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Adaptive Sugeno Fuzzy Clustering System for Intelligent Monitoring of Inorganic Materials in Wastewater Aeration Tanks

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ABSTRACT

The aim of this study is to control the performance of wastewater treatment plants for treating inorganic materials. Samples of wastewater were investigated along a year. Fuzzy logic modeling procedures were performed onto investigational data to explore with time the concentrations of inorganics in aeration tanks at two stations in Jordan. Model results show that biological treatment of wastewater is not effective to decrease the concentration of inorganic materials. The concentration of each inorganic material at given time and place is being tracked via Fuzzy system. Sugeno-Fuzzy Inference System (FIS) is herein generated by subtractive clustering. The rule extraction method first uses the subtractive clustering function to determine the number of rules and antecedent membership functions and then uses learning estimation to determine each rule's consequent equations. Training technique is conducted using hybrid learning algorithm. It applies a combination of the least-squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set. Intelligent monitoring system is then applied; sensors and data logger system provide inputs to fuzzy logic controller. The fuzzy controller uses the FIS generated from experimental data and then the monitor about certain inorganic compound is achieved. The idea of this study is to track inorganic materials concentration at place and time together in the same model that is handy to check it promptly. It provides dynamic control system that is not only records data about concentrations but also gives a decision to comply with standards.

Key words: Wastewater treatment, modeling, municipal, fuzzy logic, control

INTRODUCTION

Municipal wastewater contains different amounts of various compounds which can be divided according to their sizes into soluble and suspended substances. According to their nature the both types are divided into organic and inorganic substances (Metcalf and Eddy, 1991).

Conventional wastewater treatment is a combination of physical and biological processes to remove organic matter (Hammer, 2008). Approximately 16,000 municipal WWTPs are in operation in the United States, serving 75% of the nation's population (USEPA, 1996). These plants were designed to remove nutrients, pathogens and other contaminants from wastewater. Bacterial processes transform influent organic matter into new biomass and via respiration produce volatile gases (Westerhoff *et al.*, 2013).

Although, secondary treatment processes when coupled with disinfection may remove over 85% of the BOD and suspended solids and nearly all pathogens, only minor removal of inorganic pollutants such as nitrogen, phosphorous, soluble COD and heavy metals is achieved. These inorganic pollutants are of major concern, a tertiary wastewater treatment or advanced is required (Davis and Cornwell, 2008).

Ekama *et al.* (2006) in their experimental and theoretical investigation, they found that the influent wastewater inorganic suspended solids concentration is preserved through sludge anaerobic digestion, activated sludge and aerobic digestion unit operations.

Operation of a wastewater treatment plant is often affected by a variety of physical, chemical and biological factors (Ma *et al.*, 2006).

Apart from traditional methods in water resources planning and management, non-conventional methods for utilization of water should be considered, like wastewater treatment and reclamation. This trend can lead to a reduction of the demand for water from existing water sources (Smith and Bani-Melhem, 2012).

Natural processes are complex and interrelated; therefore fuzzy logic modeling is able to endure hazy natural systems. The importance of fuzzy logic design is due to the simplified and reduced development cycle, the ease of implementation for multifarious data and the efficient performance (Bonde, 2000).

The significant advantage of intelligent modeling is that no precise mathematical model is needed, hence it can well approach any nonlinear continuous function and overcome the shortcomings of traditional control that depends on accurate mathematical model (Wan *et al.*, 2011; Fu and Poch, 1998).

Fuzzy logic algorithms have been widely applied to pursue better effluent quality and higher economic efficiency on biological treatment processes (Ferrer *et al.*, 1998; Fu and Poch, 1998; Kalker, 1999).

Yoo *et al.* (2003) proposed a new approach to nonlinear modeling and adaptive monitoring using fuzzy principal component regression and then applied to a real wastewater treatment plant data set. The result shows that it has the ability to model the nonlinear process and multiple operating conditions and is able to identify various operating regions.

Tay and Zhang (2000) integrated fuzzy systems and neural networks in modeling the complex process of anaerobic biological treatment of wastewater. The fuzzy neural model simulated the system performance well and provided satisfactory prediction results based on observed past information.

Tay and Zhang (1999) employed an advanced neural fuzzy technology to develop a conceptual adaptive model for anaerobic treatment systems. The conceptual model was used to simulate the daily performance of two high-rate anaerobic wastewater treatment systems with satisfactory results obtained.

Neural fuzzy model based on adaptive-network fuzzy inference system is applied for a sugar factory anaerobic wastewater treatment plant operating under unsteady state to estimate the

effluent chemical oxygen demand, COD. The developed model with phase vector and history extension has been able to adequately represent the behavior of the treatment system (Perendeci *et al.*, 2009).

Pai *et al.* (2009) in their study employed three types of Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) to predict suspended solids and Chemical Oxygen Demand (COD) in the effluent from a hospital wastewater treatment plant. The results indicated that ANFIS statistically outperforms ANN in terms of effluent prediction.

Holubar *et al.* (2002) applied neural networks based on the feed-forward back-propagation algorithm to model and control methane production in anaerobic digesters. The model was trained using data generated from four anaerobic continuous stirred tank reactors operating at steady state.

Mingzhi *et al.* (2009), in their study for the coagulation process of wastewater treatment in a paper mill, employed an optimization procedure fuzzy neural network to model the nonlinear relationships between the removal rate of pollutants and the chemical dosages. The results indicate that reasonable forecasting and control performances have been achieved through the developed system.

Zeng *et al.* (2003) presents a neural network predictive control scheme for studying the coagulation process of wastewater treatment in a paper mill. The results indicated better control for the treatment system.

To increase the settling efficiency in wastewater treatment plant, Traore *et al.* (2006) successfully used fuzzy algorithm to control sludge height in a secondary settler.

The theme of this study is to assess the inorganic materials concentration in wastewater treatment plant with time and place via intelligent system to best control the treatment process for standard outputs. Consequently choosing a method of advanced treatment for inorganic materials becomes more efficient decision for certain position at certain time. Sugeno subtractive clustering fuzzy inference system is herein developed for monitoring inorganics materials in biological wastewater treatment plants. It provides dynamic control system that is not only records data about concentrations but also gives a decision to comply with standards.

METHODOLOGY

Samples of two locally acceptable wastewater treatment plants in northern Jordan were chosen which all worked with the system of continuous activated aeration sludge and with an organic loading between 0.02-0.3 kg BOD/kg MLVSS.

Samples were taken from successive sites from wastewater treatment plants in the north of Jordan. The samples were collected from places at different stages as follows: 1- samples of influent water entering the plant were taken from the entrance passage of the station, sometimes from equalization tank, detention well or before entering aeration tank; 2- samples of effluent water were taken from treated water released out of the plant.

To emphasis results and avoid confusion, analyses were concentrated on qualitative indicators in this research work. These indicators are mainly the nitrates (NO_3^-), phosphates (PO_4^{-3}), sulfates (SO_4^{-2}), chlorides (Cl^{-1}) and carbonates (CO_3^{-2}). Laboratory tests with consistent specifications (APHA, 1998) and monthly averaged samplings were taken and continued for one year with short break only for technical reasons.

Fuzzy logic modeling procedures were performed onto recorded data to explore with time the concentrations of inorganics in aeration tanks. The concentration of each inorganic material at

given time and place is being tracked via fuzzy system. Using ANFIS in MATLAB toolboxes; Sugeno-Fuzzy Inference System (FIS) is herein generated by subtractive clustering. The rule extraction method first uses the subtractive clustering function to determine the number of rules and antecedent membership functions and then uses learning estimation to determine each rule's consequent equations. Training technique is conducted using hybrid learning algorithm. It applies a combination of the least-squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set. Using SIMULINK; intelligent monitoring system is then applied; sensors and data logger system provide inputs to fuzzy logic controller. The fuzzy controller uses the FIS generated from experimental data and then the information about certain inorganic compound at certain place and time is achieved.

Case study: Due to limited water resources with growing population in Jordan and since all wastewater treatment plants were reported biological, the importance of this study arises. The biological treatment requires additional advanced units in order to treat inorganic substances in wastewater.

This work comprises the focus on two wastewater treatment plants in Northern side of Jordan; ST1 (Irbid) and ST2 (Ramtha) (Table 1). The plants are located in the boundaries of the Yarmouk watershed with location coordinates as shown in Fig. 1.

Table 1: Performance of the plants being on study for year 2002

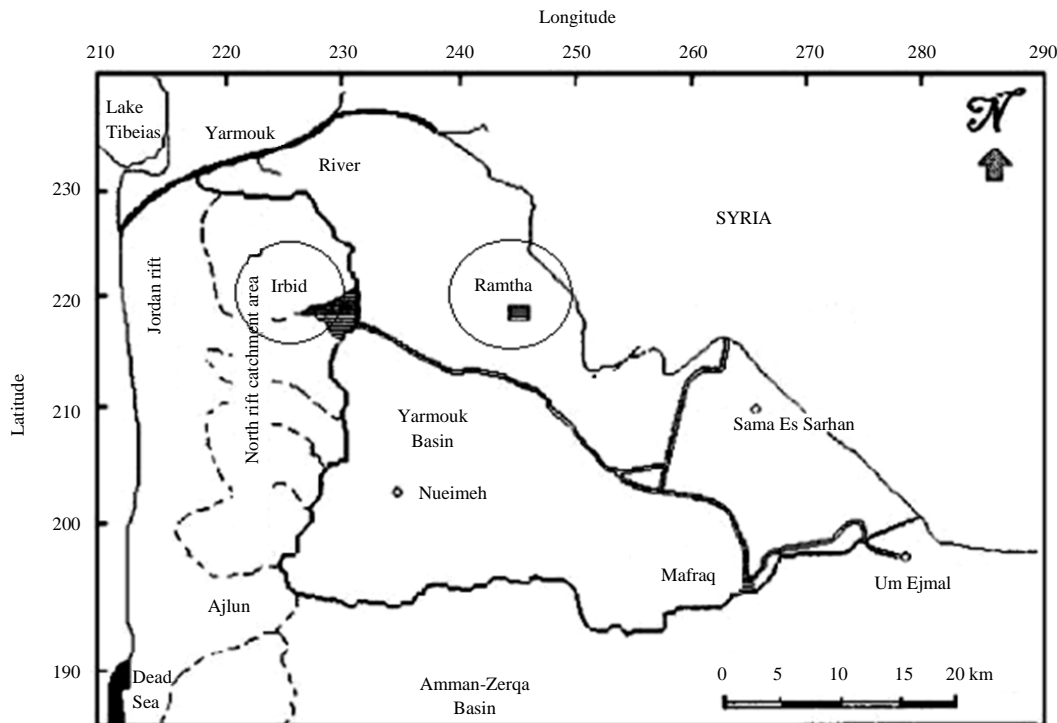| Plant	ST 1(Irbid)	ST 2 (Ramtha)
Type	AS	WSP
BOD influent (mg L^{-1})	1144	852
BOD effluent (mg L^{-1})	27	219
Efficiency (%)	97.6	74.3

Fig. 1: Location of the wastewater treatment plants

As per to the wastewater treatment plants being on study, the inorganic pollutants in wastewater are mainly the nitrates (NO_3^-), phosphates (PO_4^{-3}), sulfates (SO_4^{-2}), chlorides (Cl^{-1}) and carbonate (CO_3^{-2}). The data about these inorganic pollutants in the treatment plants were recorded monthly during one year as shown in Fig. 2.
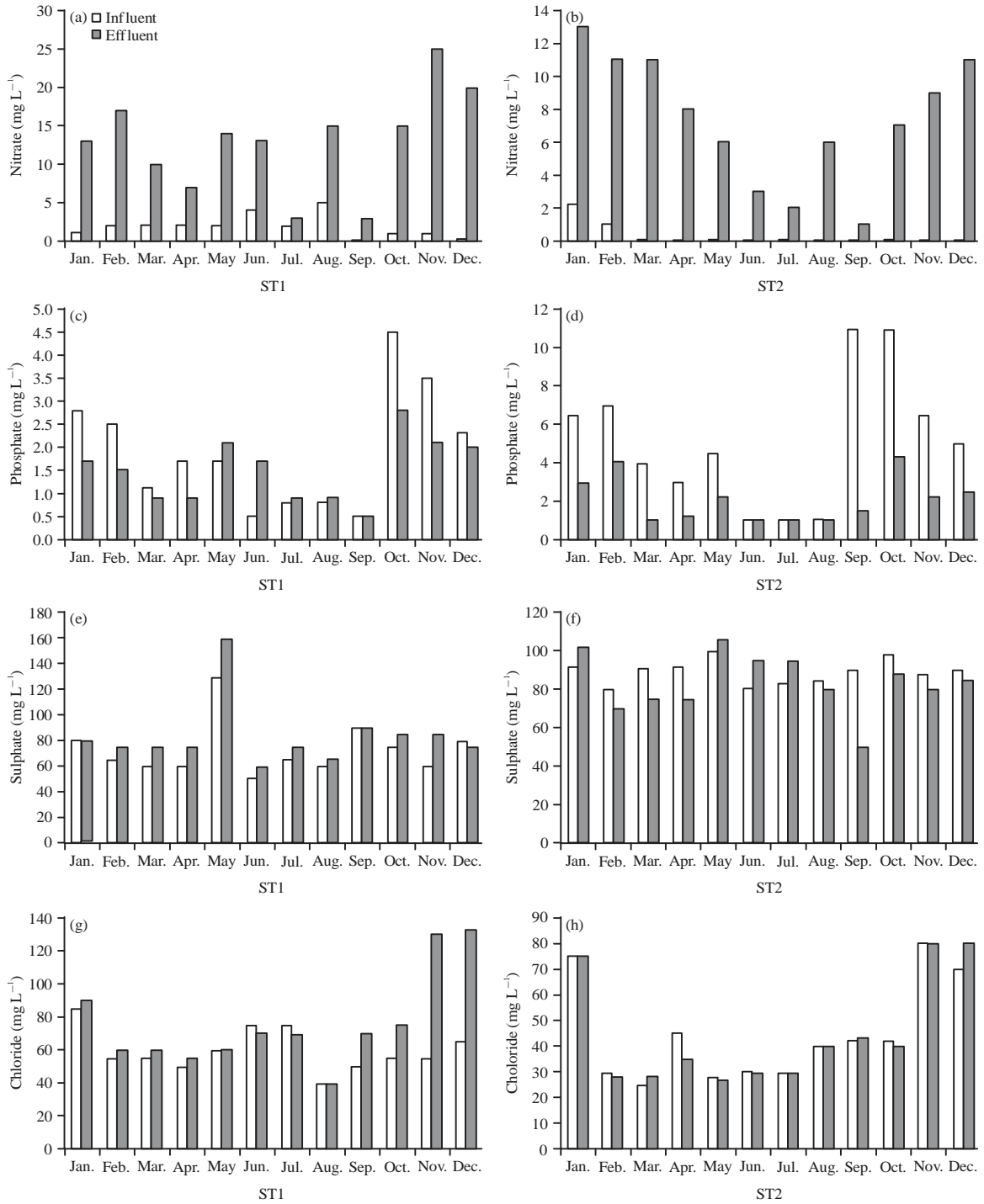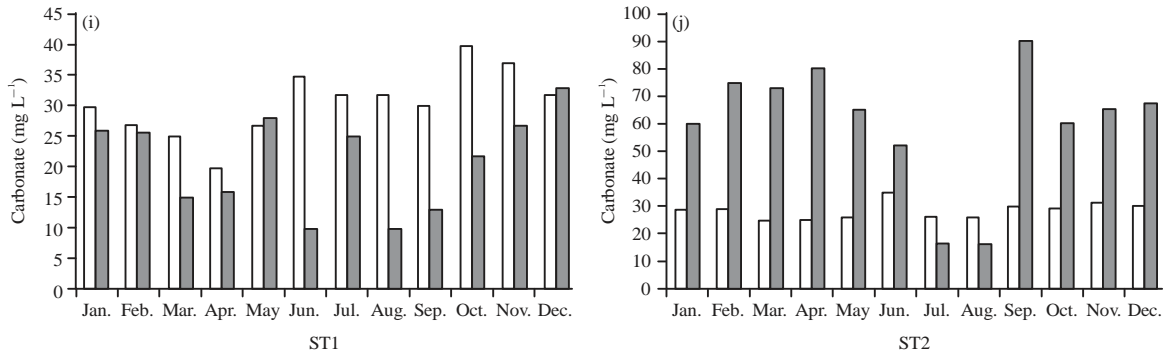

Fig. 2(a-j): Continue

Fig. 2(a-j): Inorganic concentration in the influent and effluent of aeration tanks, (a) Nitrate ST1, (b) Nitrate ST2, (c) Phosphate ST1, (d) Phosphate ST2, (e) Sulphate ST1, (f) Sulphate ST2, (g) Chloride ST1, (h) Chloride ST2, (i) Carbonate ST1 and (j) Carbonate ST2

As we may notice from Fig. 2 that some inorganic compounds are removed from wastewater and some other inorganics remains or increases due to by-products released during biodegradation and thus an intelligent system is proposed here to monitor, control and take decision.

Sugeno subtractive clustering fuzzy inference system: Fuzzy logic is a superset of conventional logic that has been extended to handle the concept of partial truth, truth-values between "completely true" and "completely false". It was introduced by Lotfi Zadeh of UC/Berkeley in the 1960's as a mean to model the uncertainty of natural language. Fuzzy Logic is a departure from classical two-valued sets and logic, which uses "soft" linguistic (e.g., large, hot, tall) system variables and a continuous range of truth-values in the membership µ interval (0,1), rather than strict binary (True or False) decisions and assignments (Bonde, 2000).

The basic structure of fuzzy inference system is a model that maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions and the output membership function to a single-valued output or a decision associated with the output.

The so-called Sugeno method of fuzzy inference was first introduced by Sugeno (1985); it is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

A typical rule in a Sugeno fuzzy model has the form:

- If Input 1 = x and Input 2 = y, then Output is z = ax+by+c
- For a zero-order Sugeno model, the output level z is a constant (a = b = 0)

The output level z_i of each rule is weighted by the firing strength w_i of the rule. For an AND rule with Input 1 = x and Input 2 = y, the firing strength is:

$$w_i = \text{And Method } (F_1(x), F_2(y))$$

where, $F_{1,2}$ (.) are the membership functions for Inputs 1 and 2.

The final output of the system is the weighted average of all rule outputs, computed as:

$$\text{Final output} = \frac{\sum\limits_{i=1}^{N} w_i z_i}{\sum\limits_{i=1}^{N} w_i}$$

where, N is the number of rules.

The subtractive clustering method is an extension of the mountain clustering method proposed by Yager and Filev (1994).

The subtractive clustering method assumes each data point is a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the density of surrounding data points. The algorithm does the following:

- Selects the data point with the highest potential to be the first cluster center
- Removes all data points in the vicinity of the first cluster center (as determined by radii), in order to determine the next data cluster and its center location
- Iterates on this process until all of the data is within radii of a cluster center

Building fuzzy inference system: In this study, the fuzzy inference system is being constructed via ANFIS Editor GUI in MATLAB; the large data of inorganic compounds in two stations during months is classified into inputs and one output as shown in Table 2.

The inputs are categorized as the following: The months are assigned values from 1-12. The stations take number 1 and 2. The five inorganic qualitative parameters take the number from 1-5. The output takes the concentration ratio of inorganic compounds with 120 values (12×2×5) as it can be seen from Table 3.

Sugeno-type Fuzzy Inference System (FIS) structure is herein generated by subtractive clustering and requires separate sets of input and output data as input arguments. It accomplishes by extracting a set of rules that models the data behavior. The rule extraction method first

Table 2: Premises of inputs and output

Inputs												
Months	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Stations	ST1						ST2					
Inorganics	Nitrate			Phosphate		Sulphate		Chloride		Carbonate		
Output	C_{eff}/C_{inf}	Experimental data of 120 values (shown in Fig. 2)										

Table 3: Digitizing of inputs and output

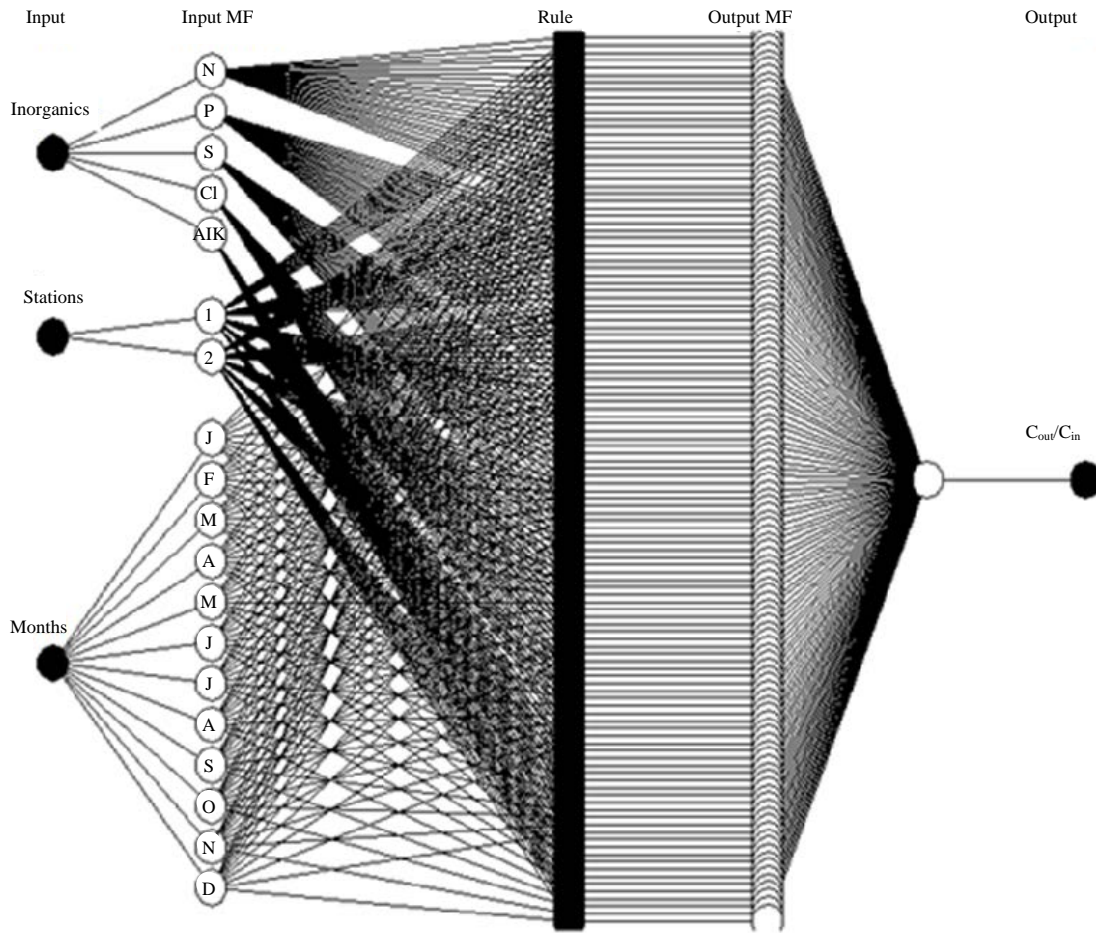| Month												Station		Inorganics					C_2/C_1
1	2	3	4	5	6	7	8	9	10	11	12	1	2	1	2	3	4	5	Data of 120 values

Fig. 3: Fuzzy inference system-FIS structure

Table 4: Clustering algorithm parameters

Parameters	Values
Range of influence	0.05
Squash factor	1.25
Accept ratio	0.50
Reject ratio	0.15

uses the subtractive clustering function to determine the number of rules and antecedent membership functions and then uses hybrid learning estimation to determine each rule's consequent equations. This function returns a FIS structure that contains a set of fuzzy rules to cover the feature space (Fig. 3).

The options vector is used for specifying clustering algorithm parameters. These components of the vector options are specified as shown in Table 4.

Building the fuzzy model is achieved via the creation of input membership functions and then input membership function is linked to rules, where a process of inference methodology takes place. The inference methods are summarized as shown in Table 5.

Table 5: Inference methods used

Inference method	Default used
AND	Prod
OR	Probor
Implication	Min
Defuzzification	Wtaver
Aggregation	Max

The rules thereby take a trend as the following:

- If Inorganics is N and Station is ST1 and Month is Feb then C_{out}/C_{in} is 8
- If Inorganics is N and Station is ST2 and Month is Feb then C_{out}/C_{in} is 1

↓

- If Inorganics is P and Station is ST1 and Month is Sep then C_{out}/C_{in} is 98

After the sugeno-fuzzy inference system is generated by subtractive clustering; the FIS model and membership function plots for both inputs and output is ready to be trained (Fig. 4).

Fuzzy inference system training: In fuzzy modeling process, training technique is conducted via intelligent algorithm. It provides a method to learn information about a set of data. Fuzzy logic computes the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data. The training routine for Sugeno-type fuzzy inference systems used here is a hybrid learning algorithm. It applies a combination of the least-squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set (Fig. 5).

The fuzzy inference is trained with hybrid technique, where the following items were achieved: Training error = 9.5×10^{-6}, Error tolerance = 0 and Epochs = 100 (Fig. 6).

Intelligent monitoring system: After the fuzzy inference system has been constructed and trained via adaptive technique; the FIS is uploaded to an intelligent monitoring system.

This part is here applied via SIMULINK in MATLAB. The FIS is uploaded to workspace in MATLAB; then blocks diagram of monitoring system is built in SIMULINK, where the FIS is uploaded from workspace to the Fuzzy logic controller block. Figure 7 shows the intelligent monitoring system that starts with data acquisition system which transfers the inputs to fuzzy logic controller that gives the decision about the effluent/influent concentration ratio. The output value is then analyzed to provide inorganic materials kinetics in terms of removal efficiency and reaction rates. While analysis; a saturation buffer is used to prevent negative value, since some materials are increased instead of decayed. A planned program at the end delivers a guide according to standards.

RESULTS AND DISCUSSION

In the intelligent monitoring system; the data acquisition system provides the inputs to the fuzzy logic controller. The fuzzy logic controller uses the FIS that was created from experimental data and then the information about certain inorganic compound is achieved. Figure 8 demonstrates information about Phosphate removal at Irbid station (ST1) in December; the Phosphate concentration fraction is 0.869, the removal efficiency is 13% and the reaction rate
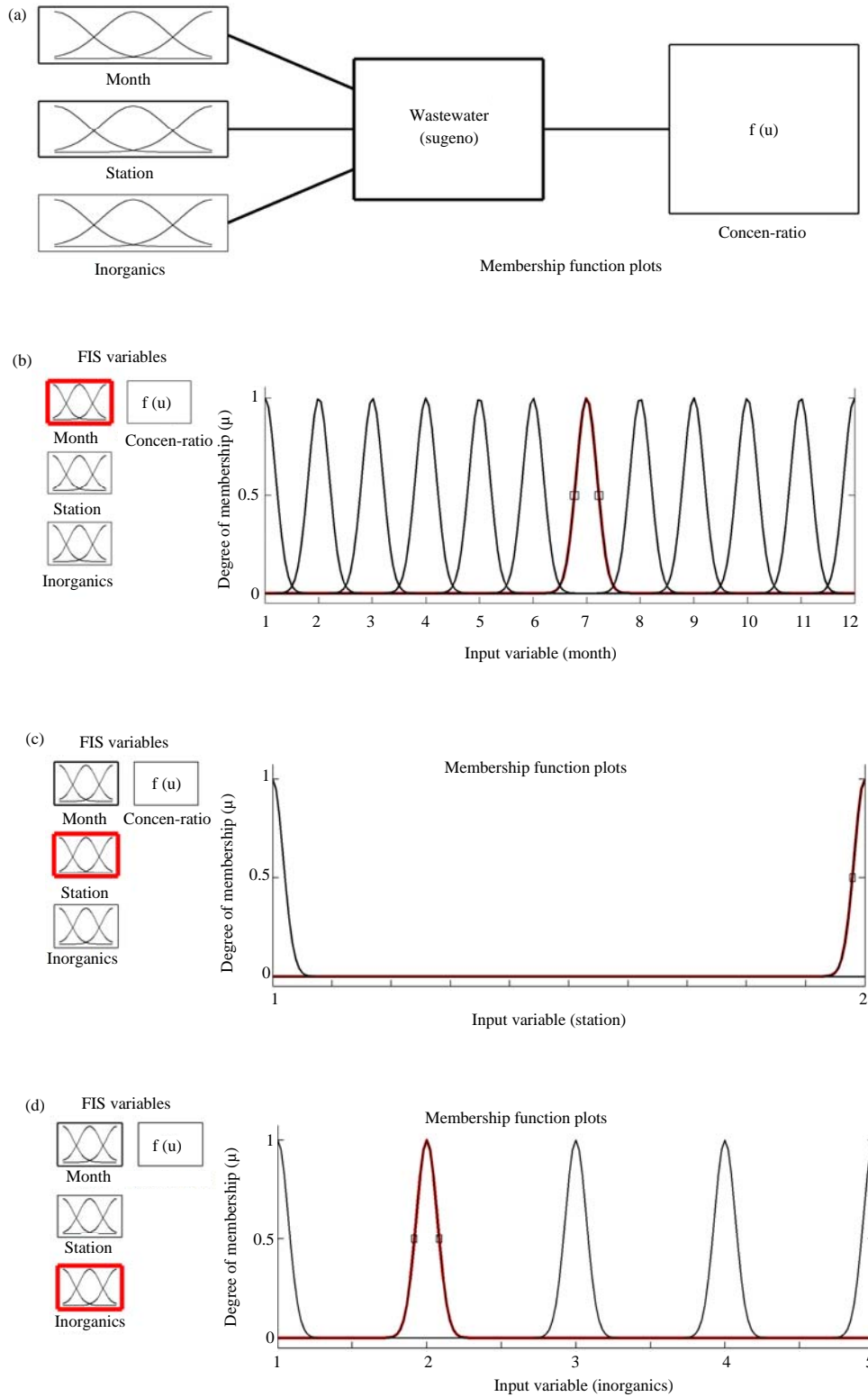
Fig. 4(a-d): Fuzzy inference system and membership functions of plots, (a) Fuzzy inference system (b) Months function plot, (c) Stations function plot and (d) Inorganics function plot
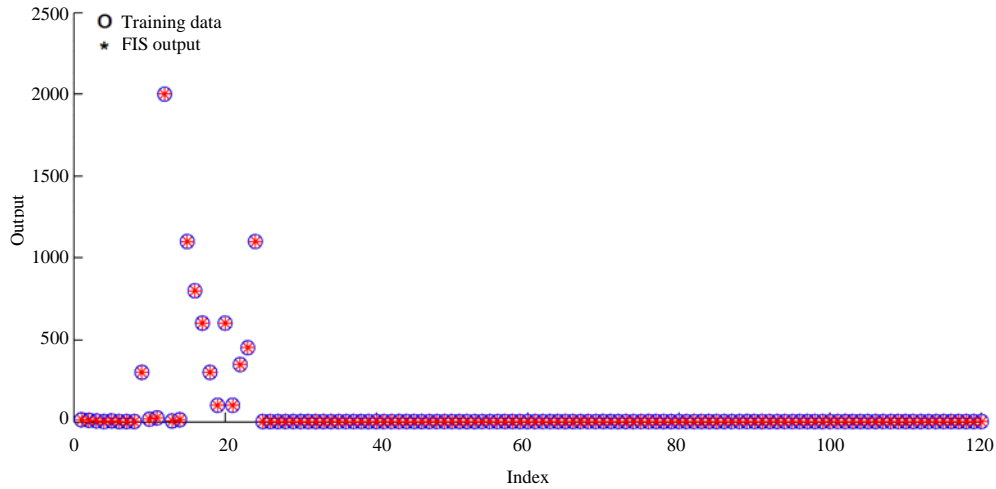
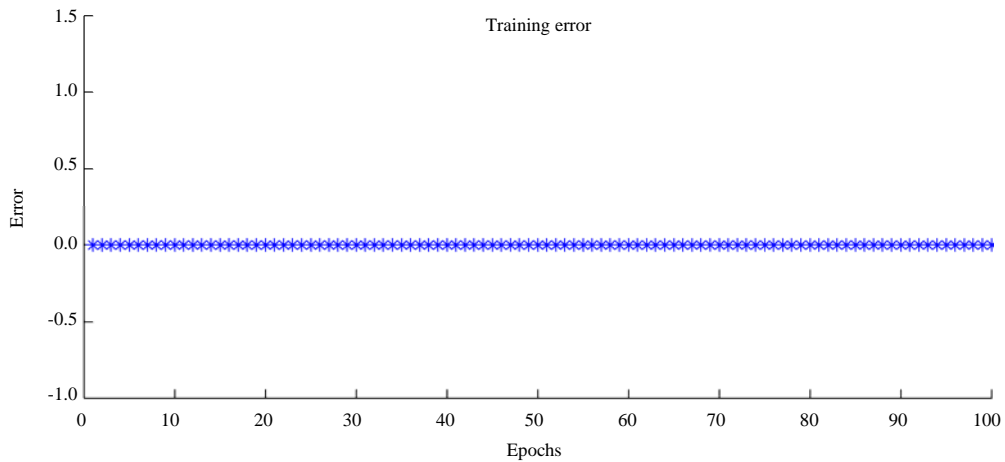Fig. 5: Trained fuzzy inference system

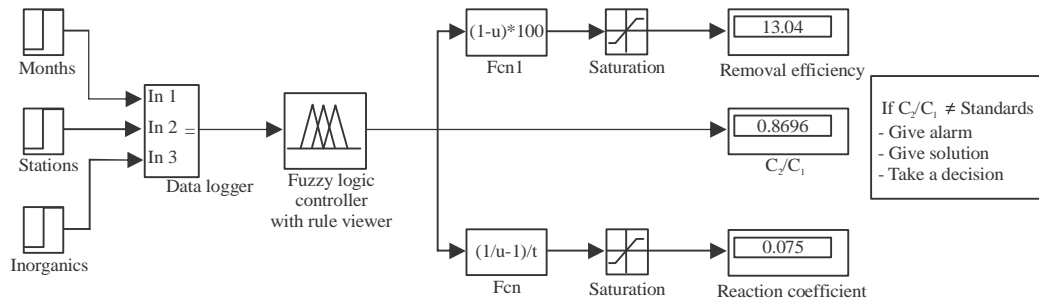Fig. 6: Fuzzy inference system training error

Fig. 7: Intelligent monitoring system

coefficient is for 2 days hydraulic retention time. This process is flexible, dynamic and automatic. It provides instant information about real wastewater inorganic compounds concentrations that are collected by means of computational and intelligent tools.
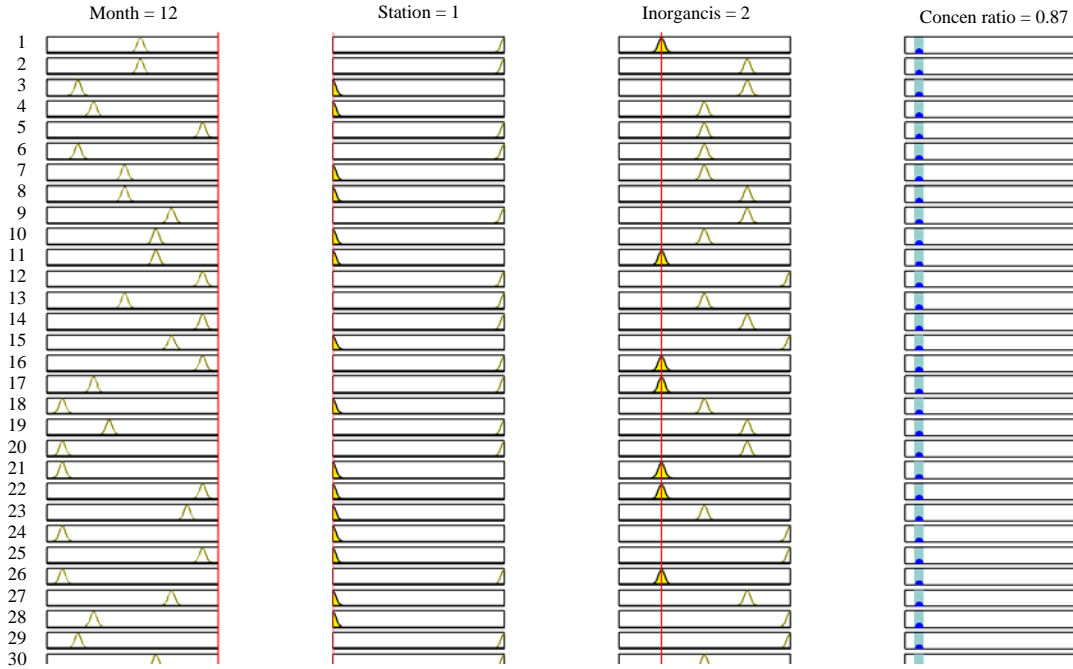
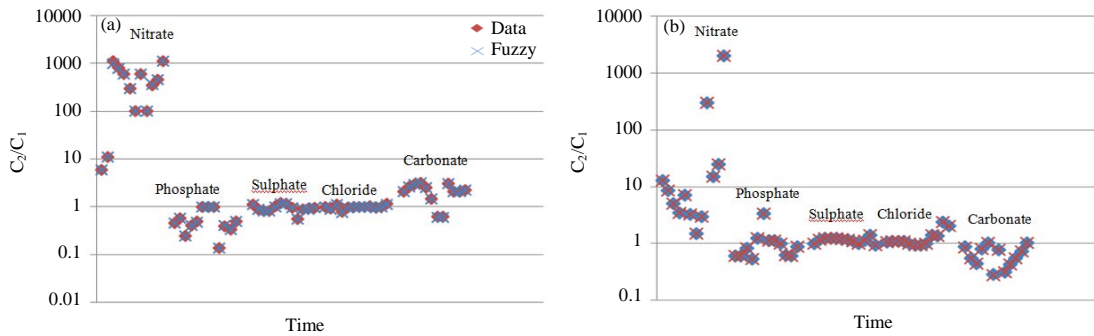Fig. 8: Information about phosphate removal in time and place with rule viewer

Fig. 9(a-b): Fuzzy logic simulating information of inorganic materials for (a) Station1 and (b) Station 2

The yield of the monitoring system provides clear view about concentrations in fast and handy technique. Figure 9 shows the concentration ratios of the inorganic compounds during time, where the inspector is able to judge easily the condition. In addition, he is able to handle the output of the system to further computational applications.

The output of the monitoring system interprets the wastewater treatment plant efficiency during months for inorganic material components for each station.

The results of the system in Fig. 9 show that nitrate is increased in the effluent. The increase in nitrate concentration in aeration tank is noticed for both plants, which is attributed to the existence of oxygen and occurrence of nitrification processes that change ammonia and organic nitrogen into nitrates (Eckenfelder, 1989; Gujer and Jenkins, 1975). This information helps the decision maker to decide when and how denitrification will be applied to remove nitrate with time at certain reactor.

For phosphate, the model shows that it is removed by almost 50%. Such result agrees with what stated in other work (Ekama and Wentzel, 2004) and is attributed to its consumption in building up the biological cell tissues. The results of model help us indicate how much we need to add from lime or alum to get rid of the remaining inorganic concentrations with time and place according to the standards.

As per to sulfates and Chloride; the model simulation with time shows that they almost remain the same without treatment in the two stations.

Carbonate is fluctuated in station 2 and decreased in station 1 and that depends upon the alkalinity components in each station. The most common are calcium and magnesium bicarbonates. The importance of alkalinity becomes evident when there is a chemical treatment. The alkalinity of wastewater comes from several sources mainly are flow water, intermixing and exchange of underground water and domestic use which adds about (50-100 mg L^{-1}) as bicarbonates (Metcalf and Eddy, 1991; Ekama *et al.*, 2006; Eckenfelder, 1989).

The idea of this study is to track inorganic materials concentration at place and time together in the same model that is handy to check it promptly. It provides dynamic control system that does not only record data about concentrations but it also gives a decision to comply with standards.

The dynamic system proposed in this work enables engineer watch the behavior of inorganic components with time and place in the plant; it is useful also for reactors in series, reactors in parallel, or reactors in other stations. This work could be applied for further steps as information system network for pollution control.

CONCLUSION

This work presents fuzzy logic scheme for scheduling and adjusting inorganic materials concentration in wastewater treatment plant to acceptable standards.

Fuzzy inference system modeling procedures were performed onto investigational data of activated sludge wastewater treatment plants at two stations in Jordan along a period of one year. This work verifies the quantitative and qualitative changes of dominant inorganic materials with time. Thus, the fuzzy approach provides an intelligent generic framework for monitoring treatment processes. The yield of the monitoring system provides clear view about concentrations in fast and handy technique. In addition, it is able to handle the output of the system to further computational applications such that the aeration tank effluents comply with standards.

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