS). Although, there are some works carried out by different authors on short and long term forecasting using ANFIS. These embrace rainfall prediction [20-25], weather forecasting [26], wind speed [27], stream flow estimation [28], multi variable ANFIS applying weather parameters [29, 30] and simulation for daily temperature [31].

Approximately, various storm water forecast models based on neural networks perform much better in accuracy than many conventional prediction models [31, 32].

Babol city is facing Storm water drainage problem due to increasing population and development activities. In this work, the existing layout of water quality based on forecasting storm water flow was evaluated. Also, planning of modified drainage system in Babol River watershed was conducted. For this investigation, based on the climate change prediction parameters in watershed, various thematic maps were generated and collated with the rainfall and water quality data in geographic information system (GIS) environment. Moreover, the critical zones for storm water formation and suggesting modification of present drainage system determined by GIS output.

MATERIALS AND METODS

Study Area

Babol City (36.544°N and longitude 52.679°E) is situated in the northern part of Iran. Babol city is the second largest city of Mazandaran state in terms of area and population. Babol River is flowing through the city ahead to Caspian Sea. River stream forms the lotic ecosystem where fish and numerous other organisms thrive. Babol River is a source of fish migration from river to Caspian Sea and vice versa, particularly for Sturgeon. Any change in river water regime-quantity, quality (physical, chemical and biochemical), velocity, turbidity, sediments, woody debris etc. may damage the riverine flora and fauna leading to their migration and/or elimination. Since the downstream of Babol River has been deteriorated with increasing levels of storm water pollution. Thus, we paid particular attention to the climate change and storm water runoff data within Babol River catchment. The study area is shown in Figure 1.

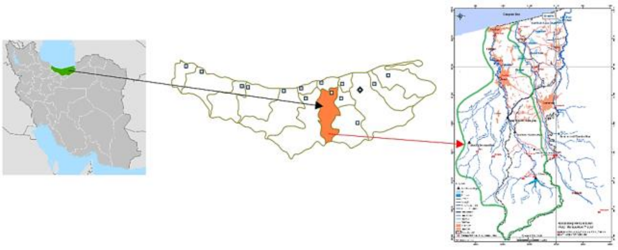

Figure 1. Location map of the study area

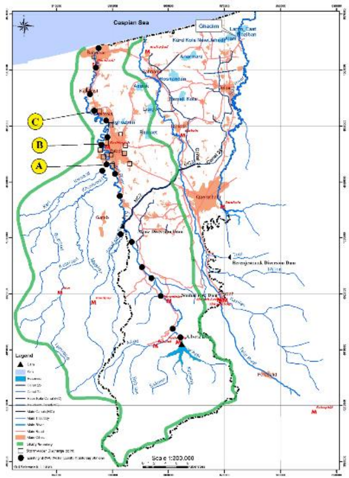

Figure 2. The dots on this map depict sampling stations. The square indicates the storm water drain

Fuzzy neural network

In the FNN method, the neuron is processed based on fuzzy logic which means the input weight grade are formulated as the fuzzy measurement stated by membership value (function) and the output fuzzy sub-collection is diverted to non-fuzzy digital measurements. The FNN model for obtaining the initial forecast is shown in Figure 3. The fuzzy dataset for rainfall, temperature, discharge, and water quality parameters are given as input. The dataset input to the FNN model consists of the membership function (MF) to the overlapping partitions of linguistic attribute to every input feature like rainfall and temperature. Hence, the linguistic dataset is integrated with the training and testing stages of the climate prediction model that increase the robustness in handling uncertain input conditions. The output layer consists of the MF to the overlapping partitions of linguistic attributes variously corresponding to the forecast load magnitude. The FNN back-propagates the errors in accordance with the specified MF at the output nodes. After the training phase, after a variety of iterations, FNN converges to a minimum error solution (MES) at through a gradient descent algorithmic program, when separate rainfall patterns applied at the input layer, the output nodes produce the MF corresponding to the linguistic properties. Therefore, a defuzzification technique is applied during this approach to obtain the initial load prediction from the MF and also the equivalent loads area obtained from the neuro functions.

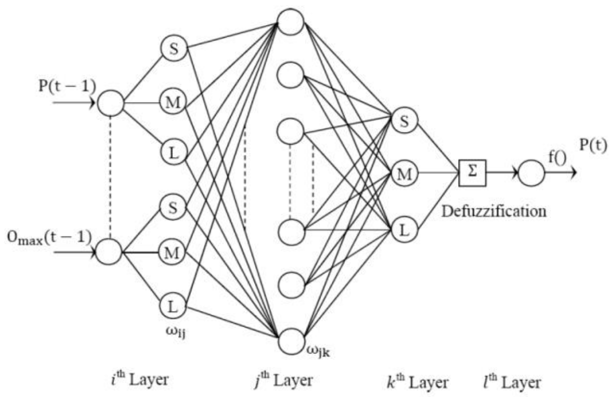

Figure 3. Fuzzy neural network for initial rainfall forecast

LoLiMoT

The architecture of the local linear model tree algorithm (LoLiMoT) is shown in Figure 4. The fuzzy neuron divides the input space into small subspaces using a locally linear model and a validity function, normalized Gaussian [33, 34]. The output of local linear model is calculated using Equation (1). Where $U = [u_1, u_2, u_3, u_4 \ldots u_p]$ is the input vector of the model.

$$\hat{y}_i = \omega_{i_0} + \omega_{i_1} u_1 + \ldots + \omega_{i_p} u_p \quad (1)$$

The output of the model is calculated as the weighted summation of locally linear models [34] according to Equation (2).

$$\hat{y} = \sum_{i=1}^{M} \hat{y}_i \phi_i(\underline{u}) \quad (2)$$

Where $\phi_i(\underline{u})$, is the validity function of each neuron and is calculated by Equation (3). Where the $\phi_i(\underline{u})$ is the Gaussian function [34] that is calculated by Equation (4).

$$\phi_i(\underline{u}) = \frac{\mu_i(\underline{u})}{\sum_{j=1}^{M} \mu_j(\underline{u})} \quad (3)$$

$$\mu_i(\underline{x}) = \prod_{j=1}^{p} \exp\left(\frac{-1}{2}\left(\frac{(x_j - c_{ij})^2}{\sigma_{ij}^{2}}\right)\right) \quad (4)$$

Local linear model tree algorithm (LoLiMoT) is an incremental heuristic algorithm to optimize the learning parameters, linear and nonlinear parameters which correspond to validity functions. The algorithm consists of two loops: the first loop updates the nonlinear parameter and the nested loop optimizes the linear parameters. The nested loop is based on least square method to optimize the M (p + 1) linear learning parameters [34], where M representing the number of fuzzy neurons' of hidden layer and p is the dimension of the input vector. According to Figure 5, the following steps explain LOLIMOT construction algorithm [34]:

Incremental (growing) algorithm: Adds one local model (LM) in each iteration.

• Split of the locally worst LM.

• Test of all splitting dimensions and selection of the best alternative.

• Local least squares estimation of the LM parameters.

• Use normalized Gaussian validity functions

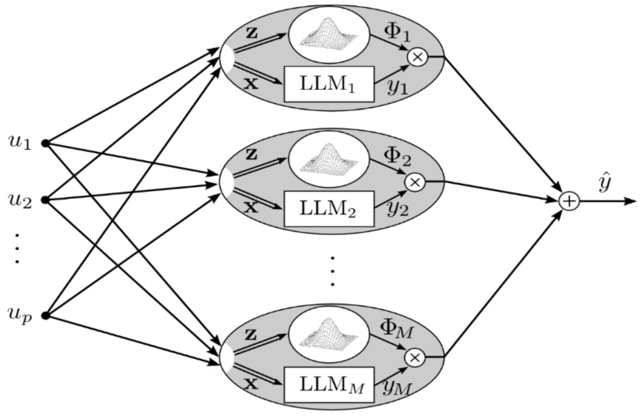

Figure 4. The structure of LoLiMoT

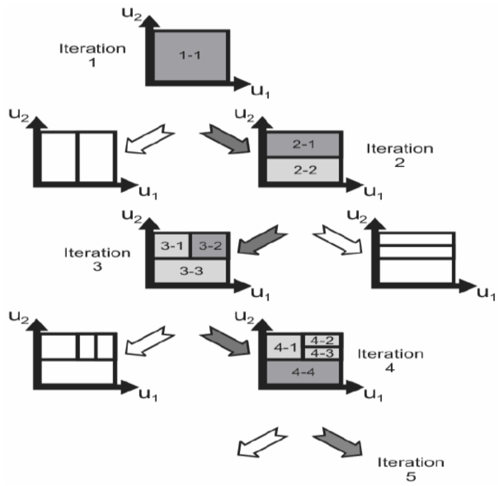

Figure 5. LOLIMOT structure search algorithm in the first five iteration for a two dimensional input space

The main preference of LoLiMoT is its low time complexity because of linear growing with the number of fuzzy neurons. However, the curse of dimensionality is a significant issue of this algorithm [34].

EXPERIMENTS AND ANALYSIS

There are lots of problems occur during research process. These problems can be formulated as:

- Collection of the historical data, facts and figures about the rainfall is a difficult process.
- Choosing the prediction technique is also a matter of concern.
- Generating technique of LoLiMoT is also challenging.
- Performance analysis of different rainfall regions, water quality, and discharge volume are also difficult.

Therefore, after analyze the above problems, we have settled the multiple objectives, Figure 6.

1) To collect real time rainfall, water quality, and volume discharge data of Babol River region using by GIS.
2) To pre-processing the data using data cleaning technique for predict the accurate result in MATLAB 2010b.
3) To use Intelligent Approach for develop the LoLiMoT System with fuzzy neural network for data forecasting.
4) To calculate the parameters such as means squared error ratio (MSE) and correlation value to identify the accuracy.
5) Generate results and compared with actual results.

Time series dataset used for climate forecast is collected from MRWC; district wise average rainfall, wind, and temperature information between years 2006 and 2015 from Babol watershed on monthly basis is depicted in Figures 7 to 10. Figures 11 to 13 show the monthly average data related to concentration of sulfate (SO_4), as an indicator of water pollution, from year 2006 to 2015 is collected from the A, B, and C stations on monthly basis, located through Babol River that is shown in Figure 2.

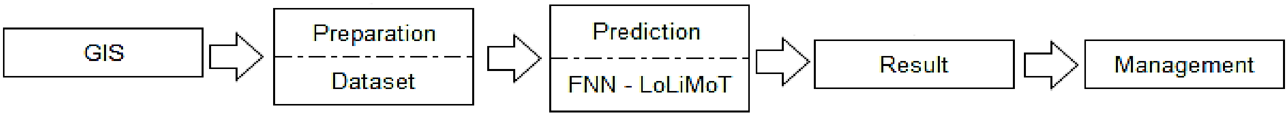

Figure 6. Stage of objectives

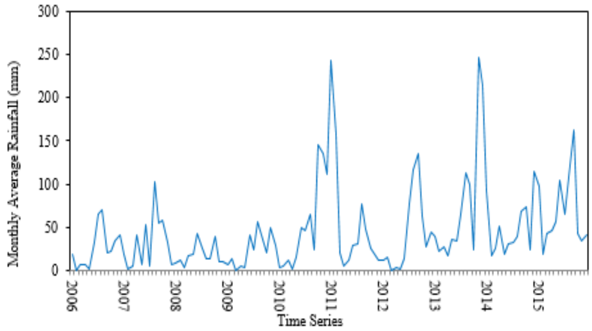

Figure 7. Monthly average rainfall in study area

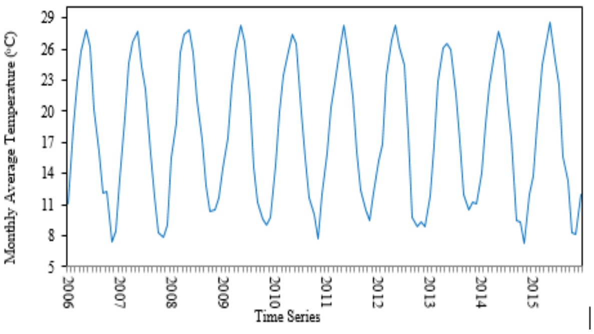

Figure 8. Monthly average temperature in the study area

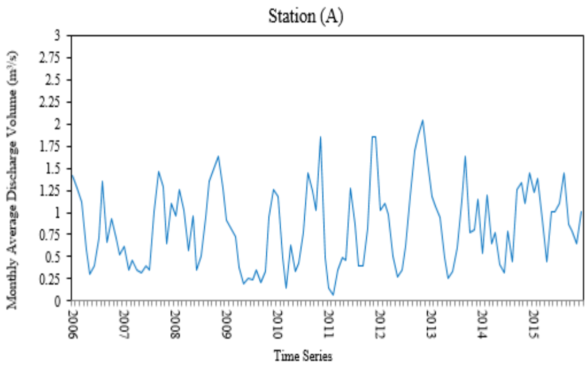

Figure 9. Monthly average discharge in station A

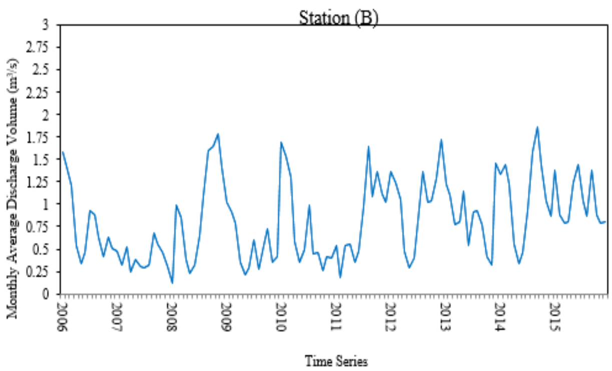

Figure 10. Monthly average discharge in station B

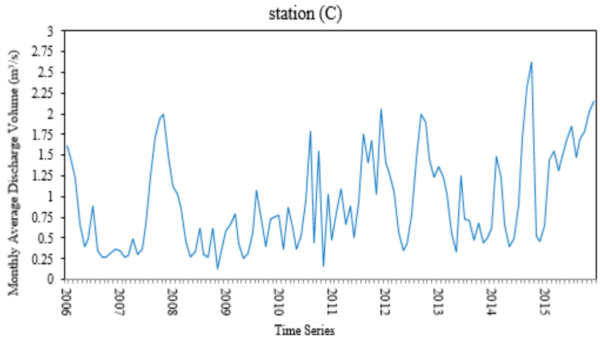

Figure 10. Monthly average discharge in station C

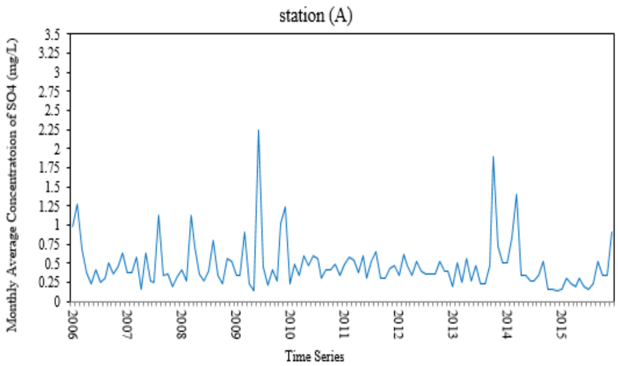

Figure 11. Monthly average concentration of SO_4 in station A

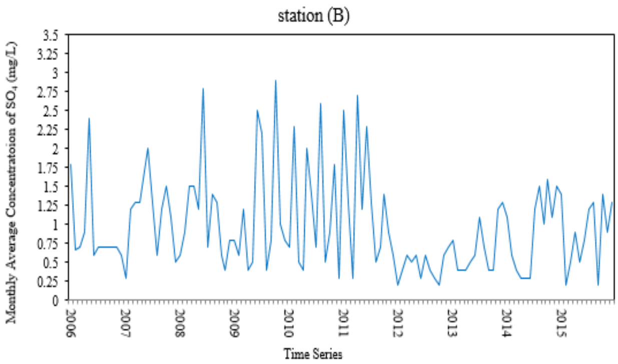

Figure.12. Monthly average concentration of SO_4 in station B

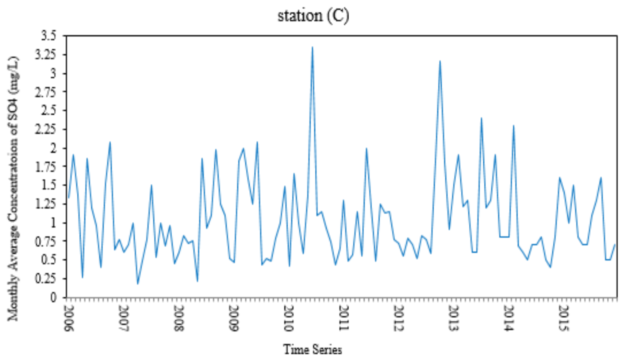

Figure 13. Monthly average concentration of SO_4 in station C

RESULTS AND DISCUSSION

Simulation of this approach has been carried out in MATLAB. The results were monitored for the purpose of assessing the performance of the proposed FNN based on LoLiMoT model. According to monthly report, in the years between 2006 and 2015, data were collected from Babol River zone. The number of actual data that applied in algorithm was 120 as input data for train and test phase. Results from Figures 14–20 and Table 1 indicate the actual and the desired values obtained from the proposed scheme. Moreover the graphs showed the results of prediction in 6 steps forward. It is clearly found that, the calculated and desired curves overlap for most of data values which shows that desired output and target were nearly similar. All outputs are in error range less than 1% at some stage in the training phase.

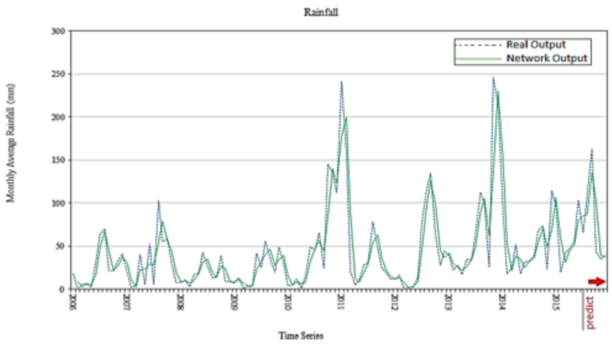

Figure 14. Testing results of fuzzy neural network (FNN) – Rainfall

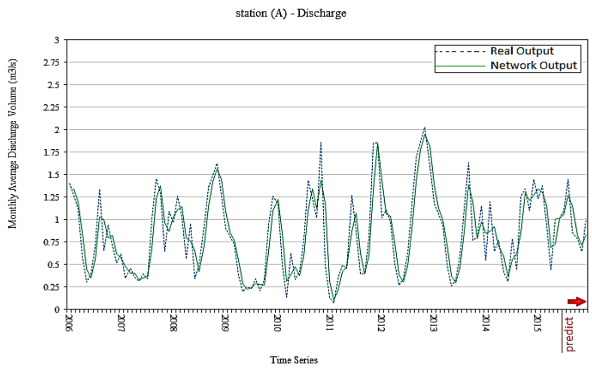

Figure 15. Testing results of fuzzy neural network (FNN) – Discharge (A)

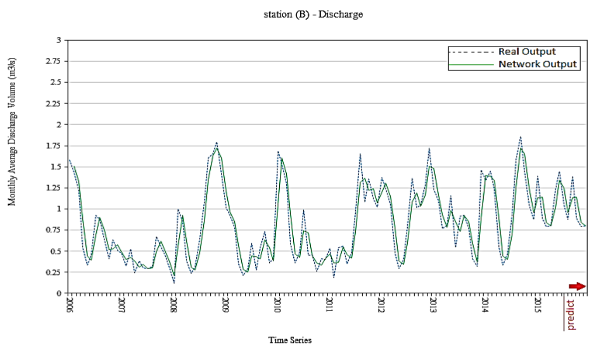

Figure 16. Testing results of fuzzy neural network (FNN) – Discharge (B)

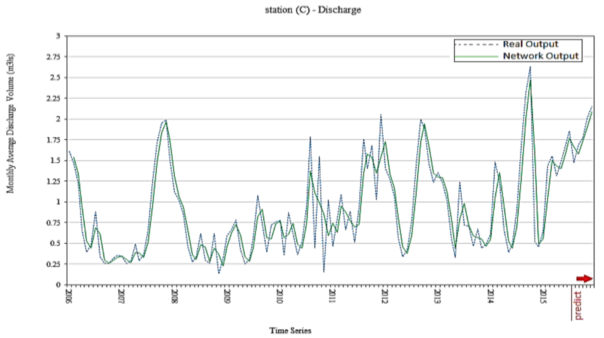

Figure 17. Testing results of fuzzy neural network (FNN) – Discharge (C)

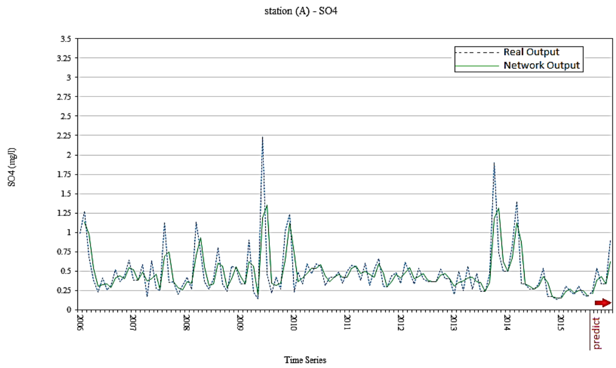

Figure 18. Testing results of fuzzy neural network (FNN) – SO_4 (A)

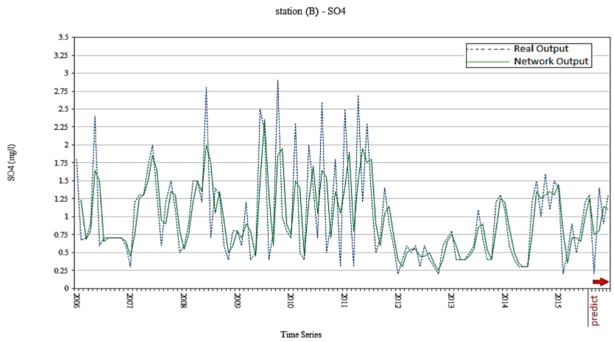

Figure 19. Testing results of fuzzy neural network (FNN) – SO_4 (B)

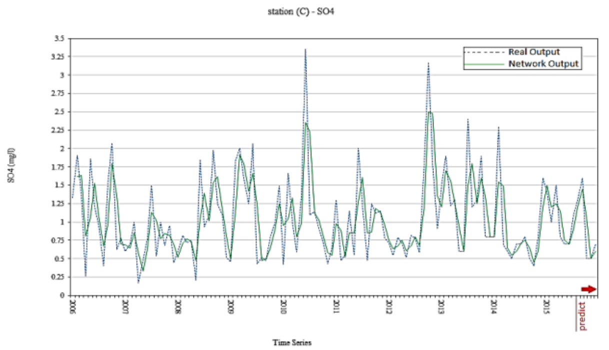

Figure.20:. Testing results of fuzzy neural network (FNN) – SO_4 (C)

Different parameters have been used to the performance of the designed network:

RMSE (Root Mean Square Error), used to compute the performance of the simulation, is valued between real and simulated data. The equation used is stated as follows:

TABLE.1: Predicting performance using FNN - LoLiMoT

Item / Method	Rainfall	Discharge			SO_4		
		A	B	C	A	B	C
RMSE	1.1165	1.2423	1.1258	1.1194	1.0924	1.1376	1.0895
Correlation	0.9857	0.9726	0.9826	0.9814	0.9724	0.9827	0.9826
MAE	1.0568	1.1487	1.0627	1.1068	1.1985	1.0481	1.0261

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (O_i - P_i)^2} \quad (6)$$

RMSE where: n = number of total observations O_i = observed data P_i = simulated data.

CORRELATION identifies the link between simulated and real data.

MAE (Mean Absolute Error) is the difference between real and simulated data. It is expressed by the following equation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |O_i - P_i| \quad (7)$$

MAE Where: n = number of total observations O_i = observed data P_i = simulated data. The parameters are evaluated for the mean - minimum - maximum temperature and are summarized in Table 1.Usually, correlation value (r) ranges between −1 and +1. As r approaches +1, the relationship between the two variables examined is positive. When r, indicates zero means there is no correlation between the variables and negative signifies negative correlation.

CONCLUSION

This paper provides a predictive model based on fuzzy neural networks with the LoLiMoT algorithm to forecast the storm water using the precipitation and the previous rainfall dataset and storm water discharge. In this research, the storm water runoff at the Babol River catchment was studied. Moreover, Babol city is facing Storm water drainage problem due to increasing population and development activities. The input data are precipitation, discharges, and water quality obtained from MRWC, according monthly report, in the years between 2006 and 2015. The experimental results show that LoLiMoT algorithm proved to be successful in training the FNN for the storm water discharge prediction. List of results:

1. The studying items are positively related to correlation value. The correlation values are high in all cases and the MAE are low and therefore acceptable.
2. The results of analysis shows that the accuracy and reliability of FNN method based on LoLiMoT for prediction of environmental parameters.
3. The rainfall prediction graph, in prediction time, shows upward trend for the next 6 months.
4. Following number 2, the discharge level at station (A) in prediction graph, shows upward trend for the next 6 months. It shows producing heavy storm water in area of station (A).
5. SO_4 in the stations (B) and (C) are high, and have upward trend, resulting in a marked increase of its values in the river water due to storm water.
6. After determination of high discharge location and its time of happening by FNN, It would be better to manage storm water using GIS tools. For instance, finding the optimum location to change the way of storm water, investigation on a place for reservoir as a retention pond, and best path for pipeline networks.
7. SO_4 in the station (A) is decreased and has downward trend during forecasting period due to the location of this station which is situated in upstream of the Babol River.
8. Since many variables and elements supplied to the receiver with rainwaters clearly affect the water quality, it is necessary to reduce the external loads and to determine acceptable impact, without affecting the native biodiversity negatively.

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Persian Abstract

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چکیده

تجزیه و تحلیل تغییرات اقلیمی شهری پایه ای برای اندازه گیری های آب آشامیدنی است. تنش های اقلیمی مانند تغییر الگوهای بارش، نوسانات دما و وقایع شدید در حال حاضر بر منابع آب تاثیر می گذارد. به عنوان مثال، الگوی بارندگی به دلیل بخار آب بیشتری در اتمسفر تغییر خواهد کرد. از این رو، آن را به طور مساوی توزیع نخواهد کرد. بعضی مکان ها باران بیشتری را می بینند، دیگران برف کمتری خواهند یافت. با این حال، تغییرات آب و هوایی، مانند مقدار، زمان بندی و شدت حوادث باران، همراه با توسعه زمین، می تواند به طور قابل توجهی میزان روان بودن آب های سیلاب که نیاز به مدیریت دارد، تاثیر بگذارد. در ابتدا، این مقاله در مورد پیش بینی تغییرات آب و هوایی با استفاده از شبکه عصبی فازی (FNN) مورد بحث قرار می گیرد و دقت این روش را برای پیش بینی آب سیلاب نشان می دهد. دوم، بر اساس نتایج فاز اول، منطقه بحرانی برای تهیه سیستم های آب آشامیدنی با استفاده از ابزار و تکنولوژی GIS تعیین می کند.