Detecting the optimal condition of Zeolite utilization in industrial wastewater treatment by using the fuzzy simulation model

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Research

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Detecting the optimal condition of Zeolite utilization in industrial wastewater treatment by using the fuzzy simulation model

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Abstract

To define optimal condition of Zeolite utilization was used the maximum industrial pollution load from the industrial wastewater discharged to treatment plant lied on the industrial town of Shiraz, Fars, Iran. In this study, chemical oxygen demand (COD) load and electrical conductivity (EC) load from this wastewater treatment plant (WWTP) along with the parameters of received industrial effluents, e.g., temperature, total suspended solid (TSS), total dissolved solid (TDS) and PH were monitored. Using the several mathematical models that defined on their relationships was resulted the correlation coefficients of 83% and 90% for COD with TDS, and COD with TSS, respectively, thus the best regression coefficient was 0.5 under linear and nonlinear forms. Autoregressive integrated moving average model (ARIMA) was also used for obtaining the better results, such that the exceeded values of TSS and TDS at before day were

defined as input variables. In this log-time of bioreactor process, curve fitting approach and clustering analysis with and without normalized data had not improved the regression coefficient of linear and nonlinear functions. The simulation model based on fuzzy inference system (FIS) has been good corresponding with the distribution of estimated and observed data of COD, so that comparing such distribution of COD with line of 1:1 resulting the regression coefficient is 0.764. This study indicated that fixed value of the soluble solids concentration on industrial wastewater discharged into treatment plant has the important role in effectiveness of Zeolite filtration, i.e., it's threshold is occurred in 1746 ppm in this case study.

Key words: Zeolite, industrial wastewater, fuzzy simulation, optimization

Highlight

- In this paper was presented an approach for defining the optimum condition of Zeolite utilization in WWTP on uncertainty conditions.
- This optimum condition was developed by FIS such that the water quality released from WWTP is enough good to be supplied water requirement of the greenspace.
- It was found that the entered soluble solids concentration into WWTP has important role in the released water quality and the effectiveness of Zeolite filtration.

1. Introduction

The water shortage is a growing problem in the world due to the freshwater resources have been becoming not enough to satisfy the demand. Although the freshwater shortage seems that the most cases of a climate-bound regional problems, it has reported in whole the world, e.g. , North Africa, the Middle East, southern Europe, Australia, and the southern states of the USA. Therefore, during the past few decades, there has been a growing interest in water alternative sources development such as the used urban water and desalinized brackish water and seawater [3]. According to UNESCO-WWAP [33] more than 70% of the water that is discharge all over the world used for the agricultural irrigation, however there is a big potential for the application of treated wastewater in irrigation [19]. The most important concerns in the agricultural use of treated urban waters [8] are related to the human and environmental health aspects, in other words, the quality and safety of the produced food [23] and the health concerns of agricultural workers. Other concerns include the salinity and water infiltration rate in the soil [36], as well as heavy metal accumulation and pollution caused by nutrient leaching [10]. Nevertheless, the use of treated wastewater is a global phenomenon in a variety of applications in more than fifty countries throughout the world as reported by [26, 12].

The key for safe irrigation is the water quality. Many standards have been to set by different institutions to control the quality of the irrigated water. The concentration and composition of the dissolved constituents in water combined with the amount of water used determines its quality for irrigation. Soils also vary in their capacity to resist adverse changes due to the components of the water. A comprehensive water analysis will indicate its suitability for irrigation use [1]. In the literature, oxygen required for the degradation of the organic matter biologically (BOD), the amount of oxygen needed to consume the organic and inorganic

68 materials, chemical oxygen demand (COD), potential of hydrogen (pH), and total suspended
69 solids (TSS) are widely used indicators of wastewater quality [11, 38].

70 Zeolites are safe and naturally occurring crystalline aluminosilicates have a three-
71 dimensional structure, which comprise assemblies of SiO_4 and AlO_4 tetrahedral joined in
72 different regular arrangements through the sharing of oxygen atoms and form a honeycomb
73 structure containing pores [31, 15, 14]. Natural zeolite is a promising adsorbent media has a
74 potential application as a metal ion adsorbent, and has particularly gained interest among
75 researchers, due to its ion exchange, molecular sieve properties and also its relatively high
76 surface area [21, 2]. The limited studies have been to carry out on the relationship between
77 loaded and exceed parameters of the industrial wastewater treatment by natural zeolite. In this
78 study, the exceeded values of chemical oxygen demand (COD) and electrical conductivity (EC)
79 from the industrial wastewater treatment plant was estimated based on other loaded factors such
80 as PH, temperature, total suspended solid (TSS), total dissolved solid (TDS). These measured
81 values are the given data, but the EC and the COD have considered as unknown variables. The
82 mathematical model of this relationship between these parameters defined.

83

84

85 ## 2. Material and Methods

86 ### 2.1. Wastewater station and monitoring

87 Water Reclamation Plant (WRP) is located in Shiraz industrial town, Fars, Iran (Fig.1).
88 The pollution points are approximately 1100 units of medium and small factories that released
89 their wastewaters to this plant network with the capacity of 2500 m3 per day, but the wastewater

flow is only loaded 1200 to 1500 m3 per day. Logons and stilling pond with anaerobic system, UABR system, UASB, Selector, SBR and wetland are the parts of this plant.

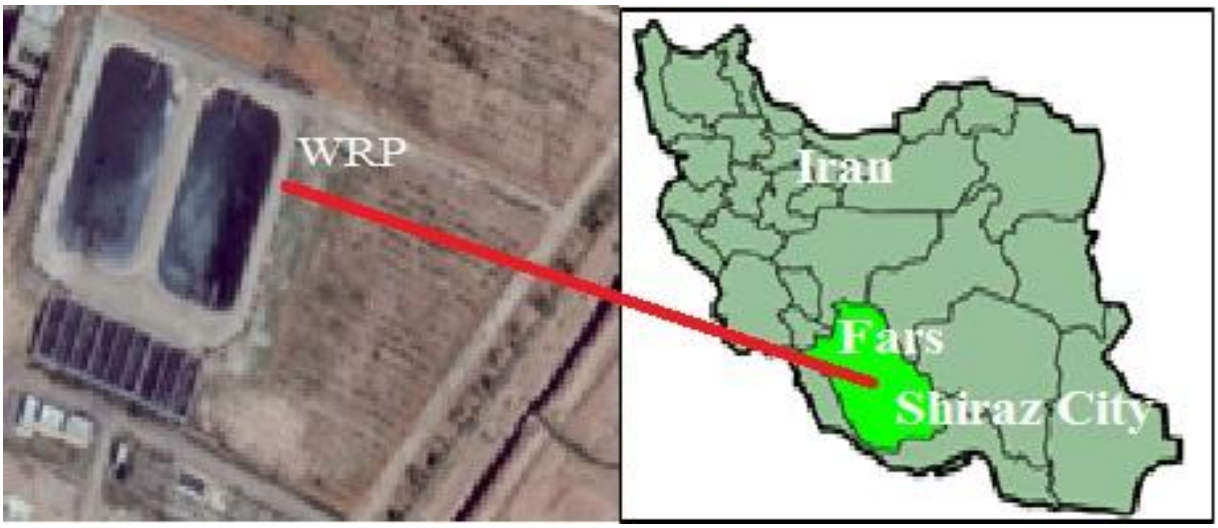

Figure 1. The location map of wastewater station

Monitoring the effluents accomplished by the discrete sampling in line with followed by chemical analysis in the laboratory. Table 1 summarized the monitored parameters and their analysis methods along with corresponding their laboratory standards. The similar analysis methods applied to determine the effluent characteristics discharged in industrial sewerage. The parameters, e.g., PH, T, EC, and TDS associated with COD have been measuring every day.

Table 1
The characteristics summary of monitored data

NO	Parameter	Analysis type	Measurement standard
1	COD	Spectrophotometer	APHA
2	PH	PH meter	APHA
3	EC	EC meter	APHA
4	TSS	Gravimetric	APHA

5	TDS	Gravimetric	APHA
6	Temperature	Temperature meter	APHA

2.2. Modeling the wastewater parameters

The environmental data characterized by high variations because of a variety of natural and anthropogenic influences. The popular approach to avoid the misinterpretation of environmental monitored data has been applying the multiple variable analyses methods for variables classification and modeling the environmental data [25]. The multivariate statistical techniques are also the appropriate tool for a meaningful data reduction and interpretation of multi-constituent chemical and physical measurements [17]. The multiple variable analyses have been widely used as unbiased methods in analysis of water quality data for drawing the meaningful conclusions [35, 24, 27, 28].

However, in this study, the raw data sets that obtained from monitoring process have used in the statistical models without any preprocess steps because importance in testing the model performances to forecast the upper and lower limits of wastewater parameters. The performance of selected statistical models was evaluated and discussed according to the root mean square error (RMSE). The statistical significant terms in forecasting the models along with the results of tests on error residuals were run to determine whether each model was adequate for this data. This process was used for finding the correlation coefficients between COD and EC of the exceeding wastewater, and other loaded factors. The curve fitting approach was also utilized to consider the several linear and nonlinear models for simulating their correlations. Time series analyses were applied, due to the non-significant correlation between these variables.

The statistical techniques for analyzing the time-series data have been included the range

from simple to very complex. However, the first step in such analyses is always to identify the characteristics of data, thus the multiple range tests are performed by using the correlation analyses to test all the pairwise comparisons among daily series means of each monitored parameter. Time series analysis was applied to establish the general trend of each effluent parameter. In the time series analysis, it is assumed that the data consists of a systematic pattern (identifiable component) and random noise (error), which makes the pattern difficult to assess. The most of time series analyses techniques involve some form of filtering out noise in order to make the pattern more salient [9]. The models of time series data have many forms and represented different in the modeling processes. During modeling variations in the level of a process, three broad classes of practical importance are the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. This one class depends linearly on previous data points. Combinations of these ideas produce autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models. Special attention has accorded to ARIMA model, which estimates and forecasts using the methods prescribed by [4, 5].

This study thus designed that the exceeded variables of COD or EC were the output of models and other loaded factors were the inputs parameters. Since, data set of the inputs and outputs factors had not the significant correlation with together, here was assumed that having the significant correlation at log-time, i.e., one to three days. This idea was generated due to the retention time of wastewater on zeolite channel is the key index to be an effect on the exceeded water quality. Hence, the models of time series analysis, i.e., ARIMA were used, then the curve fitting approach were utilized to achieve the simulation model based on the relationship between the normalized data of exceeded daily COD and loaded TDS on previous day. In such process

needs to normalize data as following:

$$(X_{max} - X_i) / (X_{max} - X_{min}) \quad (1)$$

Where X_{max} and X_{min} are the maximum and minimum values of input or output variables. The several linear and nonlinear models based on the curve fitting approach were used to find a simulation model based on defining the relationship between the normalized data of the daily exceeded of COD, and the loaded of TDS at previous day, resulting the achieved regression coefficient was less than 0.5. To improve the results of simulation process applied these relationships clustering analysis (CA) in line with the fuzzy inference system (FIS). The cluster analysis was also utilized to develop the meaningful aggregations of groups of entities based on a large number of interdependent variables. The purpose was specifically classified for sample of entities into smaller number of the mutually exclusive groups based on the multivariate similarities among entities [18]. The CA was divided a large number of objects into the smaller number of homogeneous groups under the basis of their correlation structure.

A fuzzy inference system (FIS) included a fuzzy rule-based system is a nonlinear mapping of a given input vector to a scalar output vector by using fuzzy logic. Fuzzy rules have proven to be effective for specifying how a given system should operate. Inference, “then” was defined as a procedure for deducing new facts out of existing ones in the basis of formal deduction rules. Classical mathematical tools (e.g., two-valued predicate logic, differential equations) are not well suited for dealing with ill-defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy IF-THEN rules allows for a higher degree of flexibility and expressivity to cope with problems that are too complex for exact solution but do not require a high degree of precision [*39,* 13]. FISs have been successfully applied in many fields, such as

control systems [7, 22], time series forecasting [20], intelligent robots [37], decision analysis [6], expert systems, and computer vision.

An FIS is based on fuzzy set theory, fuzzy IF-THEN rules and fuzzy inference theory, the architecture of which includes five major components: fuzzifier, rules, membership functions (MFs), inference engine and defuzzifier (as shown in Figure 2). Rules are the core of an FIS and can be extracted from historical data or generated from human knowledge. To extract rules from the numerical training data through learning or clustering algorithms is commonly to be using for industrial applications and academic researches. In this study, the rules expressed as a collection of fuzzy IF-THEN rules and extracted from the cluster analysis.

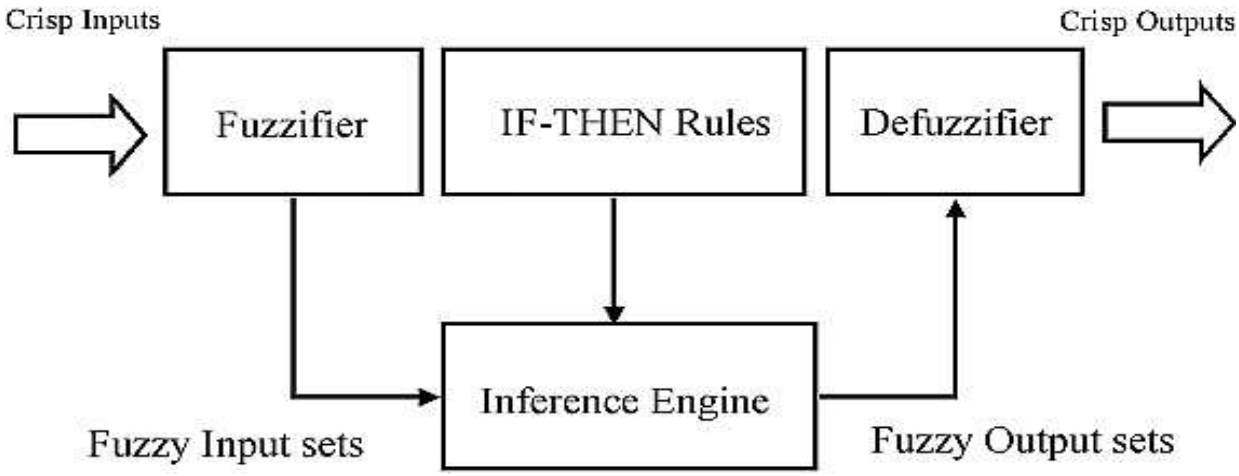

Figure 2. Architecture of fuzzy inference system.

In the basis of a set of fuzzy IF-THEN rules, the inference engine maps fuzzy input sets into fuzzy output sets through the fuzzy operations, such as T-norm and T-conorm. There only focus on algebraic product, one kind of T-norm operations, for fuzzy intersection. The T-norm operators can be thought of as the extension for fuzzy AND operations and have many kinds of

operations, e.g., algebraic product, logical product and bounded product [32]. Membership functions used in the terms appear in the antecedents and consequents of fuzzy IF-THEN rules. The common shapes of membership functions are triangular, trapezoidal, piecewise linear, Gaussian and bell-shaped functions. Owing to the statements of IF-THEN rules, the fuzzifier maps a crisp input set into a fuzzy input set that a crisp variable is characterized by an appropriate membership function.

The final component, the defuzzifier, converts a fuzzy output of inference engine to a crisp output. Through the aforementioned procedure, FIS formulates the mapping from an input vector into a scalar output, whose relationship can be expressed as $y = f(x)$. The two most common FISs are Mamdani [16] and Takagi-Sugeno-Kang (TSK) [*29*, *30*]. They both have the same antecedent structures, but have the different consequent structures. The consequent parts of Mamdani's fuzzy rules are fuzzy sets, while those of TSK's fuzzy rules are functions defined by below equation [20]:

$$\text{If x is F then y is f(x)}$$

Where F is fuzzy sets in the antecedent, while $f(x)$ is a crisp function in the consequent. Usually $f(x)$ is a polynomial. For computational simplicity, we choose the first-order TSK model as the consequent part.

3. Results and discussion

The popular statistical analysis has usually used to study the statistical characteristic of data on the wastewater variables included central tendency, variability, and shape. There have the standardized skewness and standardized kurtosis that to be applied to determine whether the sample having the normal distribution, the statistics outside of the range of -2 to +2 indicates significant departures from normality and would tend to invalidate many of the statistical procedures that normally applied on the data. The standardized skewness values outside expected range for the followed variables were shown In Table 2. The Multiple-Variable Analysis was applied to build models for predicting the exceeded values of EC and COD from other loaded factors. The days of 100 monitoring data from wastewater treatment station were applied to analyze multi-variable correlation, correlation coefficient, and P-values at over 95%, and the results showed in Table3.

Table 2

Summary statistics for each of the wastewater data variables

Item	TSS(ppm) Input	TEM Input	TDS(ppm) Input	PH Input	EC(mgl) Input	COD(ppm) Input	EC Output	COD Output
Count	100	100	100	100	100	100	100	100
Average	51.26	19.11	1566	8.60	2368	98.21	1507	62.57
St. deviation	6.37	0.53	590	0.27	569	19.59	152	13.80
Variation Coefficient	12.44%	2.80%	37.68%	3.14%	24.05%	19.95%	10.11%	22.07%
Minimum	40	18	850	8	1690	80	1200	34
Maximum	72	21	3300	9	4000	180	1750	83
Range	32	3	2450	1	2310	100	550	49

St. skewness	3.46	2.46	4.86	-1.37	4.00	8.72	-1.48	-2.97
St. kurtosis	1.95	1.99	1.93	-0.99	0.83	10.97	-1.45	-1.11

According to the investigation goal of effectiveness wastewater treatment process on water quality, the relationship between loaded and excess variables was considered. The best correlation coefficient associated with the acceptable p-vale was obtained from the exceeded values of EC and the loaded values of TSS for each day (Fig 3), besides the exceeded values of COD had the most level of regression by the loaded values of TDS. As a result, the equations form of the exceeded values of COD and EC along with the loaded values of TDS and TSS at the same time can be shown as following:

$$COD_E(t) = F(TDS_L(t)) \quad (2)$$

$$EC_E(t) = F(TSS_L(t)) \quad (3)$$

Since the electrical current conduction has been directly related to the concentration of dissolved salts in water and thus to total dissolved solids (TDS), the electrical conductivity method has been using as a measurement approach of capacity solved salts into water. Dissolved salts into the positively charged ions and the negatively charged ions, which has made the electricity circuit. Hence, the observed relationship between the exceeded of EC and the loaded of TSS was demonstrated that the concentration of Zeolite had not the effect significant on wastewater treatment process under the salt pollution. The reason of such results was that the some factories, the wastewater has been released into collection network, which their extra salt were more than the beyond Zeolite filtration capacity.

The correlation coefficients of COD with TDS, and COD with TSS were 83% and 90%, respectively (Table 3). Although, the relationship between COD and TDS is not the significant difference with the relationship between COD and TSS, measuring the TDS is easier than the TSS, thus to estimate the COD, Eq. (2) was selected. The filtration capacity reduces because decreases the Zeolite ion exchanges that is its most important characteristic, resulting the extra loaded of suspended and dissolved solid from the small factories into collection network could be the basic challenge to increase the exceeded values of EC and COD.

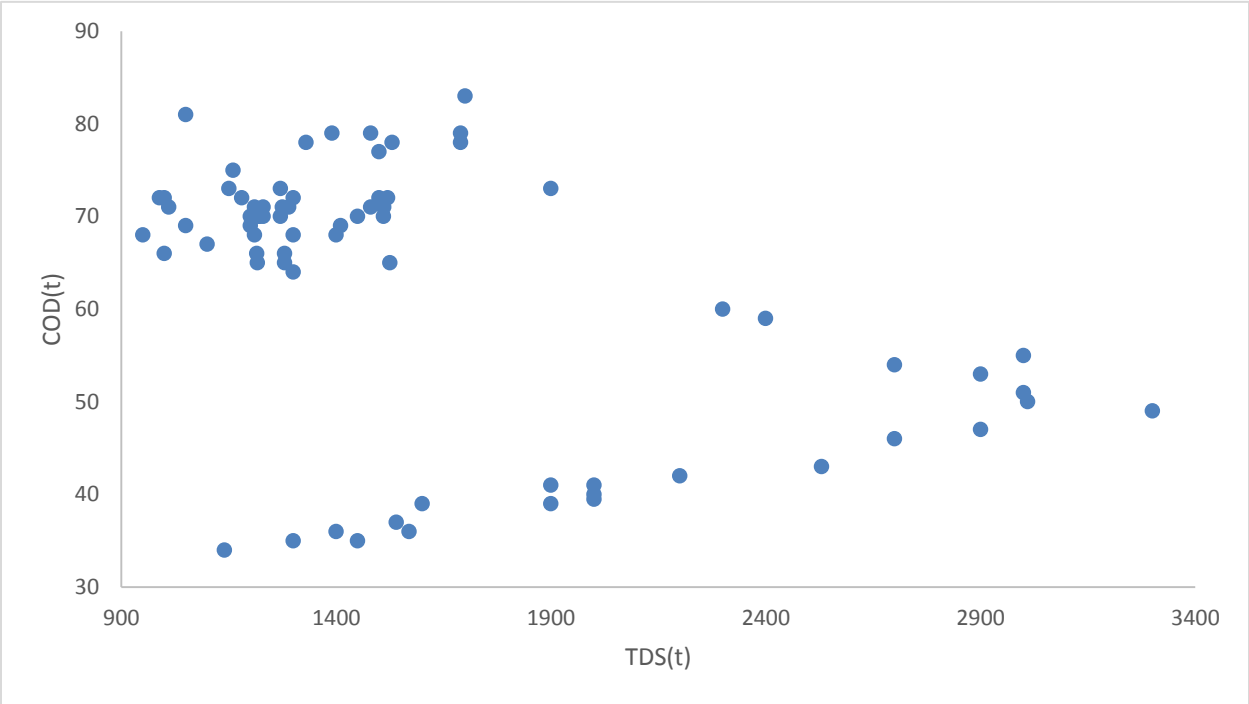

Figure 3. The exceeded values of Chemical Oxygen Demand (ppm) and the loaded values of Total Dissolved Solid (ppm) on t^{th} day.

Table 3

The Pearson product moment correlations between each pair of wastewater data variables; the indexes of "E" and "L" define as the exceeded values and the loaded values, respectively.

Variable	COD_E	EC_E	COD_L	EC_L	PH_L	TDS_L	TEM_L	TSS_L
COD_E		0.816	0.467	-0.415	-0.159	-0.472	-0.165	0.395
		0	0	0.0002	0.170	0	0.155	0.0004
EC_E	0.816		0.197	-0.348	-0.210	-0.463	-0.357	0.535
	0		0.087	0.002	0.068	0	0.002	0
COD_L	0.467	0.197		-0.357	-0.089	-0.094	0.214	-0.055
	0	0.087		0.001	0.443	0.418	0.063	0.636
EC_L	-0.415	-0.348	-0.357		0.189	0.843	0.113	-0.099
	0.0002	0.002	0.001		0.100	0	0.329	0.394
PH_L	-0.159	-0.210	-0.089	0.189		0.278	0.001	0.023
	0.170	0.068	0.443	0.100		0.015	0.990	0.844
TDS_L	-0.472	-0.463	-0.094	0.843	0.278		0.234	-0.210
	0	0	0.4182	0	0.015		0.0416	0.0675
TEM_L	-0.165	-0.357	0.214	0.113	0.001	0.234		-0.284

	0.155	0.001	0.063	0.329	0.990	0.041		0.013
TSS_L	0.395	0.535	-0.055	-0.099	0.023	-0.210	-0.284	
	0.0004	0	0.636	0.394	0.844	0.067	0.013	

The variations of exceeded values of COD with the loaded values of TDS presented in Fig. 3 has been compatible with their lack correlation coefficient, thus the highest regression coefficient of linear and non-linear models tested to simulate their changes were 0.5. As a sequence of attempt to test through the time-series analyses such as ARIMA has assumed the existed log-time from one to three days between the loaded variables, i.e., TSS and TDS. The retention time of wastewater in Zeolite channel is generally a key index for effecting on the exceeded water quality, thus these analyses and models were necessary.

The five models of ARIMA compared for selecting the best time-series (Table 4), resulting the one day log has been better matching on other models, so that predicted daily changes of TSS and TDS by their value of one day before. This model has predicted the exceeded values of EC and COD at the time of t through the loaded values of TSS and TDS at the time of t-1. As a result, the decision maker could have the optimization analysis by the means of practical strategies to change the collection network or the capacity of Zeolite filtration. Therefore, Eq. 2 and 3 have adjusted to detect the correlation above variables at different time.

$$COD_E(t) = F(TDS_L(t-1)) \quad (4)$$

$$EC_E(t) = F(TSS_L(t-1)) \quad (5)$$

Table 4
The results of time-series analysis for the loaded values of TDS.

Model	RMSE*	MAE	MAPE	ME	MPE	AIC
ARIMA(1,0,0)	3.76	2.91	5.66	0.007	-0.493	2.698

ARIMA(2,0,0)	3.78	2.87	5.57	0.012	-0.478	2.729
ARIMA(1,0,1)	3.78	2.88	5.59	0.010	-0.482	2.730
ARIMA(1,0,2)	3.75	2.79	5.43	0.054	-0.377	2.734
ARIMA(0,1,0)	3.95	2.96	5.75	-0.083	-0.465	2.747

*RMSE, the root mean squared error, MAE, the mean absolute error, MAPE, the mean absolute percentage error, ME, the mean error, MPE, the mean percentage error.

Using the curve fitting approach with and without the normalized data to achieve any function of the COD_E (t) based on the TDS_L (t-1) and ECE (t) with TSS_L (t-1) has not improved the regression coefficient for linear and nonlinear functions. The weak relationships between COD_E (t) and TDS_L (t-1) has explained how the data distribution shown in the Fig. 4. The classification analysis of data distribution based on the data normalized average K-means has used in this study (Table 5).

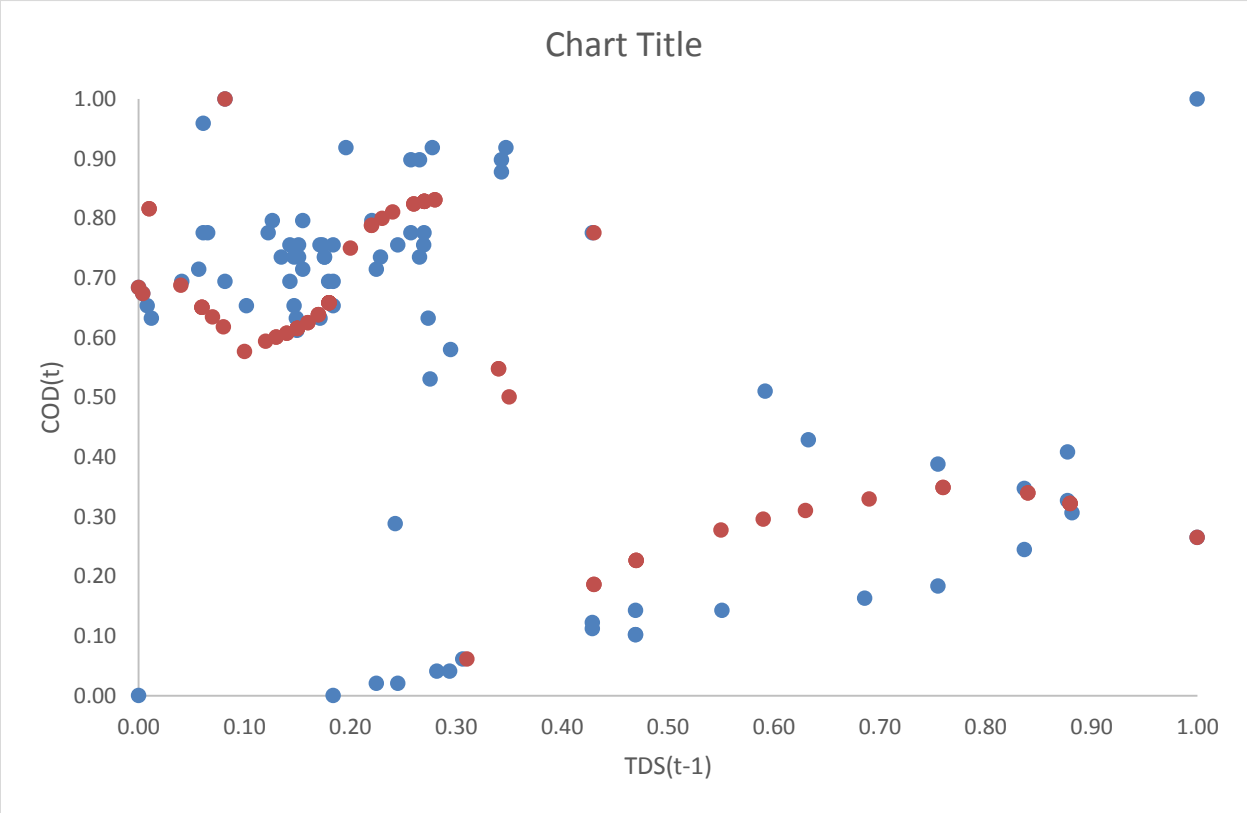

Figure 4. The exceeded values of chemical oxygen demand (COD) in the day of t, and the loaded values of total dissolved solid (TDS) in the day of t-1. The triangular points demonstrated the estimated values of COD in the day of t by the TDS in the day of t-1, and the circular points demonstrated the results of Mamdini's fuzzy inference system model.

Table 5

The results of clustering analysis for the loaded values of TDS and TSS in the day of t-1, and the exceeded values of COD and EC in the day of t.

Cluster	COD	TDS
1	0.856	0.297
2	0.331	0.775
3	0.075	0.362
4	0.749	0.166
5	0.643	0.123
	TSS	**EC**
1	0.645	0.833
2	0.296	0.658
3	0.254	0.270

Based on the results of clustering analysis, the ranges of CODE (t) and TDSL (t-1) variables classified to the five major classes as shown in Table 5. The COD is being in low class until the TDS has in moderate or high class, resulting it assumed that this trend has the fuzzy behavior, and the fuzzy inference systems (FIS) can be appropriated to simulate this distribution. Therefore, in the first, the membership functions of input e.g., TDS_{t-1}, and output e.g., COD_t

variables in Mamdini's approach was defined based on the average of each class. In this way, the five classes e.g. very low, low, normal, high and very high have described for both variables, such that the functions as “very very low” and “very very high” used to define the extreme states as 0 and / or 1, respectively; each input and output variables includes the seven bell membership functions (Fig. 5). The Mamdani's modeling process is generally to be needed a supervisor that known as the trend training. In this study, the major classes of data distribution had supervisor role, and based on their relationships, the seven fuzzy rules were defined such that the Fuzzy function results of the variables of input e.g., TDS_{t-1} and output COD_t can be established as follows:

Rules no. 1: If TDS_{t-1} is very very low then COD_t is very very high. (6)

Rules no. 2: If TDS_{t-1} is very low then COD_t is normal.

Rules no. 3: If TDS_{t-1} is low then COD_t is high.

Rules no. 4: If TDS_{t-1} is normal then COD_t is very high.

Rules no. 5: If TDS_{t-1} is high then COD_t is very high.

Rules no. 6: If TDS_{t-1} is very high then COD_t is low.

Rules no. 7: If TDS_{t-1} is very very high then COD_t is very very low.

In the next step, an artificial test dataset of TDS_{t-1} from 0 to 1 created and used in above FIS model in order to the demonstration of the features of simulation model (Fig. 5); after that calculated the values of COD_t which obtained according to measurment of the TDS (t-1) by using this model resulting they has shown in Fig. 4.

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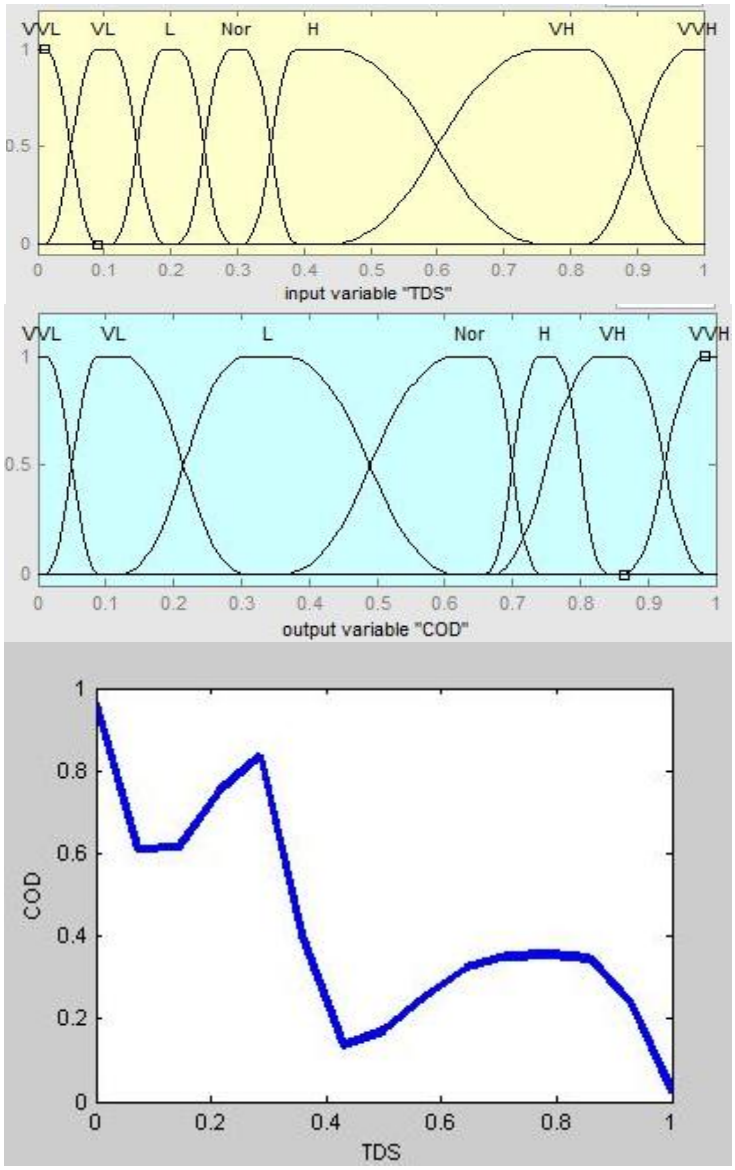

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330 Figure 5. The output's membership functions of the exceeded values of COD in the day of t, and
331 the input's membership functions of the loaded values of TDS in the day of t-1 in line with the
332 results of Mamdini's fuzzy inference system.

333

334 The results of validation process of FIS model presented in Fig. 5, has obtained by
335 comparing the measured data of COD (t) with observed data, in which it is shown in Fig. 6. This

simulation model had been good corresponding (e.g. R2 = 0.764) with the distribution of measured and observed data of COD (t) while was compared by the line of 1:1. Here is concluded that the assumption of Fuzzy behavior could be used to explain the trend distribution of TDS_{t-1} and COD_t.

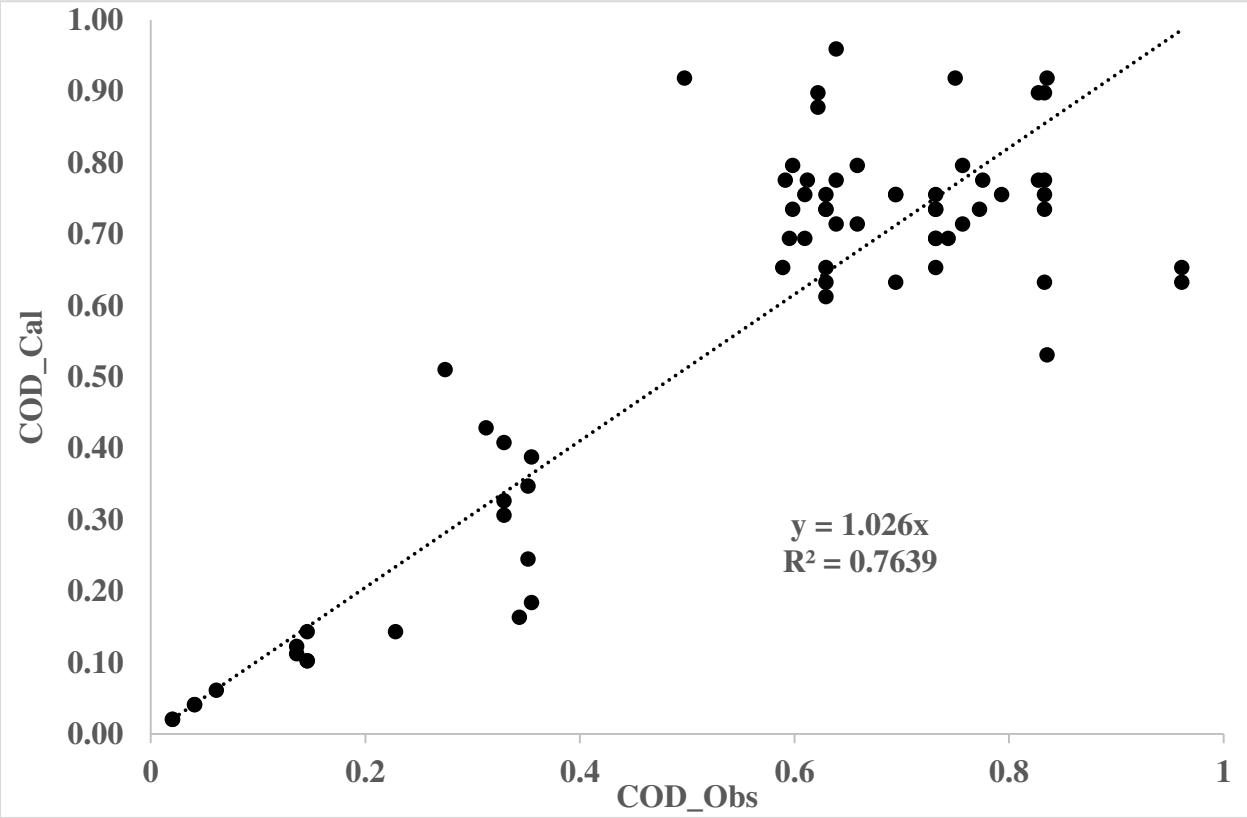

Figure 6. The results of comparing the amounts of estimated and observed of exceeded COD.

From the Fig. 4 and Fig. 5, if the TDS_L was "low" then the COD_E was "high", and conversely, if the TDS_L was "high" then the COD_E was "low", so that there had closed to the standard level. This result indicated the capacity of Zeolite filtering could be affected by other

factors. The input of "Low" for TDS observed when the rainfall had occurred, thus TDS of the entered wastewater content was affected by runoff, such that the values of TDS_L had decreased due to the volume of wastewater increased during this condition. In this condition, the loaded wastewater was more than the daily filtering capacity of Zeolite channel. Although the value of TDS was low, the volume of wastewater entering into the treatment plant had high then Zeolite channel so that here could not be appropriately operated its ion exchange capacity. Its filtration operation had better, when the few wastewater along with the more value of TDS entered to the Zeolite channel. Finally, this result can be achieved to manage, that the loaded amount of wastewater treatment pollutants and the mass-transfer of wastewater in line with Zeolite channel should be controlled together.

The highest regression coefficient of the tested linear and non-linear models to simulate the variations of EC_E with of TTS_L were less than 0.5, and after that used the curve fitting approach with and without normalized data to achieve a function of EC_E from the day of t with TSSL from the day of t-1. These approaches couldn't improve the regression coefficient of each linear and nonlinear function too [34, 12]. Based on the results of clustering analysis, the ranges of the EC_E from the day of t, and TTS_L from the day of t-1 variables had classified into three major classes. The Mamdani's modeling process was also used to simulate these changes similar there had applied for simulating the relationship between COD_t with TDS_{t-1}. The FIS simulation model had not good corresponding with distribution of the measured and observed data of EC_E from the day of t.

4. Conclusion

Upgrading the efficiency in wastewater treatment management has the goal of decision maker to model the relationship between input and output variables, due to here needs that these models to evaluate treatment process. Therefore, the purpose of this study has been achieving an appropriate model of the exceeded variables, e.g., COD and EC associated with the loaded variables, e.g., TDS and TSS. The results showed that no significant correlation coefficient were obtained by analyzing approaches such as multivariate, curve fitting with linear and nonlinear models, time series, and clustering with and without normalized data. Hence, the results of variables classification were utilized to define the mean and range of each membership function for the variables of input, i.e., TDS_{t-1} and output, i.e., COD_t.

The Fuzzy rules could been described the data distributions of input and output variables, wherein other deterministic models could not been considering subject matter. The feature of Fuzzy rules in this issue has caused goodness conformity in the estimated and measured values of the exceeded COD_t, i.e., $R^2 = 0.76$, thus the Fuzzy behavior assumption of data distribution was admitted. The result of simulation model showed that the data distribution function of input variables, TDS_{t-1} along with output, COD_t has formed similar to "S" shape curve, and could been thus used as a reference for the filtration capacity of Zeolite channel.

The certain variations range of TDS have been existing that the filtration by Zeolite could been affected, it is way that beginning of this impact is defined as such critical point, i.e., the threshold amount of TDS. In this point, Zeolite responsibility on the removal COD in wastewater treatment is to be sufficient, for example in this study, TDS threshold was occurred in 1746 ppm

in line with COD was 52 ppm (Fig. 5). Although the others of research have been trying to improve treatment efficiency from the direct determination of Zeolite quantity, the obtained results of our study indicated that the fixed value of soluble solids concentration into mass-transfer of wastewater entering on treatment plant in the Zeolite filtration effectiveness had important role, due to in the view of fact that the filtration capacity was a function of the soluble solids.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

All authors read and approved the final manuscript.

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Not applicable

5. References

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Figures

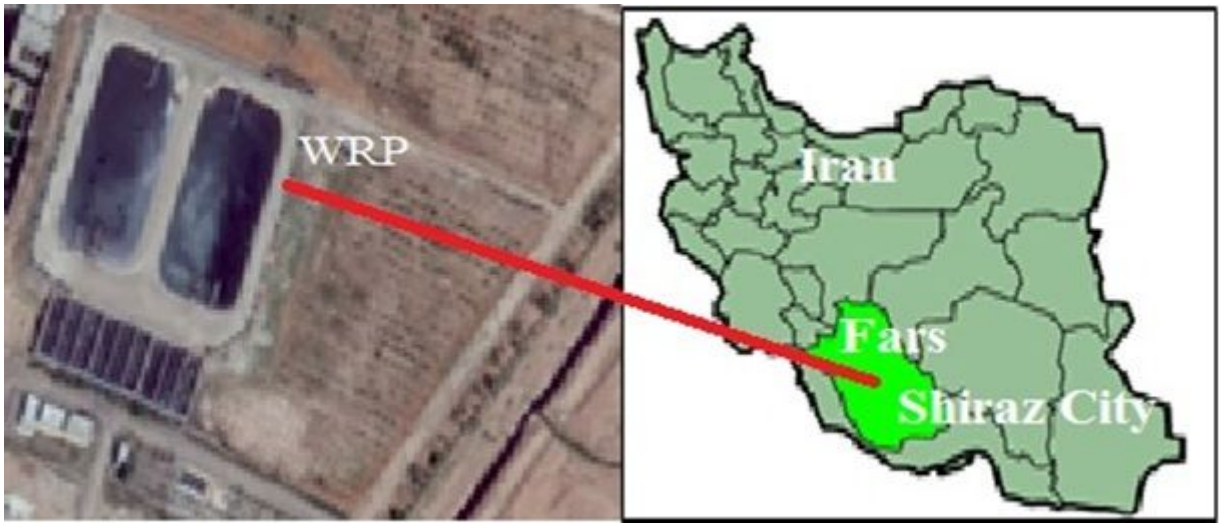

Figure 1

The location map of wastewater station

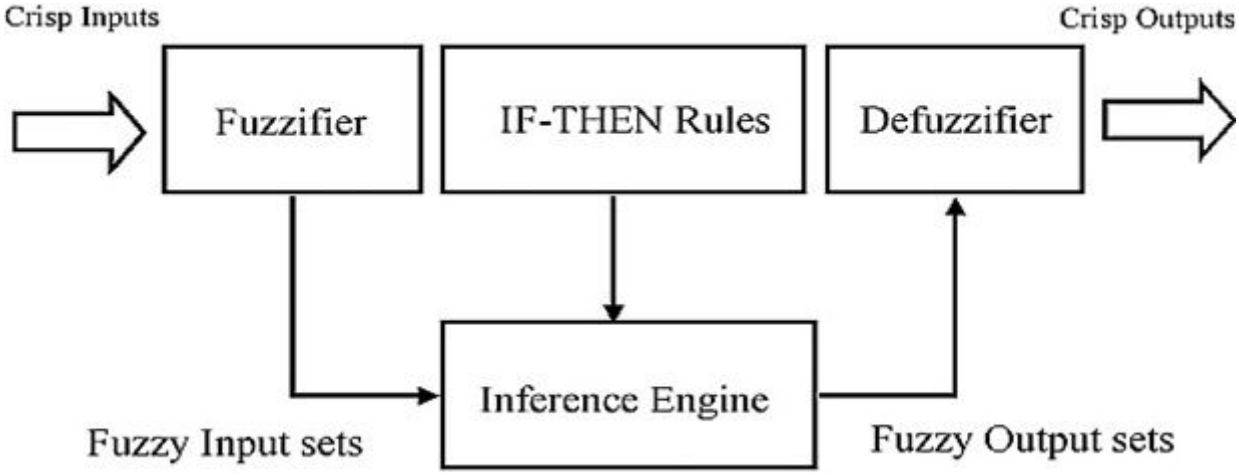

Figure 2

Architecture of fuzzy inference system.

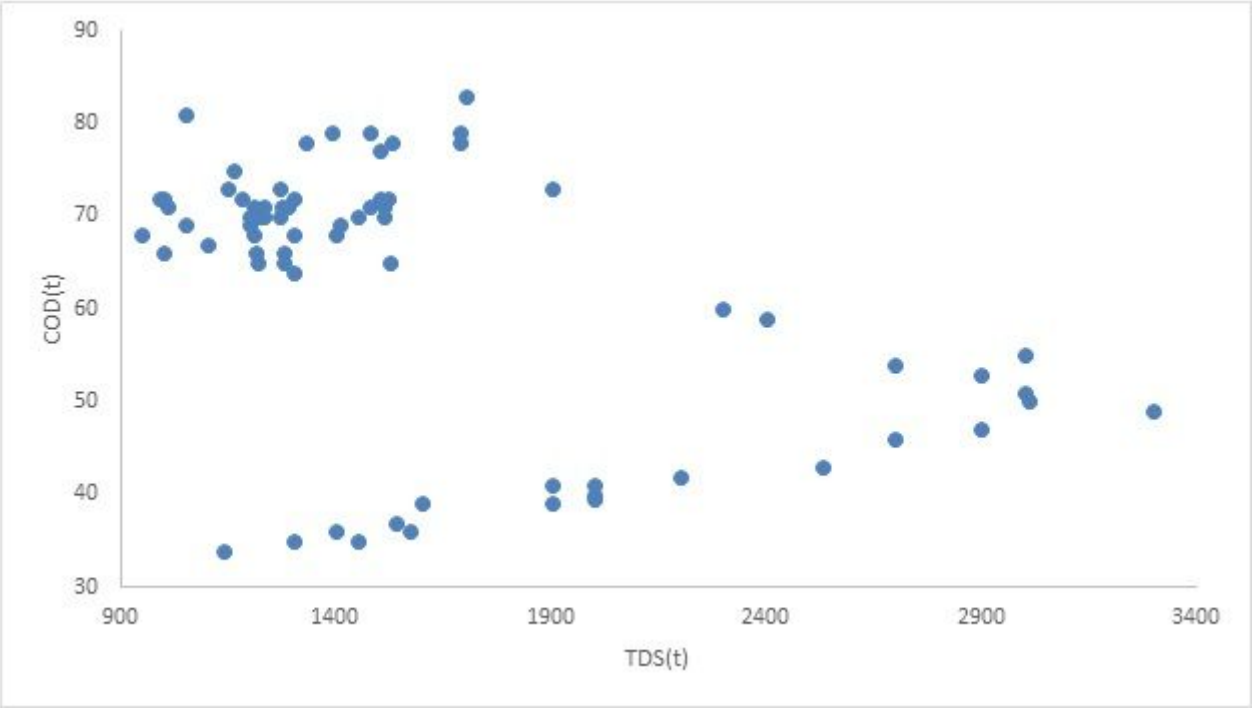

Figure 3

The exceeded values of Chemical Oxygen Demand (ppm) and the loaded values of Total Dissolved Solid (ppm) on tth day.

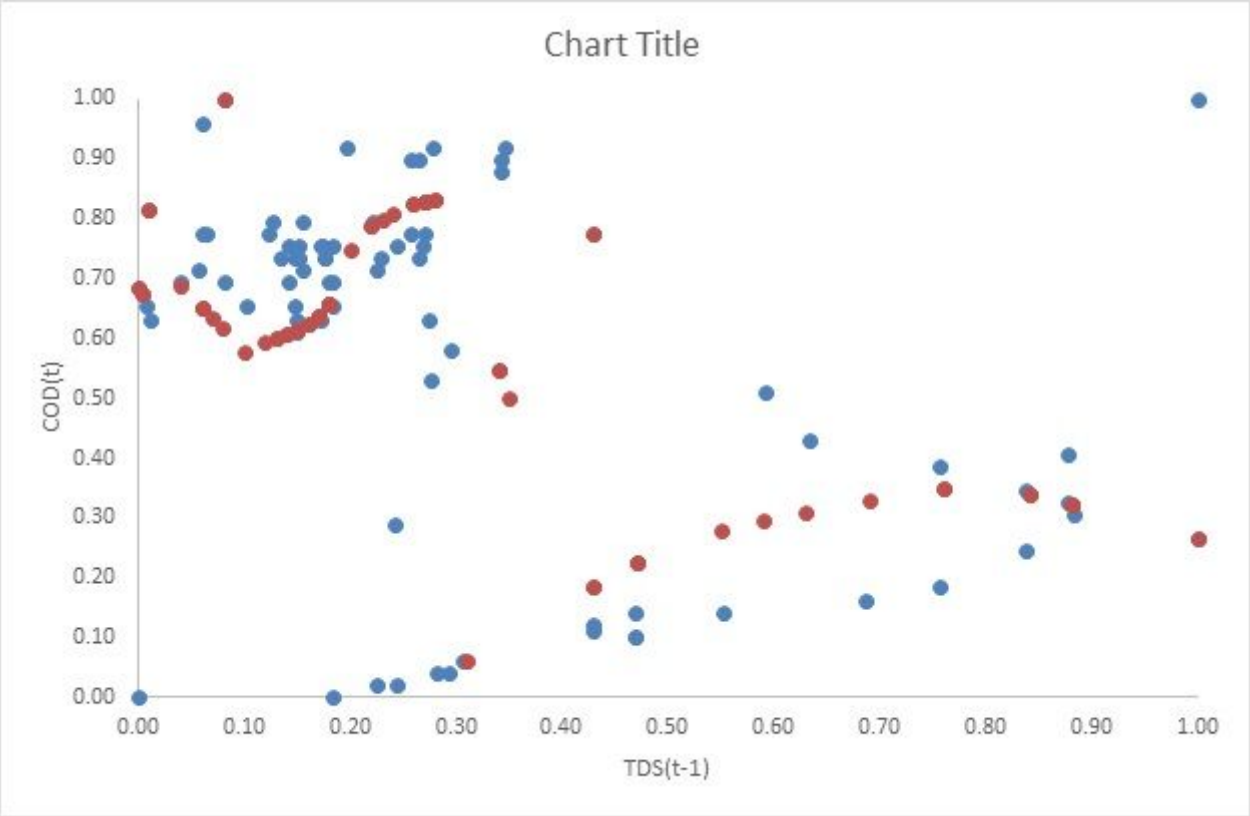

Figure 4

The exceeded values of chemical oxygen demand (COD) in the day of t, and the loaded values of total dissolved solid (TDS) in the day of t-1. The triangular points demonstrated the estimated values of COD in the day of t by the TDS in the day of t-1, and the circular points demonstrated the results of Mamdini's fuzzy inference system model.

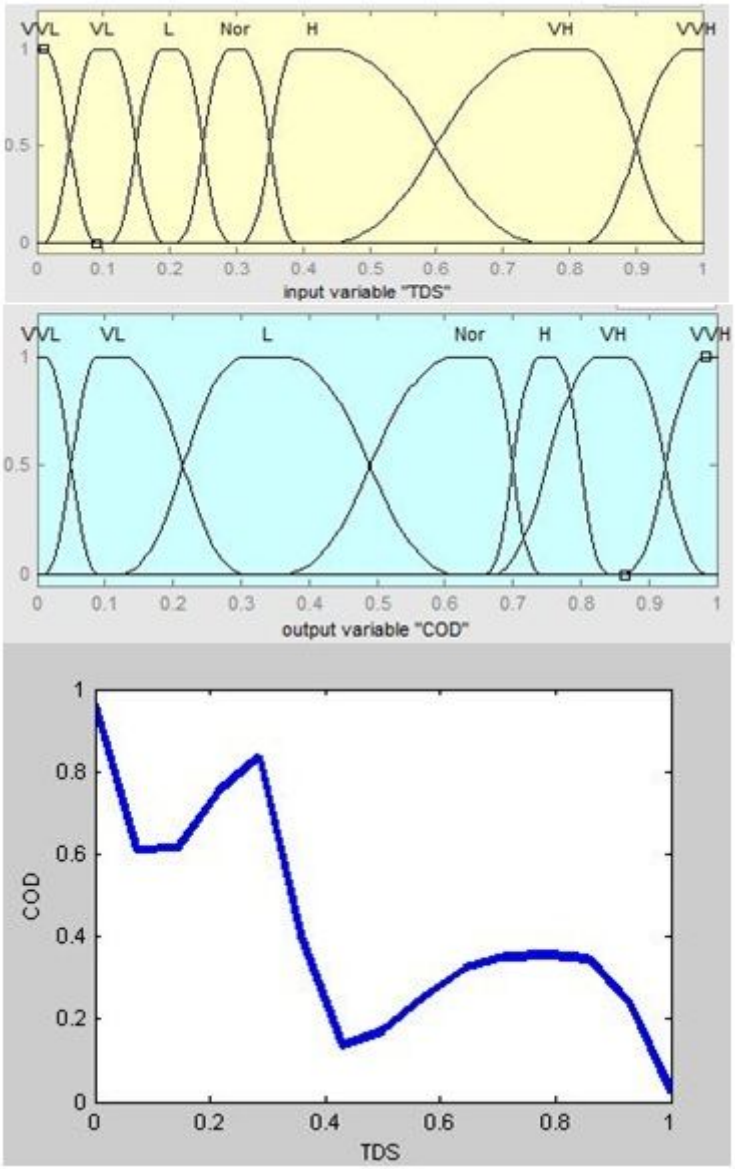

Figure 5

The output's membership functions of the exceeded values of COD in the day of t, and the input's membership functions of the loaded values of TDS in the day of t-1 in line with the results of Mamdini's fuzzy inference system.

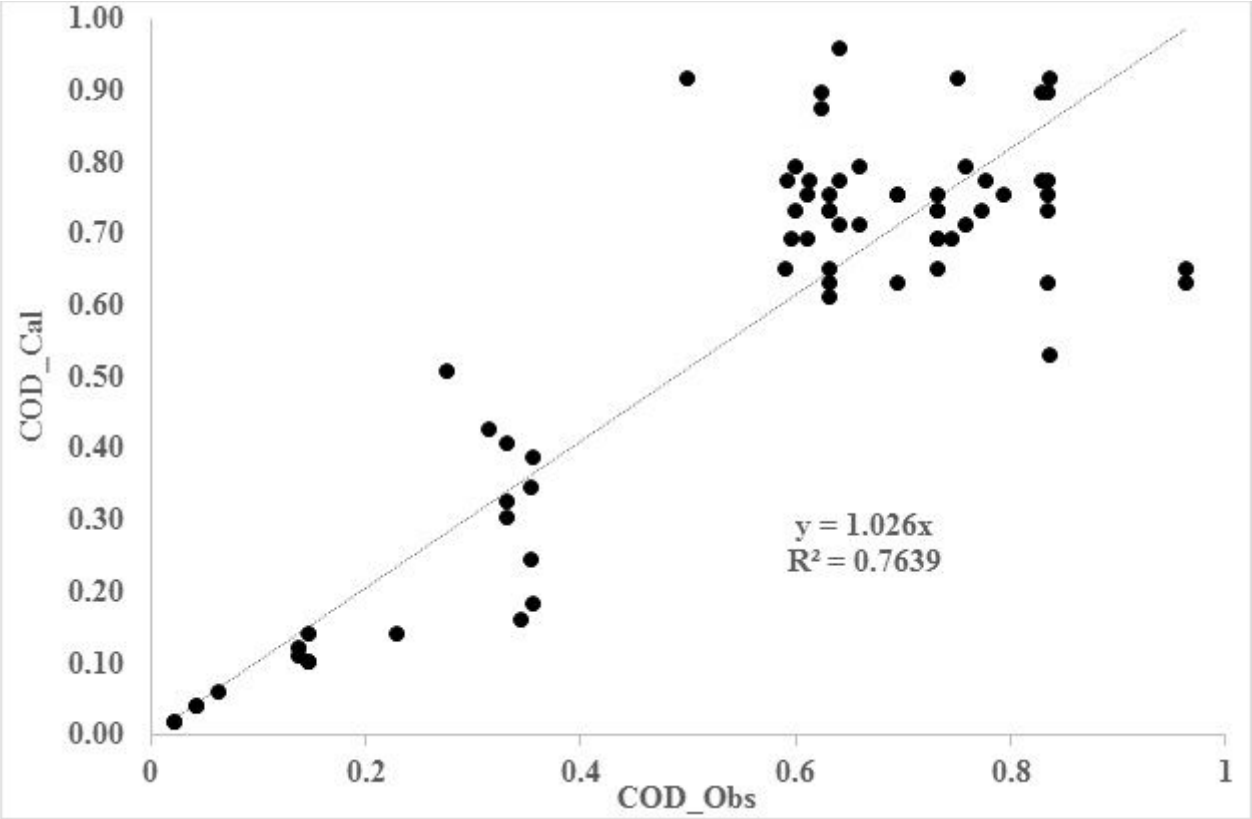

Figure 6

The results of comparing the amounts of estimated and observed of exceeded COD.