A novel approach in determination of the effluent applications

Mahdi Rahimi, Kumars Ebrahimi and Shahab Araghinejad

ABSTRACT

The demand for water has been increasing dramatically recently in domestic, industrial and agricultural sectors, due to economic development and population growth. Therefore, wastewater may be considered as a valuable water resource for some of the mentioned sectors. The main aim of this paper is to introduce a new method to determine the best applications of effluents. In order to achieve this goal, 60 monthly effluent water quality data, sample data fields which were collected and analyzed during the years 2013–2017 by the wastewater treatment plant of Arak city, Iran, were used. Two indices are developed and applied, which involved the entropy and fuzzy logic-based approaches. Six possible effluent applications were considered including industrial, artificial groundwater recharges, environmental purposes, irrigation usages for green spaces, oilseed and fodder production. The results showed that the quality of studied effluents has been improved during the five mentioned years. As in the last year, according to the indices, the effluents could be used for industrial, environmental, fodder production, oilseed production, and artificial groundwater recharge applications. Also, the fuzzy effluent quality index has produced larger values than the entropy index, such that their largest difference is equal to 32.9, and under similar conditions offered fewer possible applications.

Key words | effluent quality index, entropy, factor analysis, fuzzy logic, wastewater treatment

Mahdi Rahimi
Kumars Ebrahimi (corresponding author)
Shahab Araghinejad
Water Resources Engineering Section, Irrigation and Reclamation Engineering Department,
University of Tehran,
Karaj,
Iran
E-mail: *ebrahimik@ut.ac.ir*

INTRODUCTION

Urban population growth, industrial development and the sharp increase in water intake as well as water shortages, especially in hot and dry countries, caused the reuse of treated wastewater to be considered as an alternative source of water supply (Jing *et al.* 2017). On the other hand, it is well known that the effluents discharged from wastewater treatment plants (WWTPs) may constitute the most important point source of priority pollutants reaching the water bodies (Cabanillas *et al.* 2012), so the quality of the effluent, management and also the protection must be considered (Mourhir *et al.* 2014). So far, various indices in water resources assessment have widely been used. Moreover, indicators should be able to provide acceptable changes and values of the index in different regions. Most water quality indices have complexity and logic certainty (Mourhir *et al.* 2014). Therefore, the determination of effluent quality indices is essential owing to the fact that it has a simple calculation, can be monitored, and the wastewater quality will continuously rise with time and its utilization will cost less. The classic water quality indicators (WQIs) are definite and inflexible and the categories do not represent uncertainty in the data and general information (Lermontov *et al.* 2009). In order to compensate for this shortage, usage of fuzzy logic in water resources and all related problems is highly recommended (Araghinejad 2013).

doi: 10.2166/aqua.2019.079

Falah Nezhad *et al.* (2016) used an artificial neural network (ANN) for the design of a feed-forward, three-layer perceptron neural network model for computing the effluent quality index (EQI) for a municipal wastewater treatment plant in the south of Tehran. Their results showed that EQI predictions of this model had significant and very high correlation ($R = 0.96$, $MSE = 0.1$) with the measured EQI values. Das & Kumar (2009) assessed the effluents of various industries and developed approaches for their use in farming for a particular region. The results of their study indicated that options of industrial effluent (prospective) reuse in agriculture provide ways to combat the freshwater crisis without degrading environmental quality. It may be applied for assessing effluent before its reuse in several water-starved countries. Fang *et al.* (2017) evaluated the characteristics of activated sludge granules and flocs using a fuzzy entropy-based approach. Evaluation results show a higher overall score of granules, indicating that granules had more favorable characteristics than flocs. This new integrated approach is effective to quantify and differentiate the characteristics of activated sludge granules and flocs. The evaluation results also provide useful information for the application of activated sludge granules in full-scale wastewater treatment plants. Gorgij *et al.* (2017) estimated the groundwater quality for drinking purposes using an entropy theory, and compared results with the spatial autocorrelation of effective parameters of water quality. Using the entropy weighted WQI, they classified the groundwater quality into five categories: excellent, good, moderate, poor and extremely poor. According to the entropy weighted WQI, the groundwater quality of the study area can be classified into 'good' to 'poor' domains. Sahoo *et al.* (2017) investigated the changing trends in the water quality of the Brahmani River using the entropy weight and Bayes' rule. Comprehensive evaluation indicates that the water is acceptable for second grade surface source protection zones for centralized drinking water. Li *et al.* (2016) proposed a fuzzy improved water pollution index based on a fuzzy inference system and water pollution index. Their results show that Qu River water quality presents a downward trend and the overall water quality in 2010 was the worst. For the sake of comparison, fuzzy comprehensive evaluation and a grey relational method were also employed to assess the water quality of Qu River. The comparisons of these three approaches assessment results show that the proposed method is reliable. Hosseini-Moghari *et al.* (2015) developed fuzzy index monitoring water quality (FWQI (fuzzy water quality index)) to assess the quality of groundwater resources in Saveh city. Compared to the conventional WQI, their results showed that the elimination of some needed parameters in development of FWQI did not decrease the accuracy of water quality classification. Jianhua *et al.* (2011) analyzed the groundwater quality in Jingyan area in China using entropy water quality index (EWQI). Their research showed that the tested samples for drinking have good qualities. Usually, in the water quality index, the weight of each parameter is determined experimentally and based on the expert's opinion (Amiri *et al.* 2014). Misaghi *et al.* (2017) recommended consistent monitoring of the water quality and the establishment of a long term management plan for the use of this valuable water resource. Information due to water quality changes to be collected for effective management in the many regions of the world (Behmel *et al.* 2016).

The main aim of this paper is to present a new method to specify the best applications for effluents and compare and contrast the two new indices. The two indices used in this article are named fuzzy effluent quality index (FEQI) and entropy effluent quality index (EEQI). This paper is an improved and developed version of Rahimi *et al.* (2017).

MATERIALS AND METHODS

As mentioned above, the main aim of this paper is to determine the best application for the use of effluent. To achieve this goal, the usual application was investigated and initially six different types of the most common effluent applications including industrial, environmental, fodder production, oilseed production, irrigation of green spaces and artificial groundwater recharge purposes were considered as the possible effluent applications. The applications selected in this research are not for direct use of humans, such as drinking or washing. Also, 16 parameters were applied based on water quality indicators which are used widely in the agricultural, drinking and environmental water consumption sectors such as Wilcox diagram, Schuler diagram, FAO and WQIs. The 16 selected parameters are calcium (Ca), magnesium (Mg), nitrate (NO_3), phosphate (PO_4), pH, biochemical oxygen demand (BOD_5), total dissolved solids (TDS), total suspended solids (TSS), fecal coliform, intestinal nematodes, arsenic (As), chromium (Cr), lead (Pb), mercury (Hg), cadmium (Cd) and aluminum (Al). The above-mentioned parameters were selected as the most significant parameters that can be used as inputs of the new developed indices, which were finally developed and applied involving entropy and fuzzy logic-based approaches in this paper. After the introduction of possible effluent applications and the selected parameters, the FEQI and the EEQI were calculated for all applications.

In the fuzzy effluent quality index, at the beginning for each parameter, the membership functions in each specified application were determined. These functions specify the usable range for each parameter in each application. Due to the large number of parameters, the fuzzy system becomes complex and in order to reduce the complexity of the fuzzy system, we classified the parameters using factor analysis which will be explained below. In this study, the fuzzy system has nine fuzzy inference systems (FISs) according to Figure 3, the value of FIS9 determines the value of the FEQI. In EEQI, first the weight of the parameters was calculated using entropy and this index value was determined using the relation provided.

Eventually, according to the values of indices, the possible applications were sorted and the best one was selected. The flowchart of this procedure is illustrated in Figure 1.

Used data

For the purposes of this research, data were acquired from the monthly sampled effluents of Arak treatment plant, Markazi Province, Iran, from 2013 to 2017 (Figure 2 illustrates the location of the study area). Table 1 shows the summary of statistics and quality parameters of the effluents. Presently, the effluent of this wastewater treatment plant is used mainly for agricultural purposes, i.e. irrigation uses.

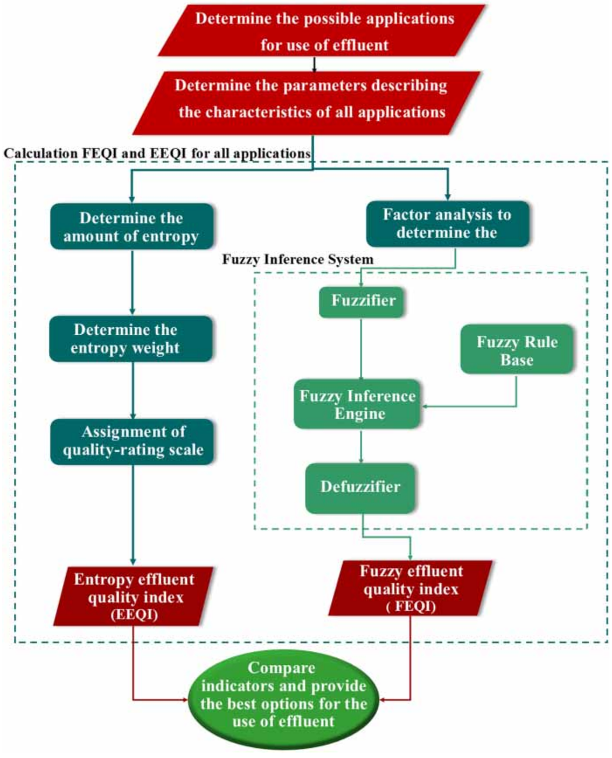

Figure 1 | Flowchart of the proposed method to determine the best option of effluent application.

The use of entropy in calculating EEQI

The Shannon entropy was first presented by Shannon in 1948 (Shannon 1948). Generally, entropy is used to express uncertainty about an accidental process or the amount of the load of a parameter (Shyu *et al.* 2011). On the other hand, entropy means disorder in physical science and it is an expression of pioneering information in communications and information science. In other words, mathematically, an inverse relationship exists between the amount of information and the probability of occurrences. If the occurrence of an event could be exactly predicted, the probability values will be major, and reciprocally, the Shannon entropy will be minor. Therefore, their weights are calculated by the amounts of uncertainties (anti-entropies) of those criteria (Ozkul *et al.* 2000; Kawachi *et al.* 2001). The calculation of the entropy has been determined in this paper in order to determine the weight and the EEQI index as follows (also see Abbasi & Abbasi 2012).

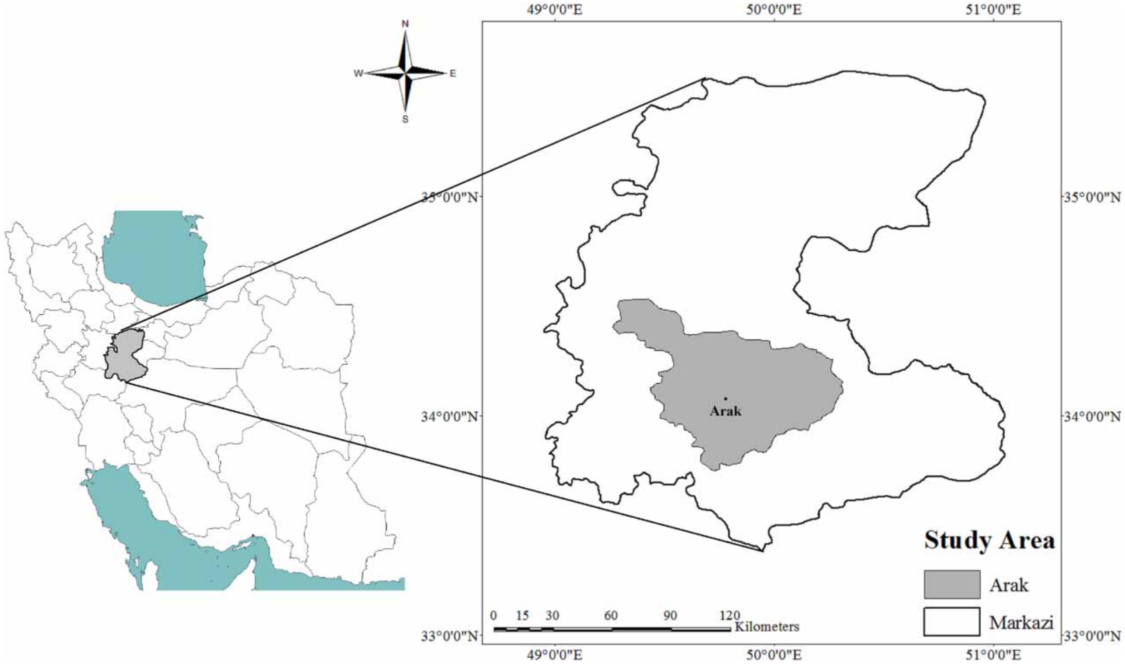

Figure 2 | Study site.

Table 1 | Statistics summary of Arak treatment plant effluent parameters, 2013–2017

Parameter	**Unit**	**Max.**	**Min.**	**Mean**	**Median**	**Standard division**
pH	mg/L	8.6	7.36	7.87	7.79	0.31
BOD_5	mg/L	72	14	25.13	24	10.06
NO_3	mg/L	29	0.98	8.71	48	8.43
PO_4	mg/L	57	1	15.85	14	10.22
TDS	mg/L	926	452	677.36	680	77.27
TSS	mg/L	212	32	78.69	64	41.26
Ca	mg/L	104.2	64	81.69	81.7	9.04
Mg	mg/L	41.79	18.27	28.35	28.1	4.88
As	mg/L	0.0007	0.0006	0.00062	0.0006	0.0000447
Cd	mg/L	0.03	0.02	0.022	0.02	0.00447
Hg	mg/L	0.0004	0.0002	0.0003	0.0003	0.000707
Pb	mg/L	0.2	0.1	0.14	0.1	0.0547
Cr	mg/L	0.08	0.06	0.066	0.06	0.08944
Al	mg/L	3.6	0.3	2.94	3.6	1.4758
Intestinal nematodes	Arithmetic mean no. of eggs per liter	2	0	0.45	0.384	0.1663
Fecal coliforms	Arithmetic mean no. of eggs per liter	1,600	79	1,318.44	1,600	485.42

For calculating EEQI, weight parameters were used to determine Equations (1)–(6) below. For 'm' effluent samples were taken to evaluate the effluent quality ($i = 1, 2, \ldots, m$), and for each sample having 'n' evaluated parameters

($j = 1, 2, \dots, n$), Eigen value matrix X was constructed using Equation (1) (Shannon 1948):

$$X = \begin{bmatrix} x_{11} & x_{12} & . & x_{1n} \\ x_{21} & x_{22} & . & x_{2n} \\ . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mn} \end{bmatrix} \tag{1}$$

The data were normalized using Equation (2) in order to remove the damaging effects of different units of the parameters:

$$y_{ij} = \frac{x_{ij} - (x_{ij})_{\min}}{(x_{ij})_{\max} - (x_{ij})_{\min}} \tag{2}$$

After the normalization, the standard-grade matrix, Y, was obtained involving Equation (3):

$$Y = \begin{bmatrix} y_{11} & y_{12} & . & y_{1n} \\ y_{21} & y_{22} & . & y_{2n} \\ . & . & . & . \\ y_{m1} & y_{m2} & . & y_{mn} \end{bmatrix} \tag{3}$$

and the ratio of the index value of the jth index in the ith sample was equal to:

$$P_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{4}$$

The amount of entropy of each category was also calculated using Equation (5) below. It is worth noting that the smaller the values of E_j, the larger the effects of jth index:

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{5}$$

Then the entropy weight can be calculated using Equation (6):

$$\omega_j = \frac{1 - E_j}{\sum_{i=1}^{m} (1 - E_j)} \tag{6}$$

Then the quality-rating scale of each criterion can be calculated using Equation (7):

$$q_j = \frac{C_j}{S_j} \times 100 \tag{7}$$

where C_j is the concentration of each chemical parameter from all water samples (mg/L), and S_j is the water quality standard of any parameter (mg/L).

The WQI method has been widely used in water quality assessments of groundwater and surface water, and it has played an increasingly important role in water resource management (Mirzabeygi *et al.* 2017). In this research, the water quality index is calculated as explained by Abbasi & Abbasi (2012), as follows:

$$EEQI = \sum_{i=1}^{m} \omega_j q_j \tag{8}$$

It should be mentioned that in the entropy method, judgments and personal opinion are removed regarding the weight of parameters. Eventually, the effluent quality index was prepared based on these weights and effluent quality standards.

In this paper, we proposed and used a summarized standard table (Table 2) which is based on FAO (1973), standards of wastewater used in irrigation (EPA 2004, 2006; WHO 2004) and finally, Iranian relevant standards (ISIRI No. 1053, No. 2439). By using the calculated values of the 'effluent quality index', the effluents were then classified into five levels from 'excellent' to 'extremely poor', as suggested by Pei-Yue *et al.* (2010) (see Table 3).

Fuzzy inference system

Zadeh (1965) presented the first concept of linguistic or fuzzy variables. One of the features of fuzzy logic is the incorporation of human knowledge and experiences and also using the 'if-then' rules that can be answered for any of the suitable system outputs according to the system input conditions. An FIS is based on these rules, as expressed below. In each rule, the part that implies the condition is called 'antecedent' and the result is the 'consequent'. Fuzzy inference is created from the combined fuzzy logic (see Yager & Filev (1994) for more details). FIS is composed of four sections: fuzzy rule base, fuzzy inference engine, fuzzifier and defuzzifier. Fuzzy logic is used to merge the most related physicochemical parameters in an integrated score, known as

Table 2 | Proposed standards for applications (FAO, WHO and Iran standards)

Parameter/Application	Industrial	Artificial groundwater recharge	Environmental	Irrigation of green spaces	Oilseed production	Fodder production
Intestinal nematodes	1	1	1	1	1	1
Al	5	5	5	5	5	5
Cr	2	1	0.5	1	1	1
Pb	1	1	1	1	1	1
Hg	0.001	0.001	0.001	0.001	0.001	0.001
Cd	0.05	0.1	0.1	0.05	0.05	0.05
As	0.1	0.1	0.1	0.1	0.1	0.1
pH_{max}	9	9	9	9	9	9
pH	6	5	6.5	6	6	6
BOD_5	250	30	30	50	150	250
NO_3	50	10	50	25	50	50
PO_4	20	6	6	15	6	20
TSS	120	250	40	50	250	250
Ca	75	200	75	400	400	400
Mg	100	100	100	60	60	60
Fecal coliforms	1,000	1,000	1,000	1,000	1,000	1,000
TDS	100	400	500	2,000	400	2,000

Table 3 | Classification of EEQI (Pei-Yue *et al.* 2010)

EEQI value	Effluent quality	Rank
<50	Excellent	1
50–100	Good	2
100–150	Poor	3
150–200	Very poor	4
>200	Uselessness	5

the fuzzy water quality (FWQ) index (Ocampo-Duque *et al.* 2007).

Development of the fuzzy effluent quality index

So far, various fuzzy models have been proposed by researchers to manage different purposes. Two of the most famous models are the Mamdani and Sugeno models. Due to its simplicity, reliability and suitability for environmental issues, the Mamdani fuzzy system is used in many water tests (Icaga 2007; Gharibi *et al.* 2012). In the current paper, the Mamdani fuzzy model has been used to classify the effluents to be allocated in different usages. To achieve this goal, 16 water quality parameters were considered to design and develop a fuzzy effluent quality system based on the Mamdani approach. In developing a fuzzy model, the variable amount of each membership function represents a degree of the membership and the effect of the amount is then definite in the outputs (for more details see Araghinejad (2013)). In this paper, the membership functions were designed for each possible application based on the standards which were explained earlier in Table 2, using Equations (9) and (10) below. The functions with four values were recognized as the trapezoidal memberships and in the same way the functions with three values were related to triangular memberships and were designed using the following equations (see also Zadeh 1965):

Triangular membership function

$$f(x, a, b, c) = \begin{cases} 0 & x \leq a \text{ or } c \leq x \\ \dfrac{a-x}{a-b} & a \leq x \leq b \\ \dfrac{c-x}{c-b} & b \leq x \leq c \end{cases} \tag{9}$$

Table 4 | Rotation load of factors based on the rotated Varimax

	Factors		
Parameter	**1**	**2**	**3**
pH	0.75		0.314
BOD_5	–0.435	0.565	
NO_3		0.893	
PO_4		0.881	
TDS	0.705		–0.0514
TSS			0.826
Ca			–0.663
Mg	0.351		0.420
Fecal coliforms	–0.734		
Eigenvalue	2.118	1.873	1.509
% of variance	27.306	23.808	19.744
Cumulative % variance	27.306	51.114	70.88

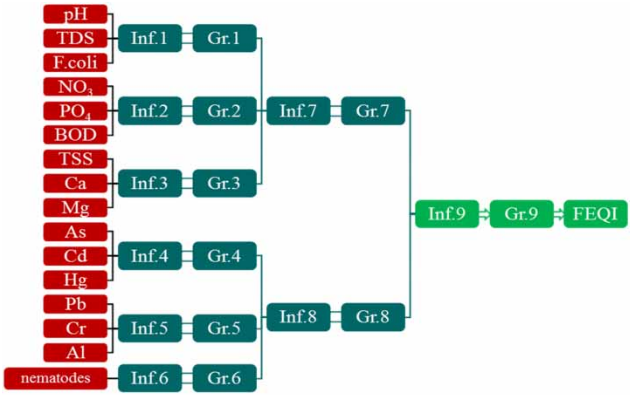

Figure 3 | Diagram of the proposed process for designing FEQI.

Trapezoidal membership function

$$f(x,a,b,c)=\begin{cases}0 & x<a \text{ or } c<x\\ \dfrac{a-x}{a-b} & a\le x\le b\\ 1 & a\le x\le c\\ \dfrac{c-x}{c-b} & c\le x\le d\end{cases} \tag{10}$$

In the next step, in order to determine the exact effect of each parameter or a set of parameters on the effluent quality index, the ‘factor analysis’ was used (Shyu *et al.* 2011). The results of the factor analysis for nine parameters of Arak treatment plant data (2013–2017) are given in Table 4. It is worth noting that the heavy metals and intestinal nematodes were divided into two separate categories because, basically, they have different characters. Moreover, as can be seen in Table 4, more than 70% of qualitative changes in the effluent have been included by three of the following factors (see the variance row). The first factor with 27.3% of changes had the maximum role and the second factor with 23.8% and then the third factor with 19.7% were the most effective factors on the quality of the effluents. According to Table 4, the first factor parameters including TDS, pH and fecal coliform are important in all applications and the second factor including NO_3, BOD_5 and PO_4 have quite important roles in the fields of artificial groundwater recharge, environmentally and agriculturally because they play an important role in soil structure. The third factor, which includes TSS, calcium, and magnesium, has a significant impact on industrial applications.

As shown in Figure 3, FEQI consists of nine FIS (i.e. Inf.1 to Inf.9). The first FIS includes the first factor and has 225 rules due to pH. In the same manner, the second and third FIS are created involving the second and third factors, respectively, and have 125 rules and an output. The fourth and fifth FIS are comprised of heavy metal parameters, contained eight rules because these parameters have two membership functions and also a sixth FIS is defined only using one parameter and two rules. Finally, the fuzzy inference system provided the FEQI index. The profile of FEQI membership function is shown in Figure 4, in the range of excellent, good, poor and so on. In the first to third FIS, for each parameter except pH, five membership functions were considered. pH has a special condition, because both small and large amounts of this parameter can create undesirable problems in water quality issues.

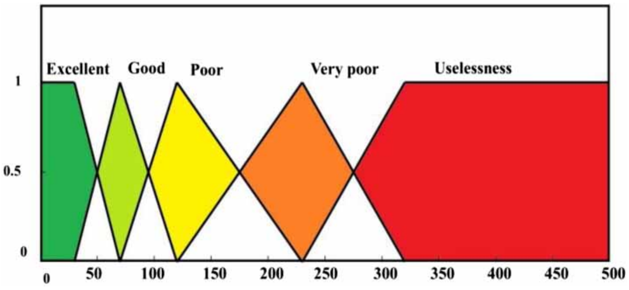

Figure 4 | Profile of membership functions, FEQI.

Table 5 | Characteristics of the applied membership functions for each parameter of the green space application

Characteristics								
Parameter	**pH**				**pH**			
Linguistic variable	a	b	c	d	a	b	c	d
Excellent	6.75	7.5	8.25	–	–	–	–	–
Good	6	6.75	7.5	–	7.5	8.25	9	–
Poor	5	6	6.75	–	8.25	9	10	–
Very poor	4	5	6	–	9	10	11	–
Uselessness	0	0	4	5	10	11	14	14
Parameter	**Fecal coliforms**				**TDS**			
Linguistic variable	a	b	c	d	a	b	c	d
Excellent	0	0	500	1,000	0	0	1,000	2,000
Good	500	1,000	2,000	–	1,000	2,000	3,000	–
Poor	1,000	2,000	3,000	–	2,000	3,000	4,000	–
Very poor	2,000	3,000	4,000	–	3,000	4,000	5,000	6,000
Uselessness	3,000	4,000	5,000	5,000	5,000	6,000	7,000	7,000
Parameter	**NO$_3$**				**PO$_4$**			
Linguistic variable	a	b	c	d	a	b	c	d
Excellent	0	0	10	25	0	0	5	15
Good	10	25	35	–	5	15	30	–
Poor	25	35	55	–	15	30	50	–
Very poor	35	55	65	–	30	50	80	–
Uselessness	55	65	100	100	50	80	100	100
Parameter	**BOD$_5$**				**TSS**			
Linguistic variable	a	b	c	d	a	b	c	d
Excellent	0	0	30	70	0	0	20	50
Good	30	70	120	–	20	50	80	–
Poor	70	120	230	–	50	80	120	–
Very poor	120	230	320	–	80	120	180	–
Uselessness	230	320	500	500	120	180	250	250
Parameter	**Ca**				**Mg**			
Linguistic variable	a	b	c	d	a	B	c	d
Excellent	0	0	200	400	0	0	20	60
Good	200	400	500	–	20	60	80	–
Poor	400	500	600	–	60	80	100	–
Very poor	500	600	650	–	80	100	200	–
Uselessness	600	650	700	700	100	200	300	300
Parameter	**Cd**				**As**			
Linguistic variable	a	b	c	d	a	b	c	d
usable	0	0	0.025	0.075	0	0	0.05	0.15
Uselessness	0.025	0.075	1	1	0.05	0.15	1	1

(*continued*)

Table 5 | continued

Characteristics

Parameter	**Pb**				**Hg**			
Linguistic variable	a	b	c	d	a	b	c	d
usable	0	0	0.5	1.5	0	0	0.005	0.015
Uselessness	0.5	1.5	3	3	0.005	0.015	1	1
Parameter	**Cr**				**Al**			
Linguistic variable	a	b	c	d	a	b	c	d
usable	0	0	0.5	1.5	0	0	4	6
Uselessness	0.5	1.5	3	3	4	6	10	10
Parameter	**Intestinal nematodes**							
Linguistic variable	a	b	c	d				
usable	0	0	0.5	1.5				
Uselessness	0.5	1.5	3	3				

Table 6 | Some utilized rules for FEQI development for green space application

		Consequent						**Antecedent**
FIS	**The rules no.**	**If**	**Is**	**And if**	**Is**	**And if**	**Is**	**Then**
Output 1	5	pH	Uselessness	TDS	Excellent	*E. coli*	Uselessness	Uselessness
	24	pH	Uselessness	TDS	Uselessness	*E. coli*	Very poor	Uselessness
	75	pH	Good	TDS	Excellent	*E. coli*	Excellent	Good
	208	pH	Good	TDS	Good	*E. coli*	Very poor	Poor

Therefore, nine memberships were considered for those parameters. The heavy metal and intestinal nematode parameters were designed using two separate membership functions, because if their values exceeded a little more than the standard limit, the effluent would be considered as an unusable source. Each parameter has different standards according to the type of effluent application, therefore the membership functions for each parameter and the type of effluent application, due to special situations and the parameter standards, were different. In this paper, fuzzy inference systems were intended for all applications, e.g. membership functions for application of effluent in green space, and also some rules of this system are illustrated in Tables 5 and 6, respectively.

It should be noted that in this paper MATLAB software, version 2014, was used to determine the weights of entropy and also in order to develop the fuzzy inference system.

RESULTS AND DISCUSSION

As shown in Table 5, pH has nine membership functions and the average amounts of that are in the range of 6.75–9. It is worth noting that the smaller or larger amounts of the mentioned limit have negative effects on the water quality. Some of the rules which were used in developing FEQI, as an example for the green space application, are shown in Table 5. Fleming *et al.* (2014) explained that a major advantage of the fuzzy logic approach for constructing environmental indices, relative to conventional approaches based on weighted averages, is that the rules of a fuzzy expert system can be built of such good quality that having it in one parameter does not hide bad quality in another. For instance, according to Table 6, in the 75th rule, although the two parameters are in the range of excellent, the result is considered as good range. Also, as

Table 7 | Entropy weights for each parameter

Parameters

Parameter	**TDS**	**pH**	**Mg**	**Ca**	**TSS**	**PO_4**	**NO_3**	**BOD_5**
Entropy weight	0.0795	0.0803	0.0698	0.0696	0.1128	0.109	0.052	0.0506
Parameter	**Fecal coliforms**	**Intestinal nematodes**	**Al**	**Cr**	**Pb**	**Hg**	**Cd**	**As**
Entropy weight	0.0995	0.0669	0.0529	0.0305	0.0497	0.0315	0.0225	0.0309

in the fifth rule, although the two parameters are in the range of very bad and one other parameter is evaluated as excellent, in consequence the quality is determined as very bad. It should be noted that, due to the importance and possible hazards of effluent usages on human health and the environment, these roles were strictly developed. The parameters with higher weights have greater impacts on the water quality index. Therefore, according to Table 7, TSS and then PO_4 with weights of 0.1128 and 0.109 are the most effective parameters. Also, Cd, As, Cr and Hg have the minimum impacts on the index. Actually, each parameter weight has shown its stability, e.g. cadmium with an amount of 0.0225 has the most variability and changes. The comparisons of the EEQI index with FEQI are presented in Figures 5–9 and Table 8. Figure 4 and Table 3 illustrate the classification of the indices and according to them, if the values of indices are greater than 100, then the effluent is unusable. Based on the results of the fuzzy index, Arak effluents of 2013 year can be used only for irrigating green spaces. However, for the same year, according

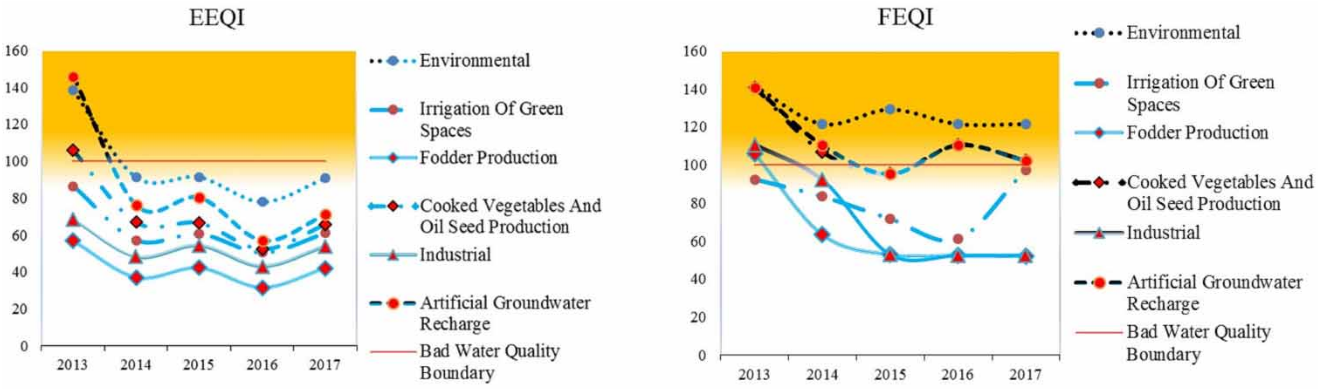

Figure 5 | Time series (2013–2014) EEQI and FEQI for applications.

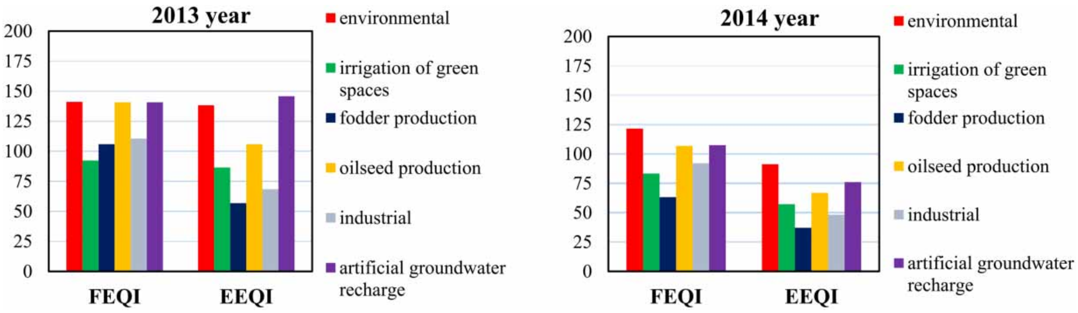

Figure 6 | Comparison of FEQI and EEQI for all applications, 2013–2014.

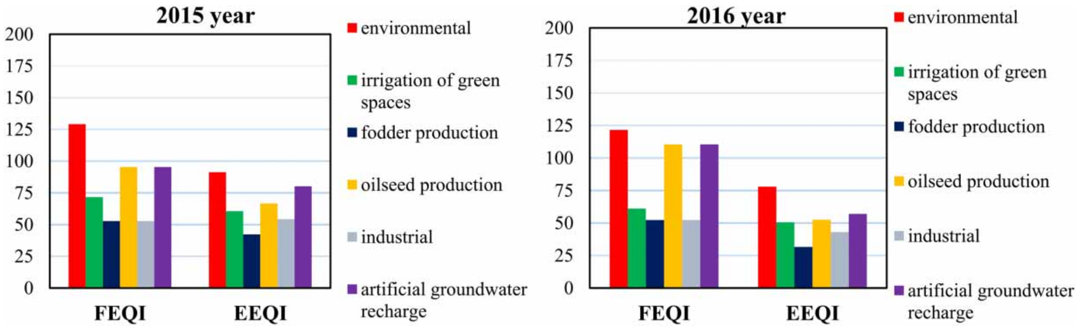

Figure 7 | Comparison of FEQI and EEQI for all applications, 2015–2016.

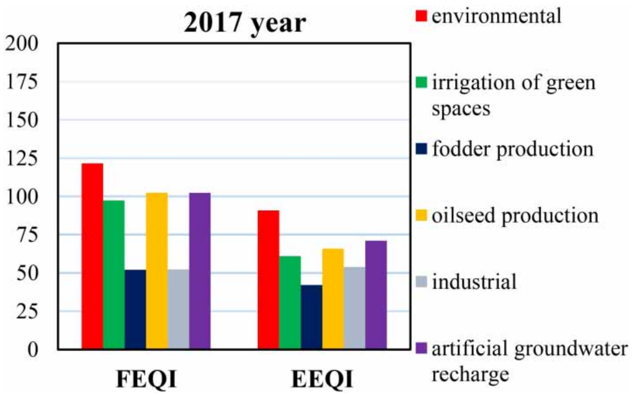

Figure 8 | Comparison of FEQI and EEQI for all applications in 2017.

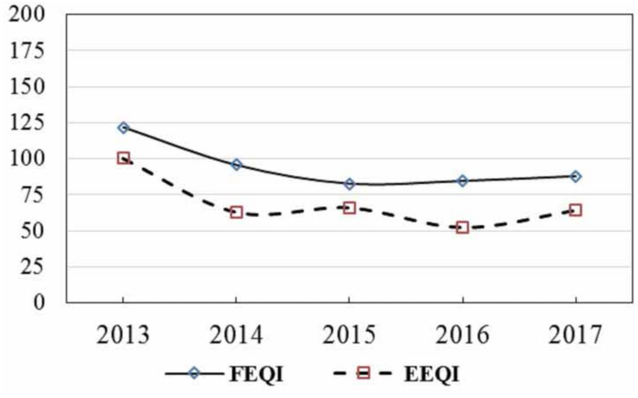

Figure 9 | Comparison of changes in EEQI and FEQI.

to the outputs of the entropy index, the effluents can be used for three applications including green space, fodder production and industrial. Based on Figures 6–8, the FEQI, three types of applications including green spaces, fodder production and industrial were approved in 2014, 2016 and 2017 years. Moreover, for 2015, this index approved all of the applications, except for environmental purposes.

According to Table 8 and Figure 5, the environmental purpose application had the largest values of FEQI among all applications between the years 2014–2017. Also, the minimum value in those years was equal to 121.58, which recommends that the effluent is not suitable for any application. The best application in 2014, according to FEQI, with an amount of 63.22, is fodder production. Also, the best options in 2015 and 2016, respectively, are fodder production and industry, with values equal to 52.75 and 52.34. Also, in 2017 fodder production again is the best possible application, with the value of 52.07.

On the other hand, according to the entropy index, the fodder production is introduced as the best type of application, with a value of 56.87 in 2013. This index showed that all applications are suitable for the use of effluent in 2014–2017. The highest value of entropy index in those years is related to the use of effluent for artificial groundwater recharge. According to this index, the best application of all years is related to fodder production which had the highest index value in 2013 at 56.87. Based on that, some items are italicized in Table 8 and highlighted in Figure 5. It can be concluded that three types of applications, including fodder production, irrigation of green spaces and industry, are top selections in most cases. Figure 9 shows the mean values of the six applications. As can be seen from the figure, the quality of the studied effluents has improved during the past five years. As a conclusion, according to Figure 9, FEQI has been larger

Table 8 | Results indicators, EEQI and FEQI for wastewater treatment plant of Arak for different applications, 2013–2017

	2013		**2014**		**2015**		**2016**		**2017**	
Applications	**EEQI**	**FEQI**	**EEQI**	**FEQI**	**EEQI**	**FEQI**	**EEQI**	**FEQI**	**EEQI**	**FEQI**
Environmental	*138.3*	*141.16*	91.17	*121.58*	91.31	*129.1*	77.9	*121.58*	90.83	*121.58*
Irrigation of green spaces	86.42	92.35	57.16	83.32	60.62	71.62	50.51	61.08	61.04	97.36
Fodder production	56.87	*105.93*	37.10	63.22	42.27	52.75	31.61	52.34	42.13	52.07
Oilseed production	*105.93*	*140.83*	66.91	*106.78*	66.7	95.37	52.54	*110.48*	65.9	*102.34*
Industrial	68.34	*110.59*	48.15	92.14	54.22	52.75	43.04	52.34	53.97	52.34
Artificial groundwater recharge	*145.81*	*140.83*	76.01	*110.43*	80.28	95.37	57	*110.48*	71.04	*102.34*

than EEQI, because FEQI has always produced higher values than EEQI. In the year 2013, fecal coliform and phosphate were two parameters that had higher than fodder production standards. Therefore, the fuzzy index shows 105.93 values. So the use of this application was not approved. In this case, Lermontov *et al.* (2009) stated that the fuzzy quality index is not dependent on particular parameters. The entropy index in this year is equal to 56.86 and the difference between these two indices shows that the fuzzy index is more sensitive than the entropy one.

In 2017, only fecal coliform exceeded the fodder production standards and the values of fuzzy and entropy indices were 50.07 and 42.13 respectively, which both proved the usage of the effluent and reflected that the effluent quality in the study period was improved and the indices were sensitive enough to the changes of different parameters as well.

CONCLUSIONS

The main aim of the current paper was to present a new method to specify the best applications of effluents according to the effluent characteristics based on fuzzy and entropy approaches. Evaluation and feasibility of the proposed approaches were investigated considering six types of common applications of effluents including industrial, environmental purposes, fodder production, oilseed production, irrigation of green spaces and artificial groundwater recharge. The characteristics of 60 monthly effluent samples from 2013 to 2017 were used, which were measured and recorded by Arak city Wastewater Treatment Plant, Iran. Factor analysis was used to analyze the above-mentioned data and determine the correlation and relationship in the parameters. Factor analysis results provided three FISs. The FISs were created according to the standards of wastewater treatment for each parameter and six possible applications. To calculate the EEQI, the weights of parameters were determined based on the entropy method and according to the standards of any application. The results showed that the fuzzy index presented higher values than the entropy index, and hence introduced fewer applications for reuse. However, it was observed that both indices in most cases offer similar change trends. According to the results the FEQI and EEQI have improved to amounts of 33.9 and 36.1 respectively over the last five years. Each of the indices has their own advantages, e.g. the FEQI proved the capability of knowledge-based models along with overcoming the uncertainties of decision-making and on the other hand, the EEQI demonstrated the ability to eliminate judgments of experts. Also, the entropy index has such simple calculations and results in a good agreement with the fuzzy index.

ACKNOWLEDGEMENTS

The authors are grateful to the University of Tehran along with the Water and Wastewater Corporation of Arak Province, Iran, for providing data and facilities for conducting the present research.

REFERENCES

Abbasi, T. & Abbasi, S. A. 2012 *Water Quality Indices*. Elsevier, Amsterdam, The Netherlands.

Amiri, V., Rezaei, M. & Sohrabi, N. 2014 Groundwater quality assessment using entropy weighted water quality index (EWQI) in Lenjanat. *Iran. Environ. Earth Sci.* **72** (9), 3479–3490.

Araghinejad, S. 2013 *Data-driven Modeling: Using MATLAB® in Water Resources and Environmental Engineering*, Vol. 67. Springer Science & Business Media, Berlin, Germany.

Behmel, S., Damour, M., Ludwig, R. & Rodriguez, M. 2016 Water quality monitoring strategies – a review and future perspectives. *Sci. Total Environ.* **571**, 1312–1329.

Cabanillas, J., Ginebreda, A., Guillén, D., Martinez, E., Barcelo, D., Moragas, L., Robusté, J. & Darbra, R. M. 2012 Fuzzy logic based risk assessment of effluents from waste-water treatment plants. *Sci. Total Environ.* **439**, 202–210.

Das, M. & Kumar, A. 2009 Effluent characterization and different modes of reuse in agriculture – a model case study. *Environ. Sci. Pollut. Res.* **16** (4), 466–473.

EPA 2004 *Guidelines for Water Reuse*. United States Environmental Protection Agency, Office of Science and Technology, Washington, DC, USA.

EPA 2006 *National Recommended Water Quality Criteria*. United States Environmental Protection Agency, Office of Science and Technology, Washington, DC, USA.

Falah Nezhad, M., Mehrdadi, N., Torabian, A. & Behboudian, S. 2016 Artificial neural network modeling of the effluent quality index for municipal wastewater treatment plants using quality variables: south of Tehran wastewater treatment plant. *J. Water Supply Res. Technol. Aqua* **65** (1), 18–27.

Fang, F., Qiao, L.-L., Ni, B.-J., Cao, J.-S. & Yu, H.-Q. 2017 Quantitative evaluation on the characteristics of activated sludge granules and flocs using a fuzzy entropy-based approach. *Sci. Rep.* **7**, 42910.

FAO 1973 *Salinity – An International Source Book, Irrigation, Drainage*. FAO/UNESCO/Hutchinson, London.

Fleming, S. W., Wong, C. & Graham, G. 2014 The unbearable fuzziness of being sustainable: an integrated, fuzzy logic-based aquifer health index. *Hydrol. Sci. J.* **59** (6), 1154–1166.

Gharibi, H., Mahvi, A. H., Nabizadeh, R., Arabalibeik, H., Yunesian, M. & Sowlat, M. H. 2012 A novel approach in water quality assessment based on fuzzy logic. *J. Environ. Manage.* **112**, 87–95.

Gorgij, A. D., Kisi, O., Moghaddam, A. A. & Taghipour, A. 2017 Groundwater quality ranking for drinking purposes, using the entropy method and the spatial autocorrelation index. *Environ. Earth Sci.* **76** (7), 269–278.

Hosseini-Moghari, S.-M., Ebrahimi, K. & Azarnivand, A. 2015 Groundwater quality assessment with respect to fuzzy water quality index (FWQI): an application of expert systems in environmental monitoring. *Environ. Earth Sci.* **74** (10), 7229–7238.

Icaga, Y. 2007 Fuzzy evaluation of water quality classification. *Ecol. Indic.* **7** (3), 710–718.

ISIRI (No. 1053) 1984 *Specifications for Drinking Water*, 4th edn. Institute of Standards and Industrial Research of Iran, Iran.

ISIRI (No. 2439) 1985 *Specifications of Industrial Effluents*. Institute of Standards and Industrial Research of Iran, Iran.

Jianhua, W., Peiyue, L. & Hui, Q. 2011 Groundwater quality in Jingyuan County, a semi-humid area in Northwest China. *J. Chem.* **8** (2), 787–793.

Jing, X., Yao, G., Liu, D., Liang, Y., Luo, M., Zhou, Z. & Wang, P. 2017 Effects of wastewater irrigation and sewage sludge application on soil residues of chiral fungicide benalaxyl. *Environ. Pollut.* **224**, 1–6.

Kawachi, T., Maruyama, T. & Singh, V. P. 2001 Rainfall entropy for delineation of water resources zones in Japan. *J. Hydrol.* **246** (1–4), 36–44.

Lermontov, A., Yokoyama, L., Lermontov, M. & Machado, M. A. S. 2009 River quality analysis using fuzzy water quality index: Ribeira do Iguape river watershed, Brazil. *Ecol. Indic.* **9** (6), 1188–1197.

Li, R., Zou, Z. & An, Y. 2016 Water quality assessment in Qu River based on fuzzy water pollution index method. *J. Environ. Sci.* **50**, 87–92.

Mirzabeygi, M., Yousefi, N., Abbasnia, A., Youzi, H., Alikhani, M. & Mahvi, A. H. 2017 Evaluation of groundwater quality and assessment of scaling potential and corrosiveness of water supply networks, Iran. *J. Water Supply Res. Technol. Aqua.* **66** (6), 416–425.

Misaghi, F., Delgosha, F., Razzaghmanesh, M. & Myers, B. 2017 Introducing a water quality index for assessing water for irrigation purposes: a case study of the Ghezel Ozan River. *Sci. Total Environ.* **589**, 107–116.

Mourhir, A., Rachidi, T. & Karim, M. 2014 River water quality index for Morocco using a fuzzy inference system. *Environ. Syst. Res.* **3** (1), 21–33.

Ocampo-Duque, W., Schuhmacher, M. & Domingo, J. L. 2007 A neural-fuzzy approach to classify the ecological status in surface waters. *Environ. Pollut.* **148** (2), 634–641.

Ozkul, S., Harmancioglu, N. B. & Singh, V. P. 2000 Entropy-based assessment of water quality monitoring networks. *J. Hydrol. Eng.* **5** (1), 90–100.

Pei-Yue, L., Hui, Q. & Jian-Hua, W. 2010 Groundwater quality assessment based on improved water quality index in Pengyang County, Ningxia, Northwest China. *J. Chem.* **7** (S1), S209–S216.

Rahimi, M., Ebrahimi, K. & Liaght, A. M. 2017 Development of an effluent quality index based on entropy approach. In: *The 4th International Conference on Environmental Planning and Management*, May 2017, Tehran, Iran.

Sahoo, M. M., Patra, K., Swain, J. & Khatua, K. 2017 Evaluation of water quality with application of Bayes' rule and entropy weight method. *Eur. J. Environ. Civil Eng.* **21** (6), 730–752.

Shannon, C. E. 1948 A mathematical theory of communications. *Bell Syst. Tech. J.* **27**, 379–423.

Shyu, G.-S., Cheng, B.-Y., Chiang, C.-T., Yao, P.-H. & Chang, T.-K. 2011 Applying factor analysis combined with kriging and information entropy theory for mapping and evaluating the stability of groundwater quality variation in Taiwan. *Int. J. Environ. Res. Public Health* **8** (4), 1084–1109.

World Health Organization 2004 *Guidelines for Drinking Water Quality: Training Pack*. WHO, Geneva, Switzerland.

Yager, R. R. & Filev, D. P. 1994 Essentials of fuzzy modeling and control. *SIGART Bull.* **6** (4), 388.

Zadeh, L. A. 1965 Information and control. *Fuzzy Sets* **8** (3), 338–353.

First received 13 June 2018; accepted in revised form 7 December 2018. Available online 5 March 2019