Assessing repair and maintenance efficiency for water suppliers: a novel hybrid USBM-FIS framework

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Abstract
A metropolitan area's water supply is imperative to the city's development. One of the main goals of the water supply utilities is to ensure the availability of water, as a lack of water would cause many social, political, or health problems. Therefore, water supply facilities must be in good condition, efficient preventive maintenance plans must be implemented, and the performance of the maintenance team monitored. In this paper, efficiency indices of Tehran water utility maintenance teams are investigated using different Data Envelopment Analysis (DEA) models. The final scores were then used as inputs to a Fuzzy Inference System (FIS) to assess the efficiency of these maintenance units. Two performance indicators based on DEA, "Availability efficiency" and "Repair time efficiency" are introduced for performance assessment. The Mean Time Between Failure (MTBF) and the Ready To Operate (RTO) are two desirable outputs that are considered in addition to one undesirable output: the Mean Time To Repair (MTTR). In addition, we suggest a new index named MRRW by combining the DEA efficiency with the RRW index. We introduce a novel approach based on DEA combined with FIS methods and the new factors for evaluating water supply maintenance systems, while most previous studies on measuring the efficiency of maintenance teams consider only limited aspects of performance measurement. Based on the results of our study, it became clear that the MRRW measures efficiency better than the traditional RRW measures. We present future improvement strategies based on the output of the FIS.

Keywords Water supply maintenance · Data Envelopment Analysis (DEA) · Risk Reduction worth (RRW) · Fuzzy Inference System (FIS)

1 Introduction

Since water supply is a continuous process that plays a significant role in people's health and wellbeing, it is considered a strategic issue. If a water supply utility fails, political and social consequences are to be expected. Three key pillars make up the European Union's Water Management Directive (2000/60/EC): water economy, social issues, and environmental concerns. An important aspect of water supply management is ensuring an efficient and sustainable supply of water (Banda and Mwale 2018; Fakere et al. 2018; Guerrini et al. 2017; Maziotis et al. 2020).

In order to purify raw water, it is first transferred through pipelines to water purification facilities after having been

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obtained from surface (such as water reservoirs) and underground resources (wells). This process of water purification involves passing raw water through filters, then adding chemical additives to achieve purified water through an infiltration process. There are times when the Iranian rivers do not have enough water or low water during periods of high water consumption which can lead to water shortages. Thus, in the past, flowing waters and extra spring water were guided to dikes for storage and used for other purposes of consumption. Water supply through underground canals is also one of the technologies used in Iran to deliver water to its citizens. As the subterranean water drains from the mountain slopes, it is excavated under the alluvium and reaches the surface of the water. Many efforts were made during the floods in Iran to conserve water to avoid further damage. There was a water storage tank in almost every house; whenever water was available, the storage tank in the house would fill with flowing water or water collected underground.

The purpose of municipal water delivery systems is to provide water from a water treatment facility to residential customers and businesses in the city. Water utility equipment and facilities face a number of challenges, especially regarding maintenance. In order to guarantee the continued supply of water to larger cities, the service centers of the water supply utilities play a key role. Maintenance managers have the primary objective of assessing the effectiveness of their maintenance activities and deciding on which measures to take to improve the efficiency of their maintenance activities which involve various factors.

A maintenance manager is responsible for ensuring that the production site is kept running smoothly and non-stop to achieve its production goals in the best conceivable way. Maintaining equipment at a consistent pace without unplanned stops is much more likely if well-planned maintenance activities are carried out. As a general rule, when it comes to planning the repair and maintenance of a building, there are two approaches In Preventive Maintenance (PM) approach, repairs are scheduled according to an estimate of the failure time of the equipment in the future. In a second approach, if the equipment fails, repairs should be made immediately. In the case of failure, this will enable the equipment to resume its normal operation as quickly as possible. To achieve good performance of the production utilities and quality system, the primary method of maintenance is called Total Preventive Management (TPM). In order to improve the performance of a TPM system, both Performance Rate and Quality Rate indicators need to be used in combination to calculate the Overall Equipment Efficiency (OEE).

Iran is located in an area with scarce supply of water. Recent facilities of water supply were built approximately fifty years ago. Although most of the facilities were modernized or substituted since, the increasing the population of Iran reinforced the need of water. Due to sanctions against Iran, the possibilities to renew the facilities became severely constrained. Therefore, it is important to keep these facilities in good condition and working properly to prevent harsh situations such as drought, poverty, or illness. Thus, maintenance units are highly important for water supply. It is therefore essential to access the performance of maintenance units regarding their prompt provision of services and the cost of maintenance, and to learn from the best ones.

There are 26 subsidiaries within the Tehran Water and Sewage Company. As part of their responsibilities, the subsidiaries receive raw water, refine it, and transfer it to the water supply network so that it can be pumped around the city. The maintenance and repair of equipment play an essential role in ensuring that the equipment is available and reliable. To achieve this, an organization must develop a maintenance and repair plan that meets business objectives (Faccio et al. 2014).

The Performance Monitoring Center (PMC) for Iranian water supply utilities described its concern about the current efficiency evaluation procedures of their maintenance departments in the following. The PMC was gathering performance-related information of each piece of equipment in order to calculate the Ready To Operate (RTO) rate. Afterwards, the unavailability of the maintenance system (1-RTO) was computed. They mentioned that their currently used index for efficiency evaluation is the Risk Reduction Worth (RRW).

To measure the worth of a feature in reducing the present risk (e.g., regarding the failure to work of facilities and machines), a logical approach is to optimize the feature and then determine how much the risk has been decreased. Thus, the RRW is formally defined to be the decrease in risk if the feature were assumed to be optimized or to be made perfectly reliable (Vrbanić et al. 2019). This measure can also be defined as a ratio.

The PMC claimed that their evaluation process does not seem to work well, and the results obtained sometimes do not correspond to reality. In order to study how to improve the water supply system's productivity, four focus group meetings were held with maintenance managers. As a result, main shortfalls of using RRW were specified as follows:

– The RRW is only able to in measure the effectiveness of preventive maintenance (PM) plans.
– Although PM plans are very useful, in the event of water utility disruption, fault detection and maintenance team skills have a great impact on supply availability.
– It seems that some maintenance centers are using excessive resources to perform maintenance, and some new indices for considering this should be used to evaluate the efficiency of the maintenance centers.

This idea motivated us to conduct this study and present a framework which has the following advantages:

- It should simultaneously measure the effectiveness of PM plans and suggest actions to the service center for fault detection and resumption of water supply.
- It should provide a list of improvements for each maintenance center
- The framework should address the RRW shortcomings while considering some more detailed indices for the performance evaluation of service centers.

Since Data Envelopment Analysis (DEA) considers a wide variety of operational inputs and outputs in its analysis, this idea motivated us to conduct our study based on DEA to analyze maintenance efficiency (time, cost, and readiness of utilities). DEA can measure the efficiency of homogenous Decision-Making Units (DMUs). As a major advantage, the approach is not affected by the units of measurement so that inputs and outputs can be measured in different units. The method can be used to identify the optimal combination of inputs and outputs leading to an efficient unit, even when there is a larger number of input values.

Uncertainty can also be conceptualized in our study as the degree of uncertainty associated with modeling repair and maintenance operations in different water supply utilities over time. There is a limited amount of data and knowledge available, but the use of information theory and soft computing offers methodological tools to mitigate uncertainty while increasing the validity and reproducibility of the research: i) sensitivity analysis, not only by running additional models, but also by using different parameters for the models proposed, and ii) use of information entropy principles to determine whether a given model is contributing to the reduction of uncertainty. An influential aspect of information theory is the concept of information entropy, which offers a constructive approach to setting up distributions of computed scores based on partial knowledge. In addition, it provides a type of inference based on the heterogeneity or dispersion of the scores that prevent the influence of extra biases or uncalled assumptions in the analysis. In this regard, fuzzy inference plays a pivotal role, and in addition to using DEA for evaluation of maintenance efficiency, we propose a Fuzzy Inference System (FIS) for achieving a more detailed view of the roadmaps that need to be considered for improving efficiency in the service centers.

Several novelties result from our study, including: (I) By using the DEA, it can be ensured that non-radial models should be used to evaluate the performance of maintenance departments. A total of two evaluation indices were defined for this evaluation, namely the "Availability efficiency" and the "Repair time efficiency". Both indices are used for detailed performance evaluation. (III) This study aims

to establish a new methodology for integrating risk-based traditional assessment models with DEA models, which will be called Modified Risk Reduction Worth (MRRW). A fuzzy inference system was developed using MRRW for input into a framework based on fuzzy logic for decision-making on maintenance department performance using a fuzzy inference system. As a general rule, the framework given to supervisors of the maintenance departments ensures that their decision-making processes are based on actual data and take into consideration different criteria to determine the performance of the maintenance departments.

This paper consists of five main sections. The second section provides a literature review. The methodology is discussed in Section 3. The results are presented in Section 4, along with a discussion about them. In Section 5, we present our conclusions.

2 Literature review

2.1 Efficiency assessment in the water industry

Multi-Criteria Decision Making (MCDM) is one of the best techniques in areas such as water allocation and infrastructure maintenance. The combination of several MCDM methods has been used in several studies (e.g., Abdulgader et al. 2018; Pancholi and Bhatt 2018; Seiti et al. 2019; Seiti and Hafezalkotob 2019; Arabameri et al. 2019; Golfam et al. 2019; Roozbahani et al. 2018).

Some studies have used Data Envelopment Analysis (DEA) to analyze maintenance problems (e.g., Dodig 2017; Rezaei-Malek et al. 2019; Geng et al. 2019; Güngör-Demirci et al. 2018; Pan et al. 2021). In recent years, the DEA technique has been widely used to evaluate the effectiveness of water supply outsourcing policies, the performance of water supply system treatment and supply units, as well as other applications (Ding et al. 2019; Entezam et al. 2020; Liu and Fukushige 2020; Murrar and Rodger 2020; Sakano 2020; Yang et al. 2020). It is possible to use standard DEA for the collection of research data under certain conditions. We briefly review some studies that have used diverse types of DEA during their study of water supply systems, since the majority of studies that have used this technique involved water supply systems. Liu and Fukushige (2020) explained the process of using DEA to measure the efficiency of Japanese water supply as a whole. For water supply and sewerage services, they used regression analysis to analyze data. According to the results of this study, there is a positive correlation between the price of sewerage services and the price of water supply services. In a recent study, Haziq et al. (2019) observed that DEA can be used to benchmark water supply units in order to improve efficiency. As a result of this research, it was demonstrated how inefficient water supply

units expand the level of services they provide and how they can be benchmarked with efficient water supply units to improve their efficiency. Wang et al. (2018) used DEA and Tobit models for measuring water use efficiency. As a result, DEA with undesirable outputs was used to analyze companies between 2008 and 2016. It was found that the majority of the efficient units in Eastern China are located in the developed part of the country. According to their research, the government can develop plans for water resource development using a model they developed. A network DEA was implemented by Gidion et al. (2019) to evaluate urban water utility efficiency. This research focuses on assessing the performance of urban units that are not involved in any type of competition. The results showed which of these units is efficient (best units) and inefficient (worst units). A DEA model was used by Pérez-González et al. (2022) to evaluate the efficiency of the water distribution network in Valencia. They employed DEA, and non-radial DEA models based on weighted Russell directional distances. It was determined which units were performing well and which units needed to improve their efficiency in order to achieve the better results.

Using DEA, Benito et al. (2019) measured the drinking water supply to small municipalities in Spain to determine the water quality. After determining inputs and outputs, the units were evaluated by the experts. As a result of the study, the effects of population density and income on water supply efficiency were found to be detrimental. In a study by Yang and Yang (2020), the SBM-DEA model was used to evaluate water use efficiency in mainland China. It is evident that this industry advanced from 2012 to 2015 since the method showed improved results during this period. A sustainable Italian water section by the DEA was analyzed by Lombardi et al. (2019). In their conclusion, they mentioned that the amount of water that was used had a strong relationship with natural factors. Based on the results of the DEA method, they claimed that decision-makers were able to make accurate decisions based on their analysis of the results. DEA has been reported to be useful in the correlation of environmental and sewage treatment analyses in water supply in China by Yang et al. (2020). SBM-DEA in environmental sewage was carried out using Constant Returns-to-Scale (CRS). There is a correlation between the results of this study, the efficiency and inefficacy of a region, and the changes related to rising social levels within that region. In fact, they concluded that these units became less efficient when there was a high population pressure.

2.2 Efficiency assessment of maintenance departments

A critical aspect of the repair and maintenance process is the assessment of the units. It helps the organization evaluate the effectiveness of the maintenance and repair programs, the performance of the maintenance and repair department's manpower, and how to use the funds that are allocated to the maintenance and repair department. In order to evaluate the performance of repair and maintenance units, a variety of methods were developed (de Sousa Oliveira Silva et al. 2022; Hur et al. 2022; Warsokusumo et al. 2020).

Akbari et al. (2020) developed a CCR-DEA model for the assessment of the efficiency of wind farms in Europe. The results showed that these offshore wind farms have an efficiency rate of 87%, which is excellent. Blagojević et al. (2020) used Entropy-Fuzzy PIPRECIA with DEA-CCR for the assessment of the safety of railway traffic. As a result of this study, it was possible to identify which railway stations performed satisfactorily and which stations performed inefficiently. A BCC model is different from the CCR model in that it allows for a variable return to scale, contrary to the CCR model. Susarev and Orlov (2020) used both the CCR and the BCC models to evaluate the system performance in their study of vehicle robotic systems. The result indicated that benchmark results can be used for the maintenance of these units, and which factors should be considered for improvement.

As part of their study, Gouveia et al. (2015) used Value-Based DEA to assess the performance of the same maintenance units, considering four input factors: maintenance and outage repairing costs, supply interruptions, complaints per customer, and the number of incidents, as well as two output factors: the number of clients and the length of water supply lines. The present study's results confirm those of Weyman-Jones et al. (2010), which had been reported previously. In another study, the performance of ten water and sewage companies and 12 water supply companies was assessed using Malmquist DEA during the period 2001 to 2008 (Molinos-Senante et al. 2017). Table 1 provides an overview of studies related to this topic. Table 12 (see Appendix) gives an overview of related studies including relevant factors used in them.

Table 1 Overview of selected previous research

Author/Authors	Model	Country
Liu and Fukushige (2020)	DEA, regression analysis	Japan
Wang et al. (2018)	DEA, Tobit model	China
Benito et al. (2019)	DEA	Spain
Yang amd Yang (2020)	SBM-DEA model	China
Yang et al. (2020)	Constant Returns-to-Scale (CRS) for SBM-DEA	China
Assaf et al. (2015)	CCR	Saudi Arabia
Akbari et al. (2020)	CCR-DEA model	European countries
Present Research	Hybrid USBM-FIS DEA	Iran

2.3 Hybrid application of FIS and DEA

One of the most popular subjects among researchers in this field is the use of a combination of DEA and an adaptive neuro-fuzzy inference system (ANFIS). For instance, a neuro-fuzzy inference system for evaluating sustainability performance is described in Tan et al. (2017). Khoshnevisan et al. (2014) used a neuro-fuzzy inference system to measure agricultural greenhouse gas emissions. In order to assess the supplier selection process, Nikabadi and Moghaddam (2021) used a neuro-fuzzy inference system in combination with DEA. Behrouznia et al. (2010) proposed an ANFIS in combination with fuzzy data envelopment analysis (FDEA) for long-term natural gas (NG) consumption forecasting and analysis. Their main concern was to analyze the gas consumption in South America and developing countries to foresee if the actual consumption improved over the selected years (1980–2007). Firstly, they constructed 104 ANFIS models and tested them to find the best model for natural gas consumption. Afterwards, population and GDP are selected as inputs and actual gas consumption is selected as output of the FDEA model. FDEA is used to examine the behavior of gas consumption.

Jahangoshai Rezaee et al. (2020) implemented an approach based on FDEA, FIS, and Failure Mode and Effect Analysis (FMEA) for health risk assessment. They suggested a hybrid approach based on linguistic FMEA, FIS and FDEA for calculating a score of shortcomings and prioritizing risks regarding health, safety, and environment (HSE). Firstly, potential risks in HSE are determined by linguistic failure mode and effects analysis (FMEA). Then membership functions of risks were defined, and the inference rules were provided to determine risk values. For defuzzification, three different methods (Smallest Of Maximum (SOM), Middle Of Maximum (MOM) and Largest Of Maximum (LOM)) are used to calculate the lower bound and upper bound of the fuzzy output. The output of the FIS is used as the inputs of the FDEA model. The proposed approach implemented in the chemical industry showed prioritized risks based on the calculated score.

Yang et al. (2017) proposed a DEA-based rule reduction method for an extended belief-rule-based system (EBRBS). Rule reduction has attracted wide attention recently. In this study, DEA was used to evaluate efficiency values of each rule in the EBRBS. This procedure helps to reduce useless rules. After reduction of the rules, a measure for DMUs is introduced to compare their efficiency. Comparison results show that proposed rule reduction can improve the accuracy of the EBRBS.

Koohathongsumrit and Meethom (2021) presented a hybrid framework consisting of a Fuzzy Risk Assessment Model (FRAM) and a FIS with the Analytical Hierarchy Process (AHP) for the selection of routes in a multimodal transportation network. In their study, firstly FRAM was used to determine membership functions of likelihood and severity scales as the inputs of FIS. Rule integration for the FIS is carried out to infer the decision maker's judgement. Afterwards, DEA was used as a tool to defuzzify output values into crisp values. In the end, AHP used to rank the relative weights of decision criteria. The suggested framework was applied for ranking and selection of transport routes between Thailand and Cambodia.

2.4 Research gap

Although the subject of repair and maintenance is certainly prevalent in existing research, there are several aspects that distinguish our work from similar works: First, the indicators that were used to determine effectiveness were related to the issue of repair and maintenance. A second advantage of our FIS is that when it is used as a decision-making tool, it helps senior managers involved in repair and maintenance to make decisions more efficiently so that they can plan better. Finally, let us mention that the framework is easy to implement, as well as the fact that system evaluations can be considered for improving performance over a certain period of time.

As mentioned above, there have been a handful of papers published in recent years related to the efficiency assessment of water supply utilities and repair and maintenance units. Most of the related papers use MCDM techniques in fuzzy form to cope with uncertainty in decision making. Some other publications only consider indices which do not properly represent all aspects of the efficiency of maintenance teams. Even though some studies focus on exact figures extracted from maintenance team operational data, there are still some gaps. The most significant of them is to suggest improvements for the teams that consider future vagueness and uncertainty.

As a consequence, we suggest using MCDM models together with variants of DEA models in a hybrid approach. One of the distinctive aspects of the current research is its use of a Unit Slacks-Based Measure (USBM) and a Fuzzy Inference System (FIS) to handle the uncertainty in the measurement of repair and maintenance efficiency in water supply utilities. Furthermore, it is pertinent to note that very few studies have been conducted in this area in recent years. A broader understanding of uncertainty may be derived from the fact that no prior knowledge has been developed as to how different contextual conditions may have an impact on the efficiency of repair and maintenance at different water supply utilities.

The approach can be described as a way of interpreting the values in an input vector and assigning values of the output vector based on a set of rules derived from the interpretations of the input vector. As a result of this mapping, it becomes

possible to determine the spatial–temporal maintenance policies that are needed to be applied by water supply utilities over a given period. Various papers have been published about DEA and FIS, but these two approaches are novel when analyzing the maintenance of water suppliers in Iran.

Therefore, this paper aims to contribute to the existing body of literature by exploring the repair and maintenance efficiency levels at water supply utilities through the use of a novel hybrid USBM-FIS system. It is a composite index that is used to make decisions about the appropriate repair and maintenance policy for each water supply utility as part of a FIS. Compared to other fuzzy approaches that use triangular or trapezoidal numbers for modeling uncertainty, the suggested FIS has the advantage of being very practical in terms of its ability to model uncertainty (Özger 2009).

Our proposed methodology has following advantages:

1) In most of the studies discussed in the literature, the efficiency indices of maintenance operations are not considered simultaneously. This study considers various aspects of efficient maintenance plans, such as time, cost, and utility readiness.
2) As identifying the most appropriate DEA model is important, we test four different models for selecting the most appropriate one for further application.
3) We introduce the MRRW index that combines the DEA efficiency index and the RRW index in a unique way and compare it to traditional RRW.
4) As compared to the current literature, the advantage of our framework is that in addition to considering exact figures of MTBF, MTTR and RTO, using a fuzzy inference system allows the decision makers to consider vagueness and express their perceptions about the performance of the maintenance system.
5) In addition to the novelty of our study, we also introduce two relevant indices in the form of "availability efficiency" and "repair time efficiency" that can help managers to be able to have a deeper insight into the performance of the maintenance departments by using undesirable SBM-DEA models. The criterion of availability efficiency for water supply is identical to its use in electricity supply, whereas the repair time efficiency is a measure of the effectiveness of all the activities that are undertaken to maintain the utilities during their life cycle.
6) By combining DEA with FIS, we are not only able to account for vague environments but also increase the reliability of our model by taking both into account. A decision can be based on the improvement performance by incorporating the efficiency of the repair and maintenance system and the use of the FIS.
7) Maintenance managers are presented with the results of the study. In Section 4.2., we discuss how the expert maintenance team investigated all inefficient DMUs and compared them to the operational situation.

3 Methodology

3.1 Fuzzy sets and fuzzy inference systems

The fuzzy sets theory (Zadeh 1965) is used to model decision-making processes based on incomplete or inaccurate information. A fuzzy set is the generalization of a classical set that allows the membership of any value in the interval [0,1]. There are many concepts based on fuzzy sets such as Z-numbers (Yazdi et al. 2022), hesitant fuzzy numbers (Gou et al. 2017), Pythagorean fuzzy numbers (Yager 2013) and so forth.

A Fuzzy Inference System (Mamdani and Assilian 1975) is based on a process for mapping inputs to outputs using fuzzy logic. Depending on the mapping, a decision is made, or a pattern is detected. Figure 1 shows the main elements of a Fuzzy Inference System.

Using a Fuzzy Inference System includes the following six steps: a) defining the membership functions of input and output, b) defining "if–then" rules, c) the product t-norm is used for the logic operator "and " as defined in (1), while, for the logic operator "or" the s-norm (maximum) is adopted as in (2) (Osiro et al. 2014). In the following, $\mu_A(x)$ is the membership function of A and $\mu_B(y)$ is the membership function of B.

$$\mu_A(x) \; AND \; \mu_B(y) = \{\mu_A(x) * \mu_B(y)\} \tag{1}$$

$$\mu_A(x) \; OR \; \mu_B(y) = Max\{\mu_A(x), \mu_B(y)\} \tag{2}$$

d) the inference engine applies an implication relation using the "min" operator (3), e) the output of fuzzy numbers is aggregated by the "max" operator $S \odot R(x.z)$ is the output result of fuzzy numbers) in (4), f) the defuzzification method is the "centroid" as specified in (5). The Center Of Area (COA) method is used here as a method for transferring verbal variables to crisp data (defuzzification).
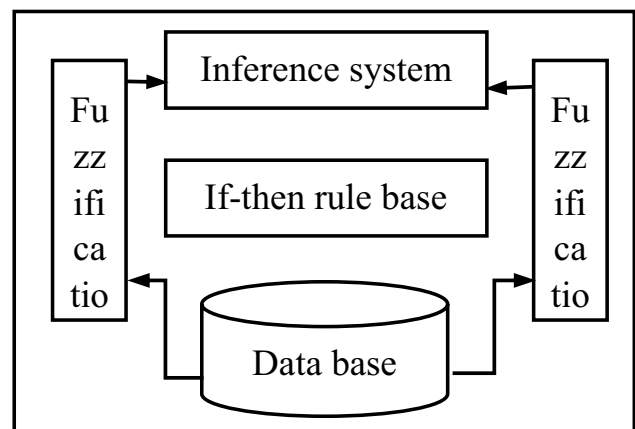
$$\mu_R(x, y) = Min\{\mu_A(x), \mu_B(y)\} \tag{3}$$

Fig. 1 Fuzzy Inference System

$$S \odot R(x,z) = Max\{\mu_S(x,y) * \mu_R(y,z)\} \qquad (4)$$

$$COA = \frac{\sum_{k=1}^{n} \mu_A(x_k) * x_k}{\sum_{k=1}^{n} \mu_A(x_k)} \qquad (5)$$

3.2 Variables

A maintenance system is meant to ensure that the equipment will always be ready to go into production with as little breakdown as possible, which is the main purpose of any maintenance system.

There is, however, a need to plan maintenance activities in such a way that they make the process as cost-effective as possible, as well.

As Tehran, with its population of 14 million, is one of the world's largest cities, water supply is crucial and essential to the existence of the city. As a result of the geographical situation and weather condition of the city, major factories are located all over Tehran, which has always resulted in water scarcity in the city. Decision Analysis (DEA) is a linear parametric programming technique that evaluates the efficiency of decision-making units based on a number of inputs and outputs based on a number of inputs and outputs (Charnes et al. 1978). There is no doubt that the results obtained by this method are more reliable than those obtained by any other method of MCDM, due to the ability of this method and the fact that it is based on the actual data of the units under study (Yousefi and Hadi-Vencheh 2010, 2016). Because of this, this approach is widely used in a variety of industries where performance evaluation is required, such as the evaluation of water supply units, the operation of bus lines (Merkert et al. 2017), the performance of airlines (Saranga and Nagpal 2016) and other industries where performance and comparison are required. It is important to note that there are different categorizations of DEA models according to the expected results. These categories include input-oriented or output-oriented models, and they can also be referred to as Constant Returns to Scale (CRS) or Variable Returns to Scale (VRS).

There is a maintenance center situated at each of the Tehran water supply subsidiaries that is equipped with specialized equipment. In order to obtain maintenance information regarding the 26 DMUs, the PMC uses a mechanized system located at the PMC. According to the literature review, a set of input and output variables were identified based on studies that had been conducted on the evaluation of maintenance departments as part of the literature review (Table 2).

Since the number of water supply equipment varies from center to center, the four indicators listed above were considered as inputs to the model, as the number of equipment varies. There is a Supervision Department called MSD that is responsible for overseeing all the maintenance activities for the 26 DMUs. As far as the Maintenance Department is concerned, the only index that is important to the department from the perspective of MSD is the RTO. On the other hand, it is also important that preventive maintenance is taken in order to increase the amount of time before a breakdown occurs. Training of the manpower should be able to reduce the duration of the repairs by a considerable amount. After a series of meetings with experts from MSD, it was decided to take three outputs into account to assess the efficiency of the maintenance department's efforts in light of the above-mentioned aspects: RTO, MTTR and MTBF. In most cases, MTBF and RTO outputs should be maximized, while MTTR should be minimized regarding MTBF and RTO. Table 3 presents descriptive statistics for maintenance departments.

The reasons for selecting the inputs are as follows: This study includes the use of human resources as one of the inputs of the model, as labor recruitment for each maintenance center plays a crucial role for the considered companies although some other studies considered it a criterion of lesser importance. Some centers strongly focus on the workforce overtime or a lack of workforce due to the control and monitoring activities of the Performance Monitoring Center (PMC). Our decision was made based on the above-mentioned problem to contribute manpower to the efficiency evaluation process.

There are a number of reasons why maintenance costs are included in the study: If maintenance procedures are not followed correctly, high rework costs will occur. Taking into consideration the aging of water supply facilities which leads to increasing costs for improving the performance of these utilities, it was decided to include the maintaining costs in the efficiency evaluation of the service centers for a better understanding of the effects of these costs on output variables (such as MTBF and RTO).

Table 2 Input and output variables

Inputs	Unit	Outputs	Unit
Manpower	persons	Mean Time Between Failure (MTBF)	minutes
Maintenance cost	Million Rial (currency unit of Iran)	Ready To Operate (RTO)	percentage
Number of utilities	number	Mean Time To Repair (MTTR)	minutes
Man-hour training	hours		

Table 3 Descriptive statistics for input and output variables

		Min	Max	Mean	Std. Deviation
Inputs	Manpower	10	40	24.27	9.96
	Maintenance cost	6590	104,000	65,323.00	28,507.00
	No. of utilities	198	4694	2331.00	1173.00
	Man-hour training	20	45	39.27	5.86
Outputs	MTTR	1	4	1.95	1.03
	MTBF	111	515	189.00	100.00
	RTO	97	100	98.74	0.80

There are several reasons why the PMC decided to include man hour training in the study. Since the utilities are old, the PMC decided to prepare a knowledge database for various kinds of breakdowns that occurred and the solutions that were found for resolving these issues. In most cases, technicians attend training workshops to share their knowledge of maintenance with each other. The PMC strongly believes that training courses are helping the technicians to perform maintenance better, which would lead to a lower mean time to repair.

Including a number of utilities in this study is necessary because they play very different roles in the water supply system in each maintenance service center. There are several utilities at huge centers, while the normal centers can mostly empower the huge centers in terms of water purification and transmission. In the operation of the business, this subject significantly impacts the labor force and the cost involved. Due to the fact that this variable is an essential input, we decided to include it in the model.

Using the Spearman test, we were able to determine whether the input variables are dependent on each other. The results of the Spearman test are shown in Table 4.

In order to check the independency of the input variables the following steps are carried out:

Step 1: Seven high ranked managers from maintenance departments are invited.
Step 2: A questionnaire for pairwise comparison of input variables is presented to the expert managers.
Step 3: They provide their answers to the questions from Step 2 using a five-point Likert scale.
Step 4: Their opinions are aggregated and tested with SPSS software by considering the Spearman test.

The results reveal a slight correlation between manpower and the number of utilities. Since Sigma values in a 2-tailed test are not significant using a 5% confidence level, we consider these two inputs as independent variables.

3.3 Sample data and research procedure

The data for 26 Decision Making Units (DMUs) was gathered in the present study. The study framework is organized into four phases and one conclusion, as shown in Fig. 2, and explained in the subsequent subsections.

3.4 Radial and non-radial DEA models

Phase I

This phase is subdivided in four steps.

Step 1: Slacks Based Model (SBM)

The evaluation of DMs can be performed in a number of ways. A method that was introduced by Charnes et al. (1978) is DEA, or differential equation analysis. Among this method's variants are the BCC (Banker et al. 1984) model and CCR (Charnes et al. 1978) model. However, it must be noted that these models are not useful when taking into account

Table 4 Descriptive statistics for input and output variables

		Manpower	Maintenance cost	Man hour training	Number of utilities
Manpower	Correlation Coefficient	1.000	-0.223	-0.445	0.458
	Sig. (2-tailed)		0.631	0.317	0.301
	N	7	7	7	7
Maintenance cost	Correlation Coefficient	-0.223	1.000	-0.255	0.262
	Sig. (2-tailed)	0.631		0.581	0.570
	N	7	7	7	7
Man hour training	Correlation Coefficient	-0.445	-0.255	1.000	-0.544
	Sig. (2-tailed)	0.317	0.581		0.207
	N	7	7	7	7
Number of utilities	Correlation Coefficient	0.458	0.262	-0.544	1.000
	Sig. (2-tailed)	0.301	0.570	0.207	
	N	7	7	7	7

Fig. 2 Framework of the study
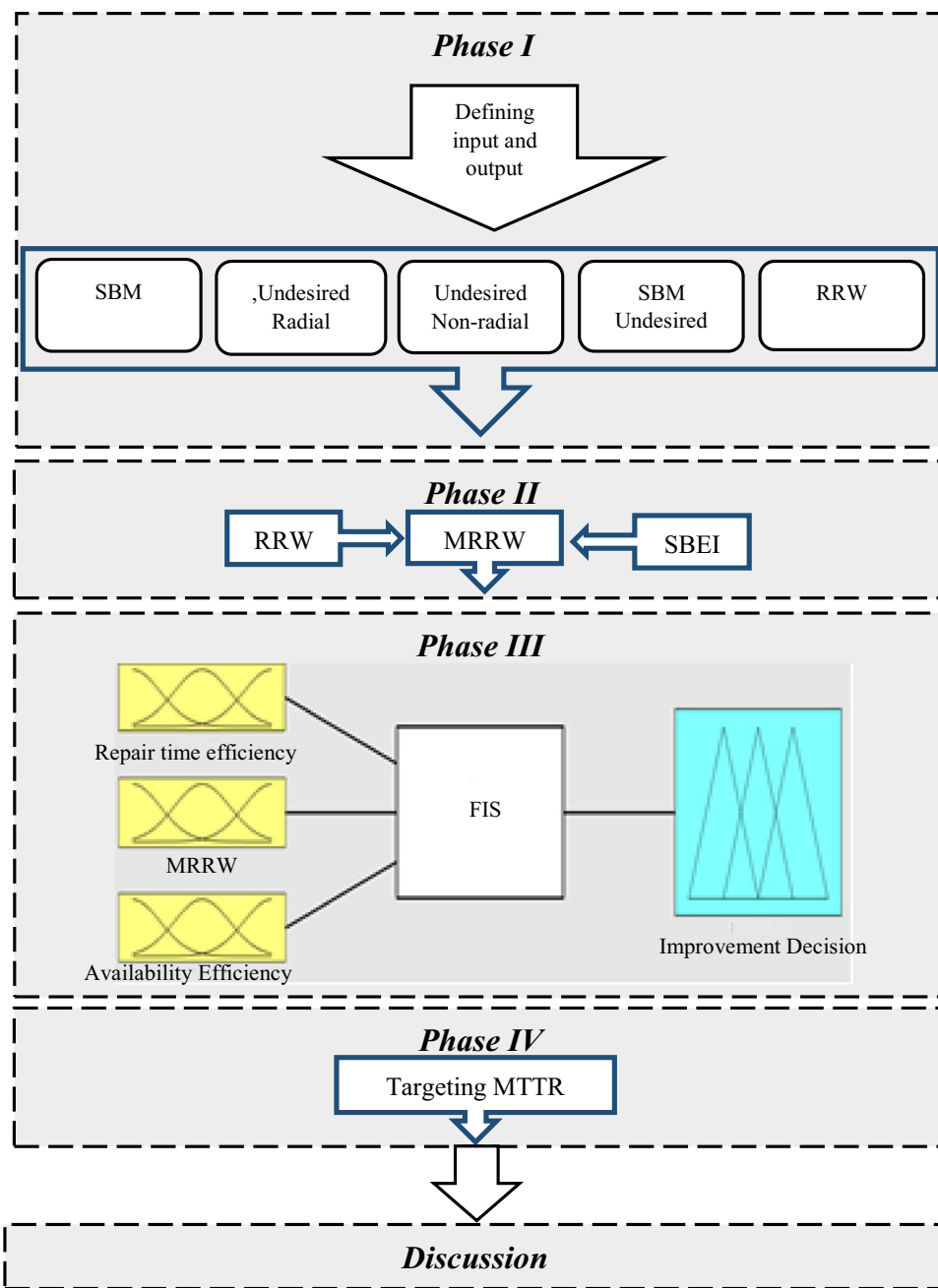
undesirable inputs or outputs. Therefore, the BCC and CCR methods can be applied whenever either the inputs or outputs of the system are desirable. Due to the fact that several inputs and outputs are undesirable in our study, a non-radial DEA must be used. It is common for us to try to increase the efficiency of output while reducing inputs at the same time in many cases.

There is a need to ensure that maintenance departments will use fewer resources, such as manpower and time, and provide better results in terms of RTOs and MTBFs by using fewer resources, such as manpower and costs. It was necessary to temporarily exclude the undesirable output MTTR in order to concentrate on this aspect. The classical Slacks Based Model (SBM)

has been widely used for efficiency analysis. The linear programming model of SBM is formally specified in (6) (Tone 2001):

$$\min \ \tau = t - \left(\frac{1}{m}\right) \sum_{i=1}^{m} \frac{S_i^-}{x_{i0}}$$

$$s.t$$

$$t + \frac{1}{s} \sum_{r=1}^{s} \frac{S_r^+}{y_{r0}} = 1 \tag{6}$$

$$tx_0 = X\Lambda + S^-$$

$$ty_0 = Y\Lambda - S^+$$

$$\Lambda \geq 0, S^- \geq 0, S^+ \geq 0, t > 0$$

In this model, n DMUs ($j=1,2,\ldots n$) are considered, and a mathematical planning model is solved to evaluate the efficiency of each DMU. The input vector is specified as $X = (x_{ij}) \in R^{m \times n}$ and the output vector is defined as $Y = (y_{ij}) \in R^{s \times n}$. The production technology is defined as $= \{((x,y)|x \geq \lambda X, y \leq \lambda Y, \lambda \geq 0)\}$, while λ is a non-negative scalar defined in R^n. Notation $S^- = ts^-, S^+ = ts^+, \Lambda = t\lambda$ is used to analyze the excess of inputs and the shortfall of outputs. x_0 and y_0 are DMUs, $\sum_{j=1}^{n} \lambda_j = 1$ and $0 \leq \rho \leq 1$. The results of solving the model for the mentioned inputs and outputs of our study are shown in Table 6.

Step 2: Undesirable Radial and Non-Radial Output

In order to reduce Mean Time To Repair (MTTR) as well as Increased Ready To Operate (RTO) and Mean Time Between Failures (MTBF), it is imperative to conduct an in-depth analysis of the inefficiency of maintenance departments. There is a possibility that the breakdown time can be reduced if the training courses are efficient, and the repair activities are carefully planned in order to minimize the breakdown time. As a result of the calculations made in the following subsection, MTTR will be considered as an undesired output, as well as the formulation (7) proposed by Peng Zhou et al. (2007) will also be applied. As the term "radial efficiency" suggests, the main concern is assessing the efficiency of a DMU, either assuming a proportional reduction of inputs or a proportional increase of outputs. This paper aims to identify the best DEA model for efficiency evaluation of the present problem. To accomplish this goal, we performed both radial and non-radial analyses and hereby seek to answer the following question: "Can a proportional increase in the inputs such as training courses or costs have the same effect on the outputs or not?".

x_{ij} is the amount of input i used by DMU j. variables y_{rj}, b_{tj} is the desired output r and undesired output t produced by the jth DMU.

$$min \ z = \sum_{j=1}^{n} W_{bj} \lambda_j$$
$$s.t.$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1, \ldots, s \tag{7}$$
$$\sum_{j=1}^{n} \lambda_j b_{tj} = \lambda_j b_{t0}, t = 1, \ldots, k$$
$$\lambda_j \geq 0, j = 1, \ldots, n$$

Note that undesirable output in this formulation should be transformed as $b_{tj} = -y_{rj}^b + 1 + max(y_{rj}^b)$. The results obtained by model (8) and model (9) are shown in Table 6.

Step 3: Slacks Based Model with Undesirable Output (Slacks Based Efficiency Index)

The objective function of model (7) does not consider the slack variables as part of its objective function. There is a possibility that the objective function may not be well reflected by

a DMU which has lower values for lower inputs and outputs, even if it has lower values for lower inputs and outputs. As a result, Zhou et al. (2006) proposed a model to calculate the operational efficiency and environmental efficiency together in order to take into consideration the simultaneous reduction of inputs and undesired outputs as well as the increase of desirable outputs in order to achieve an overall reduction in inputs and an increase in outputs. Firstly, environmental efficiency denoted as λ^* is determined by model (8).

$$\lambda^* = min\lambda$$
$$s.t.$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1, \ldots, s \tag{8}$$
$$\sum_{j=1}^{n} \lambda_j b_{tj} = \lambda b_{t0}, t = 1, \ldots, k$$
$$\lambda_j \geq 0, j = 1, \ldots, n$$

Considering our outputs and that MTTR is to be reduced, we denote λ^* as "*repair time efficiency*". This efficiency shows the λ^* expertise in the repair of the water supply utilities. Economic efficiency ρ^* is obtained by solving model (11).

$$\rho^* = min\left(t - \ ^1/_m \sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}\right)$$
$$s.t.$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = tx_{i0}, i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = ty_{r0}, r = 1, \ldots, s \tag{9}$$
$$\sum_{j=1}^{n} \lambda_j b_{tj} = t\lambda^* b_{t0}, t = 1, \ldots, k$$
$$t + \ ^1/_s \sum_{r=1}^{s} \frac{s_r^+}{y_{r0}} = 1$$
$$\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, j = 1, \ldots, n$$

Considering our outputs, here we denote ρ^* as "*availability efficiency*". The Slacks Based Efficiency Index (SBEI) was introduced by Zhou et al. (2006) as efficiency score which simultaneously calculates inputs and undesired outputs reduction through an increase of desirable output.

$$SBEI = \rho^* * \lambda^* \tag{10}$$

Step 4: Risk Reduction Worth (RRW)

Different indices have been defined to determine the importance of risk, e.g., Risk Reduction (RR), Fussell-Vesel (FV), Risk Reduction Worth (RRW), Critically Importance (CI), and Risk Achievement (RA).

$$RRW = \frac{Current \ unreliability}{Expected \ unreliabilty} \tag{11}$$

RRW represents the ratio of the unreliability of the existing system with the unreliability of a conditional system whenever a component denoted here as *a* is replaced by a perfect component denoted as *b*.

The procedure of computing is as follows:

a) The RTO index is calculated by the maintenance manager as percentage.
b) Then the unavailability of the maintenance system (1-RTO) is computed. This is equal to "current unreliability" in this formula.
c) "Expected unreliability" is the maximum time the system was unavailable (Van der Borst and Schoonakker 2001).

As mentioned before, deducting 1 from the RTO amount of RRW was calculated in the MSD department and considered the main index for the efficiency analysis of maintenance subsidiaries. Due to the importance of the on-time supply of water, the expected unreliability was set at 0.5%. The e 5 indicate that only unit 13 has an RRW less than 1.

Phase II: Defining the New Index of RRW (MRRW)

To evaluate the performance of a unit, it is not appropriate to consider the RRW alone, as discussed above. Those DMUs that have a RRW less than 1, according to the opinions of MSD experts, are regarded as efficient DMUs, since their RRW is less than 1. When we presented the results of the DEA to the MSD experts, they all agreed that in addition to taking into account the RTO when evaluating performance, the efficiency of the resources should also be considered. On this basis, Eq. (12) was specified:

$$MRRW = w_1(1 - efficiency) + w_2RRW \tag{12}$$

As it is desired simultaneously to reduce RRW and the inefficiency, Eq. (12) considers the reduction of both factors. $w_1.w_2$ are considered as weights resulting from the judgment of experts regarding the importance of inefficiencies and the RRW that can be obtained with any MCDM technique. This equation allows MSD experts to consider the expected importance of the RTO.

Phase III: Future Roadmap of DMUs by FIS

In the previous steps, the availability efficiency index was developed in order to assess the availability of water supply equipment as part of the previous step. Furthermore, DEA calculated the repair time efficiency in order to determine the efficiency with which repairs were made. It has been the tradition of the directors of the MSD department to use RRW to make their decisions, but the results of the DEA were acceptable and applicable to them as well. To improve the performance of each DMU, it was decided to use a FIS to help determine how to improve the performance of each of them.

It is important to note that there are three inputs for the FIS (availability efficiency, repair time efficiency, MRRW) and an output called improvement decision. The rules for the FIS can be defined so that it can be decided on how to improve the performance of the DMUs by defining the rules for the FIS.

Using the view of three senior managers in MSD, 27 rules were defined. In order to define fuzzy numbers for input and output variables the following steps were performed:

Step 1: A group of five high ranking maintenance managers is nominated.
Step 2: A fuzzy membership function and its application is explained and presented to them.
Step 3: Each expert describes his own understanding of fuzzy verbal values by a questionnaire.
Step 4: Using a Delphi method, all the opinions regarding verbal values a consolidated.
Step 5: Finally, input indicators are defined at three levels, and the output index is defined at four levels. The membership functions of the input and output variables are described in Table 5.

Figure 3 (in the Appendix) shows the membership function of each input and output

Since this data is uncertain, two kinds of fuzzy data are used: 1) Triangular fuzzy numbers which have three parameters (*a, b, c*). Parameter *a* is the lower number, *b* the middle number and *c* is the higher number.

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{m-a}, & a \leq x \leq m \\ \dfrac{b-x}{b-m}, & m \leq x \leq b \\ 0, & otherwise. \end{cases} \tag{13}$$

2.) Trapezoidal numbers which have four parameters (*a, b, c, d*). Parameter *a* is the lowest number, *b* is low, *c* is higher, and *d* is the highest number. Then, membership functions based on these scores and numbers are created as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a}, & if \ a \leq x \leq b \\ 1, & if \ b \leq x \leq c \\ \dfrac{d-x}{d-c}, & if \ c \leq x \leq d \\ 0, & otherwise \end{cases} \tag{14}$$

Phase IV: Targeting MTTR of DMU's

After evaluating the efficiency of DMUs, it is necessary to target improvements.

3.5 Reasons of Using Diverse DEA Models

As mentioned above several types of DEA models are used in this paper. The reasons for that can be illustrated as follows:

Table 5 Membership functions

Input	Low (Trapezoidal)	Normal (Triangular)	Good (Trapezoidal)
Input — Availability efficiency	(0,0,0.77,0.92)	(0.88,0.93,0.97)	(0.96,0.96,1,1)
Input — MRRW	Weak (Trapezoidal) (1.7,2.7,4.8,4.8)	Good (Triangular) (1.2,1.5,1.8)	Desired (Trapezoidal) (1.8,2.7,4.8,4.8)
Input — Repair time efficiency	Weak (Trapezoidal) (0,0,0.7,0.8)	Good (Triangular) (0.75,0.85,0.95)	Acceptable (Trapezoidal) (0.93,0.97,1,1)
Output — Re-engineering the repair process (Trapezoidal) (0,0,0.7,0.75)	Presenting action plan (Triangular)	Target planning (Triangular)	Maintain the current situation (Trapezoidal)
Future planning	(0.72,0.76,0.79)	(0.78 0.81 0.85)	(0.83,0.92,1,1)

a) **Slacks Based Model (SBM)**: In this paper, we face an excess of inputs and a lack of outputs for DMUs. The SBM is one of the best suited DEA models to resolve this problem.

b) **Undesirable Radial and Non-Radial Output**: Both the radial and non-radial models aim to reduce input rates. However, the methods of achieving this are different. In the radial model, it is sought to reduce the resources of inputs. A non-radial model, as used in this paper, helps maximize the input reduction rate. Both methods allow us to achieve our goal.

c) **Slacks Based Model with Undesirable Output**: As slacks of both inputs and outputs affect their proportion, this model is used when the data units are invariant. Furthermore, the model considers that the slacks must be reduced in each input and output.

4 Results and discussion

4.1 Results

Based on methods introduced in the previous section, we show the results of data analysis in this section. Based on Eqs. (6–9), all maintenance units are evaluated to determine whether they are efficient. The results are presented in Table 6.

In our analysis, SBEI is the product of "availability efficiency" and "repair time efficiency" according to Eq. (10). Maintenance of water supply utilities can be improved by making the utilities more available. On the one hand, technicians should repair the utilities in the shortest time so as not to waste time on the water supply. If the repair team is not agile, the λ^* value will decrease, which results in inefficiencies. On the other hand, if water supply utilities have a low RTO or the time between breakdowns is small (low MTBF), the result would be low efficiency even if the technicians work efficiently. Table 7 shows the "availability efficiency" and the "repair time efficiency" obtained by the models (8), (9), and (10).

The undesirable output model is solved in the radial, non-radial form since the MTTR is to be considered when assessing the performance of maintenance departments. In order to determine whether there are significant differences in the efficiencies obtained by the radial and non-radial models, we used the Spearman test, which is one of the most commonly used tests to recognize differences in correlations between two samples. The corresponding results are shown in Table 8.

The p-value indicates a significant difference between the radial and the non-radial models. The findings show that non-radial models better reflect the actual production process. So, we conclude that *any efficiency assessment model which is used for judgment of the maintenance department activities shall be based on the non-radial model.*

In the MRRW index, departments with MRRW less than one will be considered efficient. Table 6 shows the MRRW results for $w_1 = 0.5, w_2 = 0.5$.

Table 6 Results of the solved models

DMU	(SBM)	Undesired radial	Undesired non-radial	SBEI	RRW	MRRW
1	0.60	1	0.95	0.89	1.94	1.02
2	1	1	1	1	0.92	0.46
3	1	1	1	1	2.47	1.23
4	1	1	1	1	2.84	1.42
5	0.95	1	0.94	0.94	1.99	1.03
6	0.44	1.01	0.47	0.24	2.28	1.52
7	0.41	1.01	0.39	0.18	2.64	1.73
8	0.51	1.01	0.30	0.17	2.32	1.57
9	0.44	1.01	0.29	0.15	3.39	2.12
10	0.62	1	0.77	0.58	1.07	0.75
11	0.64	1.01	0.29	0.25	4.11	2.43
12	1	1	1	1	6.13	3.06
13	1	1	1	1	0.23	0.12
14	0.55	1	1	1	2.20	1.10
15	1	1	1	1	1.56	0.78
16	1	1	0.94	0.91	2.20	1.15
17	0.89	1	1	1	2	1
18	1	1	1	1	1.40	0.7
19	0.40	1	0.49	0.24	1.80	1.28
20	0.41	1	0.35	0.16	1.40	1.12
21	0.48	1.02	0.30	0.16	4.80	2.82
22	0.45	1.01	0.29	0.15	2.80	1.83
23	0.59	1	0.73	0.52	1.40	0.94
24	0.63	1.02	0.31	0.27	5.20	2.97
25	1	1	1	1	6.13	3.06
26	1	1	1	1	0.23	0.12

Table 7 "Availability efficiency" and "repair time efficiency"

DMU	Operation time efficiency	Availability efficiency	SBEI	DMU	Operation time efficiency	Availability efficiency	SBEI
1	0.953	0.934	0.890	14	1	1	1
2	1	1	1	15	1	1	1
3	1	1	1	16	0.944	0.963	0.909
4	1	1	1	17	1	1	1
5	0.944	0.993	0.937	18	1	1	1
6	0.468	0.518	0.242	19	0.492	0.478	0.235
7	0.386	0.455	0.176	20	0.349	0.454	0.158
8	0.300	0.570	0.171	21	0.300	0.546	0.164
9	0.293	0.498	0.146	22	0.293	0.506	0.148
10	0.766	0.751	0.575	23	0.725	0.724	0.525
11	0.291	0.862	0.251	24	0.310	0.867	0.269
12	1	1	1	25	1	1	1
13	1	1	1	26	1	1	1

In model (14), the effects of the weights for RRW and the inefficiency indices are significant. Therefore, it is necessary to examine weight changes. To do this, the changes in the weights are defined as follows:

$$(A1, B1, C1, D1, E1) = [(0.5, 0.5), (0.4, 0.6), (0.3, 0.7), (0.2, 0.8), (0.1, 0.9)]$$
$$(A2, B2, C2, D2, E2) = [(0.5, 0.5), (0.6, 0.4), (0.7, 0.3), (0.8, 0.2), (0.9, 0.1)]$$

First, we have the weight of the SBEI in parentheses, and then we have the weight of the inefficiency in parentheses. The results of the study indicate that as the weight of SBEI is increased, the MRRW values have also increased which means that for increasing the overall performance, we should take a closer look at SBEI. MRRW changes resulted in an increasing effect on RRW as a result of changes in MRRW. According to this analysis, it can be concluded that to evaluate the efficiency of water supply maintenance activities, the MRRW index, a combination of the DEA efficiency and the RRW index, was the most suitable index for use. In order to build a FIS, three inputs are defined as Availability efficiency, Repair time efficiency, and MRRW, and an output is defined as an improvement decision. By defining the fuzzy inference rules, one can be able to determine how to improve the performance of the DMUs by deciding on the rules for the fuzzy inference system. It was determined that 27 rules were to be defined by MSD using the views of three senior managers. The input indicators are defined in three levels, and the output indicators are defined in four levels. In order to obtain the crisp output, the output based on the FIS method is defuzzified using the if–then rule related to the Mamdani method (Mamdani

and Assilian 1975), which gives us an improved decision factor based on the membership function.

In the definition of the membership functions, the input and output variables of the triangular and trapezoidal membership function are used as needed to best reflect the decision-making conditions. Figure 4 (in the Appendix) shows the decision-making output of different values of availability efficiency. Values above 90%, imply decisions about efficient DMU. Figure 5 (in the Appendix) shows changes of MRRW, considering the membership function. Values above 1.5 imply decisions about the inefficiency of a DMU. To understand how FIS decisions are made, the effect of MRRW and Availability efficiency on output decisions are shown in Fig. 6 (in the Appendix).

The fuzzy inference system is designed to help MSD executives quickly assess the DMUs by changes in inputs and output. In Fig. 7 (in the Appendix), the schematic representation of the system output (rule viewer) is presented. The input values of

Table 8 Spearman correlation of two models

	Model radial	Model non- radial
Model radial	1	-0.859
Model non- radial	-0.859	1

Table 9 Output of the FIS

DMU	FIS score	decision	DMU	FIS score	decision
1	0.93	Maintain	14	0.927	Maintain
2	0.939	Maintain	15	0.936	Maintain
3	0.923	Maintain	16	0.917	Maintain
4	0.936	Maintain	17	0.93	Maintain
5	0.928	Maintain	18	0.938	Maintain
6	0.362	Re-engineering	19	0.374	Re-engineering
7	0.369	Re-engineering	20	0.758	Re-engineering
8	0.364	Re-engineering	21	0.36	Re-engineering
9	0.368	Re-engineering	22	0.37	Re-engineering
10	0.759	Re-engineering	23	0.759	Re-engineering
11	0.368	Re-engineering	24	0.368	Re-engineering
12	0.815	Target Planning	25	0.815	Target Planning
13	0.939	Maintain	26	0.939	Maintain

availability efficiency = 0.5 and MRRW = 0.188 and repair time efficiency = 0.5, with an output of 0.759 are shown.

Using the FIS, decisions on improving the performance of DMUs are summarized in Table 9.

4.2 Discussion

In order to ensure water supplies to citizens in large cities, water supply system managers must carefully analyze the utility performance and avoid supply interruption. Their main focus is to be on improving policies that will ensure that the water supply works properly and without interruptions at all times. Using this framework, policy makers can make efficient decisions regarding the maintenance of water supply systems. The following are some of the advantages of this framework:

– Efficient equipment is distinguished from inefficient one.
– The indices to be improved and their targets are defined for each equipment.
– A utilities policy for maintenance should be planned.

We can simply say that this research helps maintenance managers of a water supply system re-consider simultaneously the "Ready To Operate" rate, the "Mean Time Between Failure" and the "Mean Time To Repair" indices and map future strategies in maintenance planning of each equipment.

The main objective of the present study is to evaluate the performance of water supply and maintenance departments. After this assessment, we should define the expectations from these DMUs for future cooperation. Some results obtained from the case study are as follows:

1. Since the MTBF and RTO indices are incremental and MTTR is an index to be minimized, the SBM model does not calculate the performance of the maintenance departments correctly. For example, units 14 and 17 are efficient in the SBEI model, while SBM does not detect them as efficient.
2. The result of the correlation analysis in Section 4.1 helped us introduce two crucial factors denoted as "*Availability efficiency*" and "*Operation time efficiency*". The results of the case study shows that by considering these factors, policy makers can clearly assess the efficiency of the maintenance team.
3. Efficient DMUs: units 2, 3, 4, 12, 13, 15, 18, 25, and 26 are efficient in all methods. Based on MSD experts' opinions, those DMUs with RRW less than 1, are referred to as efficient DMUs. Considering this index, only three DMUs 2, 26 and 13 are selected as high-performance units. This analysis shows that *RRW cannot correctly reflect the efforts of the maintenance department.*
4. To clearly understand the difference between efficient and inefficient units, we compare the data and the results of DMU3 and DMU16 in Table 10. Manpower and the number

Table 10 Comparison of DMU3 and DMU16

DMU3	Index	DMU3	DMU16
Undesired output	MTTR	1.7	1.8
Desired outputs	MTBF	136.0	134.0
	RTO	98.8	98.9
Inputs	Manpower	10.0	10.0
	Budget	50,214.4	54,000.0
	No. of facilities	1463.0	1463.0
	Training(man/hour)	40.0	42.0

of facilities are identical for both DMUs (inputs), but other inputs are changed. Regarding desired outputs, RTO has grown slightly for DMU16, but MTBF has decreased. MTTR is an undesired output which was increased in DMU16.

5. Inefficient DMUs: Table 6 reveals that 17 DMUs are inefficient. Table 11 classifies the inefficient DMUs based on the results of SBEI. These DMUs are divided into three categories. Category one includes DMUs with high-efficiency potential (DMUs 1, 5, 16). In category two, there are DMUs with middle potential for efficiency (DMUs 10, 23) and DMUs with low potential for efficiency. The results of the models can then be used to indicate which performance of inputs or outputs must be increased so that DMUs of these categories achieve efficiency. For category three, the SBEI score was less than 0.5. Not only are major changes needed, but more than these two factors must be changed to achieve efficiency.
6. It would be impossible for RRW to disclose the performance of its maintenance departments, as mentioned before. It has been observed that DMUs 1,5, and 16 do not have acceptable RRWs, but their SBEIs are above 0.89, which means that the MRRW, which is the sum of SBEI and RRW, detected them as being near to efficient departments when compared to their RRWs. It is important to note that prior to the MRRW, DMU 10 was not known to be efficient, but the unit was determined to be efficient. As a result of this, DMU10 was close to the acceptable level in terms of both the SBEI index and the RRW index, so by using the MRRW indicator, which is a combination of both indexes, DMU10 is able to achieve satisfactory results.

Table 11 Classification of inefficient DMUs

DMU	SBEI score	RRW	MRRW
1, 5, 16	More than 0.89	1.94, 1.99, 2.20	1.02 ,1.03, 1.15
10, 23	Between 0.5 and 0.89	1.07, 1.4	0.75, 0.94
Other inefficient DMUs	Less than 0.5		

7. As shown in Table 7, eight of the 26 DMUs, such as 6, 10, 14, 17, 19, 20, 23, and 24, can achieve the maximum efficiency by reducing their inputs.

8. Operation time efficiency (Table 7) shows that DMUs 8, 9, 11, 20, 21, 22 and 24 have very low scores. This means that the time to repair the water supply utility is too long. By presenting the results to experts, lack of spare parts (83.5%) and outsourcing of some repair activities (7%) are the main reasons for low operation efficiency.

9. Availability efficiency (Table 7) shows that DMUs 7, 9, 19 and 20 have meager availability. Scrutiny analysis of the maintenance department's performance revealed various reasons for the bad performance. The main reasons were no safety stock of the spare parts and wrong ordering of additives for water treatment and not considering water supply alternatives. So, the suggestion for these DMUs is to consider a re-engineering plan which is following the FIS output.

10. The decision on DMUs 1–5 and 13 is to maintain the existing conditions. DMUs 6 to 11 are not acceptable from a functional point of view and need to be reviewed regarding repair and maintenance.

11. In order to review the performance of the FIS, it was decided to change all the rules and re-examine the responses to see if this would affect the evaluation results. There can be errors in an expert's evaluation, which will lead to a MRRW value of more than 1, indicating that the DMU is efficient, which is completely wrong. Therefore, it would be understood that there was an error in the expert's evaluation. To verify the correct operation of the FIS, as a sample, two DMUs (6 and 7) were selected that needed an assessment of their maintenance methods as well as worker instructions for the maintenance process. It is assumed that if accurate inferences are not made in the system, these two units will decide to keep the present conditions in place. The availability efficiency and the repair time efficiency of units 6 and 7 are low, as well as a the MRRW value that is higher than 1 for their respective units. Due to the above, it is evident that the decision to maintain the existing conditions is not the right one, and this is evident from the charts of the FIS system. Basically, it means that based on the findings of the FIS, this condition is unsuitable and needs to be changed to be suitable.

5 Conclusions

Providing an effective and efficient maintenance and repair system requires a variety of functions such as monitoring the performance of the repair departments, preparing the equipment to be repaired, identifying the weaknesses of the equipment, and ultimately devising a plan to improve the equipment's performance. During the present study, a DSS framework was developed with the aim of evaluating the effectiveness of the water supply maintenance departments.

An assessment of maintenance water departments using the DEA method was conducted in this study. By using this method, DMs are able to compare the inputs and outputs of each DMU (maintenance water department) and their efficiency is evaluated in terms of inputs and outputs. A DMU that is inefficient can be benchmarked against a DMU that is efficient to improve its performance. Thanks to DEA, we introduced two key indexes, namely "availability efficiency" and "repair time efficiency", enabling managers to better understand the performance of their maintenance departments.

As another common measure that is used to assess the efficiency of maintenance plans, the Risk Reduction Worth is also a common measure that is often used.

As a result of this study, a new index, named MRRW, is presented, which is the result of integrating the risk of inaccessibility of the equipment with the criteria for evaluating its performance. It is important to note that this index is applicable to evaluate the performance of maintenance departments to determine how they perform. It is possible to specify the future strategy for maintenance departments using the developed Fuzzy Inference System (FIS). This framework allows managers to define their expectations of the maintenance department in terms of MTTR and other performance indicators using the presented framework.

The proposed framework can be integrated in a complete PDCA cycle (Plan-Do-Check-Act) which provides advantages such as:

– Assessment of the performance of water supply maintenance departments
– Define MRRW as the integrated index of performance and risk of the inaccessibility
– Specify a future strategy of water supply maintenance departments
– Target the improvement indices such as MTTR for the future

By combining DEA and FIS, we are able to consider not only a vague environment, but also the reliability of our model in the future. The decision on performance improvement policies can be made by combining the efficiency of the repair and maintenance system with the use of the FIS to achieve a certain level of efficiency.

When starting our study, the maintenance department's policy makers had to consider several indicators which caused confusion in the decision-making processes. The company's management believes that the pilot implementation of this framework and the presentation of the results are convincing to policy makers and can provide a clear picture of what needs to be done to proceed in the future.

It is important to note that the main limitation of this research is access to data since it was difficult for companies to provide data for this study. Future studies can be conducted using other types of fuzzy numbers such as Z-numbers,

D-numbers, or Pythagorean numbers to compare the results with those obtained using the FIS method in the current study. The objective of this study was to introduce a hybrid framework for assessing the maintenance of the utilities of the water supply systems that was used in the past. It is suggested that in future research, it would be prudent to exclude major breakdowns that rarely occur from the achieved data before assessing the system's efficiency. A better judgment can be made by considering the performance of the DMUs over a period of many years to make better assessments of the situation.

Appendix

Abbreviations	
MTBF	Mean Time Between Failure
RTO	Ready To Operate
MTTR	Mean Time To Repair
DEA	Data Envelopment Analysis
FIS	Fuzzy Inference System
RRW	*Risk Reduction Worth*
PM	Preventive Maintenance
TPM	Total Preventive Management
OEE	Overall Equipment Efficiency
MCDM	Multi-Criteria Decision Making
DMUs	Decision Making Units
USBM	Unit Slacks-Based Measure
VRS	Variable Returns to Scale
SBM	***Slacks Based Model***
RR	Risk Reduction
FV	Fussell-Vesel
RRW	Risk Reduction Worth
CI	Critically Importance

Abbreviations	
RA	Risk Achievement
SBEI	Slacks Based Efficiency Index
CRS	Constant Returns-to-Scale

Notations	
$\mu_A(x)$	membership function of A
$\mu_B(y)$	membership function of B
$S \circ R(x,z)$	output result of fuzzy numbers
X	Input vector
Y	output vector
λ	non-negative scalar
S^-	shortfall of outputs
a	fuzzy lower number
c	fuzzy higher number
x_0	DMUs
y_0	DMUs
y_{rj}	desired output r
b_{tj}	undesired output t
λ^*	repair time efficiency
ρ^*	availability efficiency
S^+	excess of inputs
b	fuzzy middle number
d	fuzzy highest number

Table 12

Table 12 Previous studies

Author/Authors	Method/Methods	Factors
Haziq et al. (2019)	DEA	water supplied, no. of connections, total expenditure, staff size, technical efficiency
Lombardi et al. (2019)	DEA	water distributed, water pumped, network length, residents, materials cost, cost of services, cost of leases, labor cost, capital cost and percentage delivery of water
Zhou et al. (2019)	DEA	GDP of unit water consumption, comprehensive production capacity of water supply, per capita daily water consumption, daily urban sewage treatment capacity, ratio of sewage treated
lo Storto (2020)	DEA	users (drinking water service), users (sewerage service), users (wastewater depuration service), municipalities (drinking water service), municipalities (sewerage service), municipalities (wastewater depuration service), total production cost, aqueduct network length, sewerage network length, wastewater depuration facilities
Gidion et al. (2019)	DEA network	Non-Revenue Water (NRW) as a percentage of total production, personnel expenditures as a percentage of billing revenues, staffing per 1000 connections, proportion of the population served with water, service continuity (pressurization), metered customers per total connections

(a)

(b)

(c)

(d)
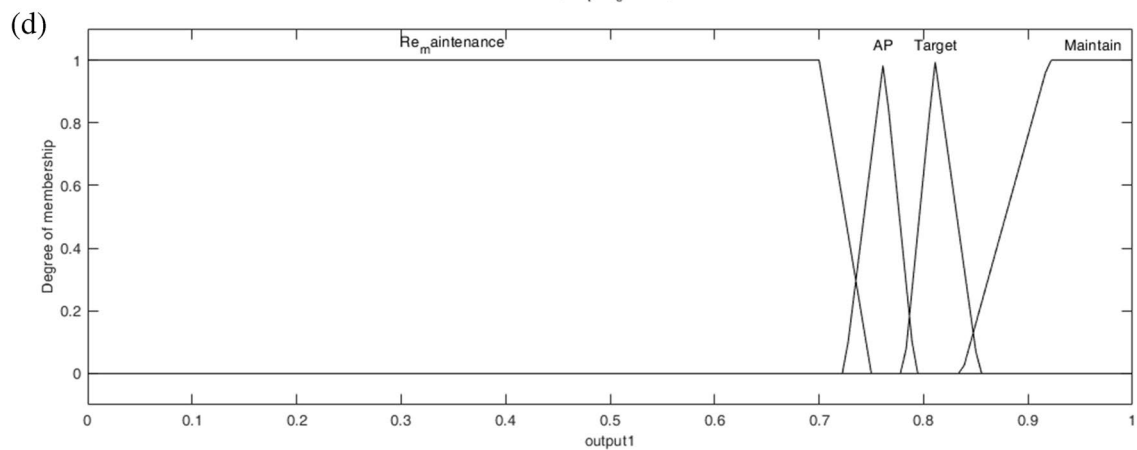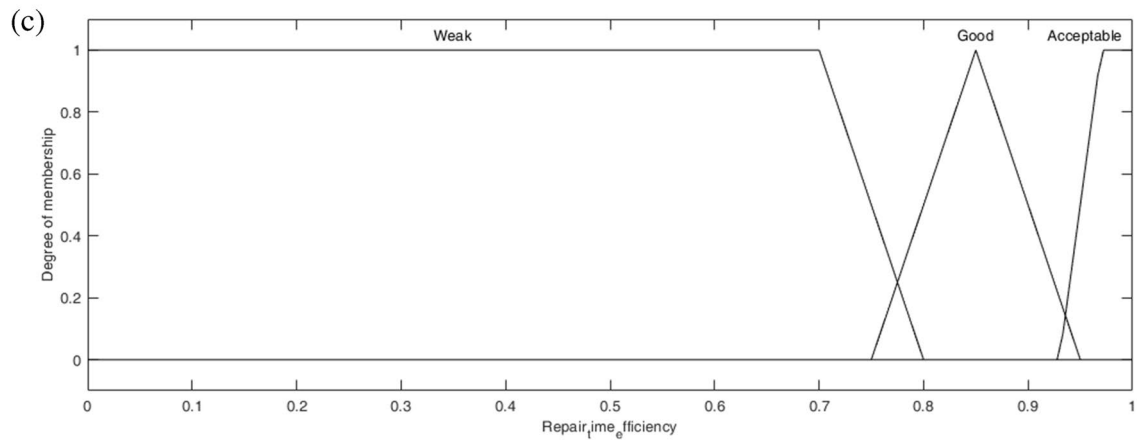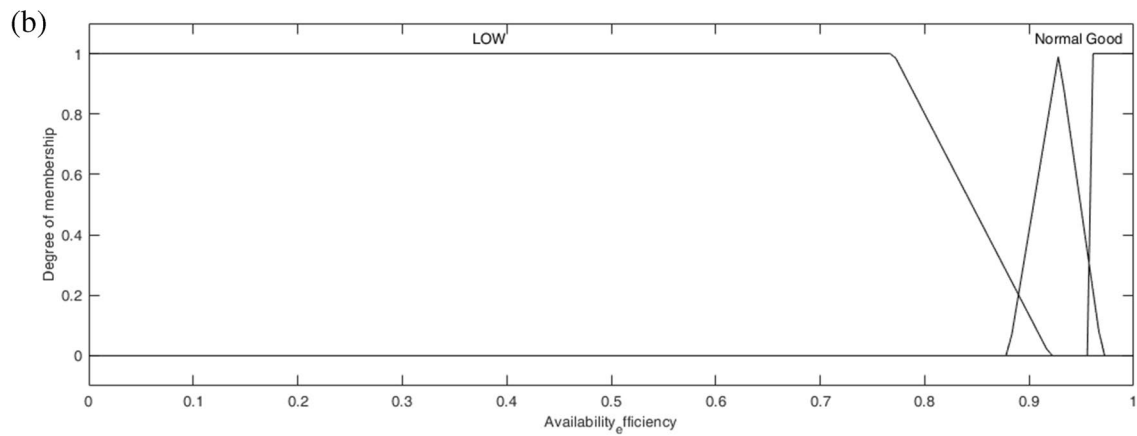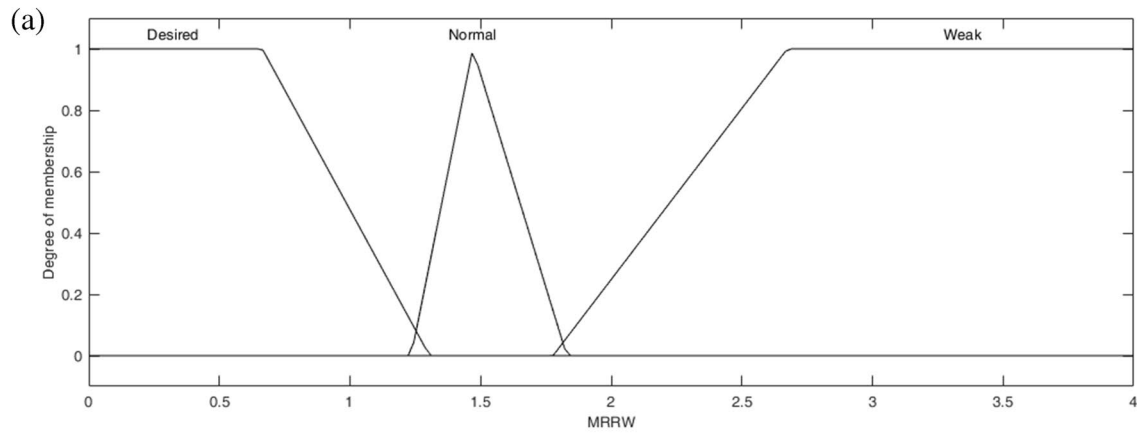
◄**Fig. 3** (**a**) membership function of MRRW, (**b**) membership function of availability efficiency, (**c**) membership function of repair time efficiency, (**d**) membership function of decisions
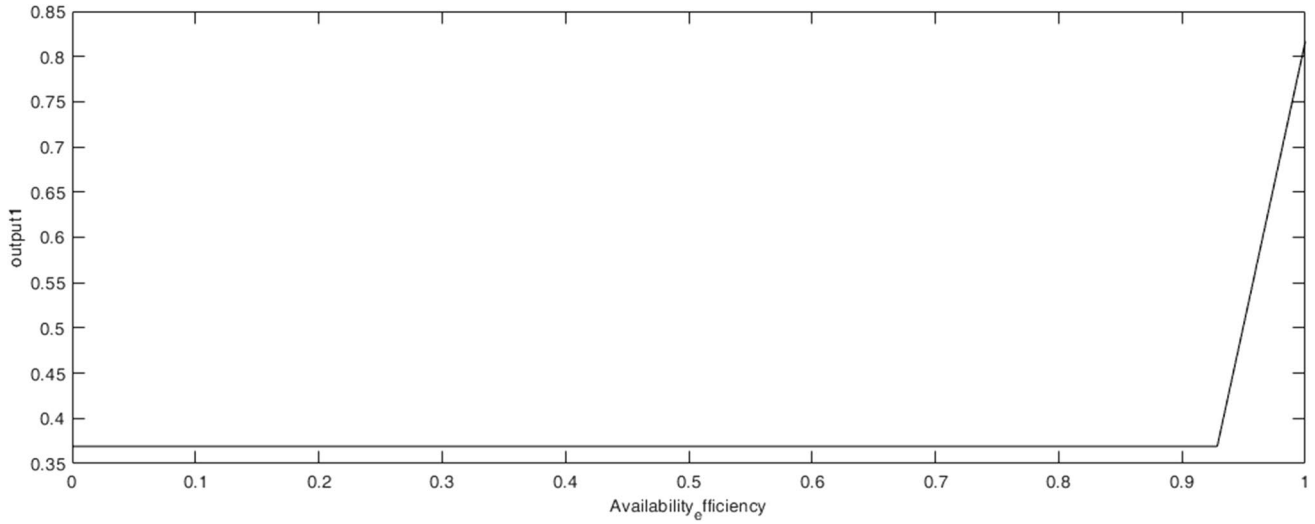

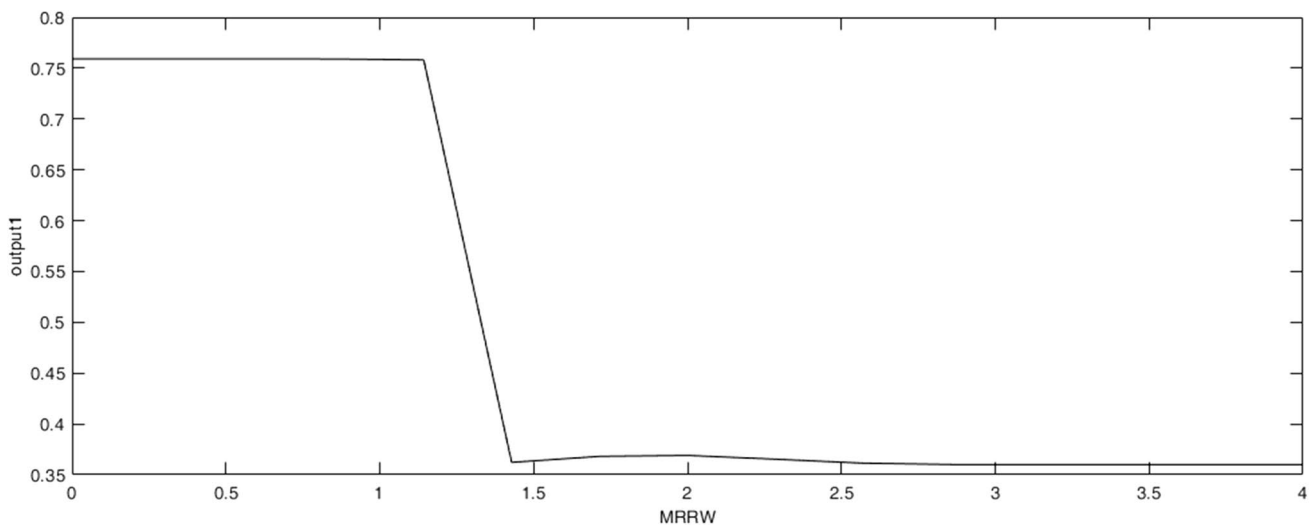**Fig. 4** Changes of availability efficiency considering its membership degree
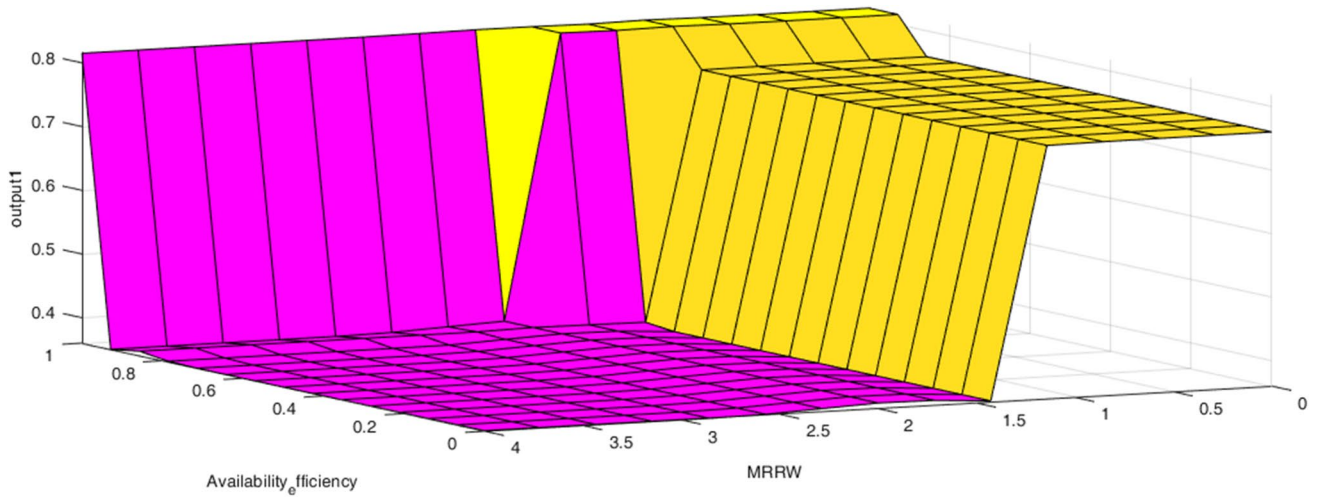

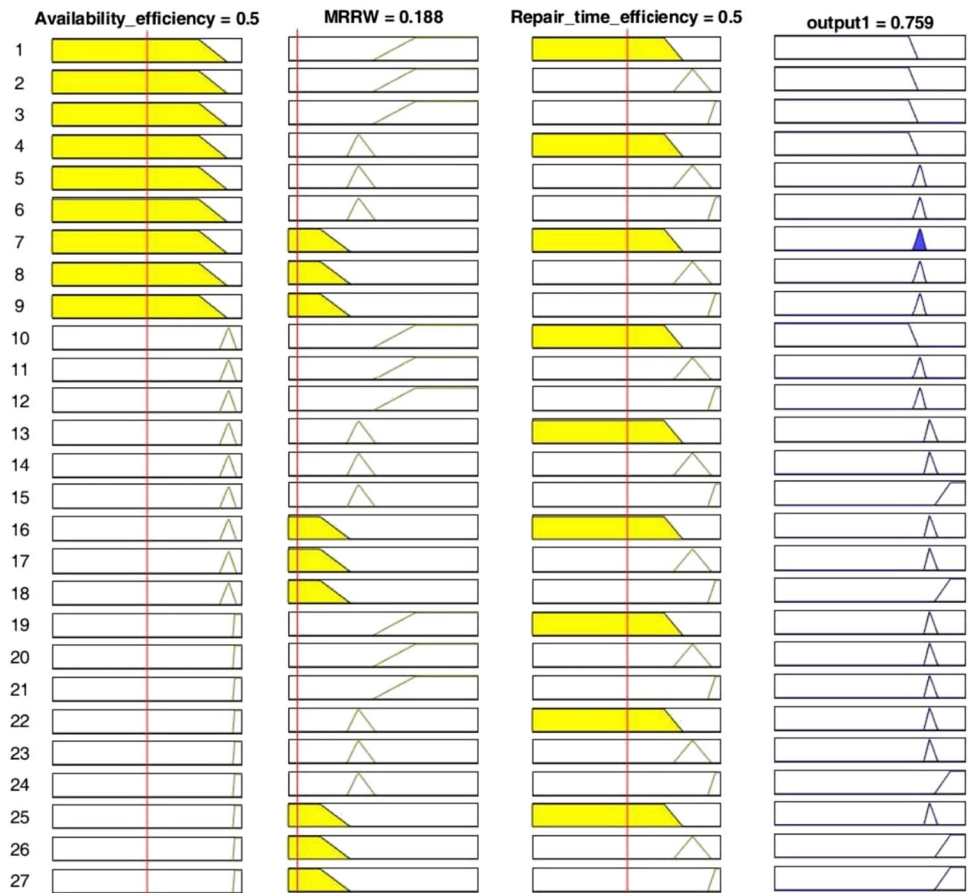**Fig. 5** Changes of MRRW considering its membership degree

Fig. 6 Surface of the output considering availability efficiency and MRRW

Fig. 7 Rule viewer of the FIS

Declarations

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