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# Evaluation of water supply alternatives for Istanbul using forecasting and multi-criteria decision making methods

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## ABSTRACT

Water scarcity is one of the most serious problems of the future due to increasing urbanization and water demand. Urban water planners need to balance increasing water demand with water resources that are under increasing pressure due to climate change and water pollution. Decision makers are forced to select the most appropriate water management alternative with respect to multiple, conflicting criteria based on short and long term projections of water demand in the future. In this paper, we consider water management in Istanbul, a megacity with a population of 15 million.

*Purpose:* The purpose of this paper is to develop a method combining demand forecasting with multi-criteria decision making (MCDM) methods to evaluate five different water supply alternatives with respect to seven criteria using opinions of experts and stakeholders from different sectors.

*Methodology:* To combine forecasting with MCDM, we design a data collection method in which we share our demand forecasts with our experts. For demand forecasting, we compare Holt-Winters, Seasonal Autoregressive Integrated Moving Average (S-ARIMA), and feedforward Artificial Neural Network (ANN) models and select S-ARIMA as the best forecasting model for monthly water consumption data. Generated demand projections are shared with experts from different sectors and collected data is evaluated with Fuzzy Theory using two distinct MCDM models: Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE). Also our analyses are complemented with two sensitivity analyses.

*Findings:* Our results indicate that greywater reuse is the best alternative to satisfy the growing water demand of the city whereas all experts find desalination and inter-basin water transfer as the least attractive solutions. In addition, we adopt the PROMETHEE GDSS procedure to obtain a GAIA plane indicating consensus among experts. Furthermore, we find that our results are moderately sensitive to the number of experts and they are insensitive to changes in experts' evaluations.

*Novelty:* To the best of our knowledge, our study is the first one incorporating water demand and supply management concepts into the evaluation of alternatives. From a methodological perspective, water demand projections have never been used in an MCDM study in the literature. Also, this paper contributes to the literature with a mathematical construction of consensus and Monte Carlo simulations for the sufficiency of experts consulted in a study.

## 1. Introduction

As fresh water supplies decrease in quantity and deteriorate in quality, water resource management is more critical than ever before, and the way forward is integrated water resources management. Water resources management is a complex task requiring consideration of social, economic, and environmental aspects to ensure publicly accepted solutions that foster economic growth and improvement in the quality of life in subsequent decades. From a practical perspective, water management can be exercised with two distinct approaches: *Water supply management*, referring search of water resources to be utilized for the city; *water demand*

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*management*, referring control of water demand with better distribution infrastructure, responsible consumption, and reuse management (smart collection and wastewater treatment to utilize treated water to satisfy a portion of urban water demand).

All urban water planning studies consist of two main phases. First, water demand projections are generated by considering trend and seasonality on historical consumption data for short and long term horizons using statistical techniques. Second, different water management solutions are evaluated with respect to a heterogeneous, consisting of quantitative and qualitative, set of criteria for a given water demand projection. Quantitative evaluation criteria can easily be integrated into optimization models. However, qualitative criteria, such as public acceptance and environmental-friendliness, are difficult to measure and quantify using mathematical methods. The heterogeneity of the criteria set required for water management issues motivates us to utilize Multi-Criteria Decision Making (MCDM) methodologies for a comprehensive evaluation of water management alternatives. The capability of including different types of criteria is one of the most well-known advantages of MCDM methods.

Some of these evaluation criteria are quantitative and can easily be integrated into optimization models while many are impossible-to-quantify, e.g. public acceptance and environmental-friendliness. The existence of such heterogeneous decision making criteria requires the utilization of Multi-Criteria Decision Making (MCDM) methodologies for evaluation of water management solutions.

In this study, we evaluate various solution alternatives of supply, demand, and reuse management approaches for meeting the city's increasing water demand, which follows seasonal cycles over a year. To evaluate the alternatives, we utilize a combination of forecasting and MCDM methods by considering the perspectives and opinions of different stakeholders after sharing the water demand forecast of Istanbul with them. Then, calculated results are analyzed to measure their sensitivity to variations in experts' judgements. The main motivation behind this paper is evaluating water demand and supply management alternatives by combining forecasting with MCDM methods, a research gap that has never been addressed before. The combination of the two methods is suggested for reaching a consensus on the best ranking of alternatives for the water management problem of Istanbul.

For demand forecasts, we utilize monthly water consumption data between 2009 and 2019 supplied by the Istanbul Metropolitan Municipality as a part of their open data program (https://data.ibb.gov.tr/en/). Using the collected data, we compare three different methods, Holt-Winters, Seasonal Autoregressive Integrated Moving Average (S-ARIMA), and Artificial Neural Network (ANN), and generate demand projections. These demand projections are shared with water management experts and various stakeholders to collect their evaluations of five distinct water supply alternatives; inter-basin water transfer, rainwater harvesting, greywater reuse, desalination and irrigation with reused water, with respect to seven criteria (Section 3.2).

Expert evaluations are processed with fuzzy logic and two respective MCDM methods: Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE). The main motivation of selecting TOPSIS is that the method is not affected by the correlation between criteria which might be an issue in our case. Also, TOPSIS has a simple structure and can easily be interpretable by the decision makers (Behzadian et al., 2012). PROMETHEE is motivated by its suitability for criteria in different magnitudes, e.g. volume, cost, flow rate, public acceptance. Besides, the results of PROMETHEE can be successfully visualized and interpreted on a GAIA plane which facilitates the communication of findings (Behzadian et al., 2010) and provides additional insights.

Compared to the other alternatives in the literature, TOPSIS with linear normalization is recognized as an efficient outranking method. Using *Euclidean* metric TOPSIS leads to the similar results with VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), which utilizes a general $L_p$ metric and more calculation coefficients (Opricovic and Tzeng, 2004). TOPSIS with vector normalization is reported to generate more realistic and stable results (Antucheviciene et al., 2012; Mousavi-Nasab and Sotoudeh-Anvari, 2017). Similarly, Peng and Dai (2018) compare Multi-Attributive Border Approximation Area Comparison (MABAC) and TOPSIS on a MCDM problem. Reportedly they reach the same results as they essentially aggregate function for distance to negative and positive ideal solutions. Mousavi-Nasab and Sotoudeh-Anvari (2017) compare TOPSIS and Complex Proportional Assessment (COPRAS) and conclude that both methods can handle qualitative and quantitative criteria, can handle a large number of alternatives, provide perfect ranking of options and is not influenced by any supplementary parameter. Su et al. (2020) report that there are more than 70 different techniques for solving MCDM problems and they may lead to different results due to their methodological differences. Hence, it is important to utilize multiple methods from different solution approaches for the same problem and apply sensitivity analysis to the results.

Our results indicate that Istanbul's water demand is growing over time and expected to be higher than 100 thousand $m^3$ per month by 2021 (Fig. 4). To satisfy this rapidly growing water demand, two solution alternatives of reuse management, reuse of greywater and irrigation with reused water, are found to be the two most attractive with respect to both quantitative, e.g. operational cost, investment cost, and qualitative, e.g. ease of operation and public acceptance, criteria. We also detected that academics and public sector practitioners have similar preferences for the alternatives, which we quantify and depict by adopting the PROMETHEE GDSS method (suited for group decision making (Brans and De Smet, 2016)), to our problem.

Our paper provides a solution ranking for water management problems in Istanbul and it also contributes to the MCDM literature. The main achievements and the contributions of our study can be listed as follows:

- Our results provide guidance to city planners and policy-makers which, according to our results, should consider reuse management practices for the future rather than focusing on supply management solutions.
- As a novel approach to evaluation of the water solution alternatives, we combine water demand forecasting with MCDM methods by sharing our future projections with experts to obtain more realistic evaluations and limit the effect of subjectivity. We believe that our approach will be beneficial for future researchers who are interested in these methods.
- We adopt the PROMETHEE GDSS procedure to visualize consensus among experts. To determine the sufficient number of experts for reaching a consensus, we apply a simulation-based method by using a mathematical definition of consensus for a given number of experts (Appendix B). Our simulations imply that the expert size leading to a consensus on alternative rankings is moderately sensitive to variations in experts' evaluations.
- Also, we analyze the sensitivity of solution rankings to variations in experts' opinions. We find that the results are insensitive to variations in experts' evaluations. Particularly, F-TOPSIS is found to be generating more insensitive results compared to F-PROMETHEE.

This paper consists of five sections. In Section 2, brief background information on water management issues in Istanbul and a literature review on the suggested methodologies are provided. Section 3 discusses decision criteria and various water supply alternatives for Istanbul. This discussion is followed by the application of the two MCDM models to the water management issues of Istanbul. The results of our analyses and their interpretations are presented and discussed in Section 4. Section 5 concludes the paper with the implications of our findings, limitations and future research directions.

## 2. Literature review

### 2.1. Brief background information on water management in Istanbul

As mentioned above, there are two possible solution approaches for water scarcity: supply management (providing new sources of supply to meet the demand) or demand management (optimizing the use of existing water supplies to avoid the need for new resources). In Istanbul, water management activities are still at the supply management level, mainly due to lack of measures to control water consumption.

Water supply has always been an issue in Istanbul throughout the entire history. In order to meet the increasing water demand in Istanbul, large-scale water transfer schemes were put into practice as no perennial water resources exist within the municipal boundaries (Burak et al., 2017). Inter-basin water transfer relies on water diverted from donor to recipient basin and this strategy is practiced to satisfy the ever-expanding metropolis' demand, as also it has been the most preferred solution in other water-scarce regions of the world (Burak and Margat, 2016; Burak and Mat, 2020; Gohari et al., 2013). Currently, in Istanbul, inter-basin water transfers meet 45% of the water requirements of a population exceeding 15 million (ISKI, 2019). Water transfer from neighboring watersheds is expected to meet 70% of Istanbul's water demand whose urban population is expected to grow to over 19 million by 2040 (Turkish Statistical Institute, 2018; Islar and Boda, 2014). Some properties of inter-basin water transfer schemes in Istanbul are presented in Table 1.

Several studies on water demand projection by Istanbul Water and Sewerage Administration (İSKİ) report domestic, industrial, commercial, institutional (schools, government and other public buildings), touristic and unaccounted-for water consumption. Water Resources of Istanbul are Terkos, Büyükçekmece, Sazlıdere and Alibeyköy lake reservoirs for the European side and Elmalı, Ömerli, and Darlık lake reservoirs for the Anatolian side. There are five main water treatment plants, Kağıthane, Büyükçekmece, İkitelli (Fatih Sultan Mehmet Han), Ömerli, Elmalı, that serve Istanbul.

Water demand management can also be highly beneficial in terms of protecting water resources through the efficient use of fresh water and proper handling of wastewater. In comparison to water supply efforts, wastewater treatment and demand management in Istanbul have taken significantly slower steps. Presently, there are 14 major wastewater treatment plants (WWTPs) in Istanbul; nine primary WWTPs, two biological (secondary) WWTPs and three advanced biological (tertiary) WWTPs. Secondary and tertiary treatment plants constitute just 5 and 12% of Istanbul's overall WWTP capacity respectively and only a small part of the treated wastewater from these plants is used in the city for irrigating gardens, parks and recreational areas (Burak and Demir, 2016; Burak and Margat, 2016; Burak and Mat, 2020; ISKI, 2019). Reuse of wastewater is not a common practice in Istanbul for several reasons such as outdated agricultural practices, inadequate technology for wastewater treatment, and insufficient infrastructure for reuse. According to Mutailifu (2019), nothing serious has been done to control water consumption in the society and Istanbul is currently practicing supply management combined with sufficient wastewater treatment systems.

### 2.2. Literature on short term water demand forecasting

Forecasting water demand is one of the most important tasks of water resource management. Scholars have addressed this problem since the 1950s and a significant body of literature has been accumulated on the subject since then. As reviewing the entire literature on this subject is beyond the scope of this paper, we only consider the most relevant studies and refer to Memon and Butler (2006), and Donkor et al. (2014) for reviews of the literature.

The forecasting part of our study includes three different methods: Holt-Winters, Seasonal Autoregression Moving Average (S-ARIMA) and feedforward Artificial Neural Network (ANN). Holt-Winters is a classic forecasting method, first introduced by Holt (1957) and extended by Winters (1960), for modeling seasonality and trend by means of an additive (or multiplicative) model for a given length of seasonal cycles (years in our case). Caiado (2010) compared Holt-Winters, ARIMA and GARCH models for daily water demand and concluded that the best performance can be obtained by combining Holt-Winters and GARCH models.

S-ARIMA, the second method considered for our short water demand forecasting, is a flexible model that can address autocorrelation, trend and seasonality (Box et al., 2015) in a time series. In S-ARIMA, the model parameters are estimated using the least-squares method or maximum likelihood estimation as residual terms are assumed to follow normal distribution with zero mean and constant variance (Box et al., 2015). One important point of modeling time series with S-ARIMA is the determination of hyperparameters of the model. Specifically, the number of autoregressive and moving average terms included in the model significantly affects the model's forecast accuracy. Usually, the calculation of these hyperparameters is manually conducted by using (partial) autocorrelation and trend analyses (Box et al., 2015). Froukh (2001) combined multiple forecasting models and generated a decision support system for domestic water demand. In this study, we contributed to this literature by comparing Holt-Winters, S-ARIMA and single layer feedforward ANN models for monthly water consumption data.

Feedforward ANN models are a popular technique for modeling time series. An increasing amount of studies on different kinds of ANN models has been published since the 1990s and ANN methodology is extended to deep learning applications with the joint

**Table 1**
Some properties of inter-basin water transfer schemes in Istanbul (ISKI, 2019).

| Project Name | Volume of Transferred Water (million $m^3$/year) | Distance (km) | Purpose |
|---|---|---|---|
| Istranca | 365 | - | Domestic, Industrial |
| Yeşilçay | 335 | 60 | Domestic, Industrial |
| Great Melen | 1180 | 185 | Domestic, Industrial |

use of forward and backpropagation (Ghatak, 2017) and larger networks, which sometimes suffer from overfitting due to the large number of parameters. Feedforward ANN models with a single hidden layer including a finite number of neurons can approximate any continuous function on compact subset of $R^n$. This important result is known as Universal Approximation Theorem in the machine learning literature (Alpaydin, 2014; Goodfellow et al., 2016). In addition to the number of neurons in the hidden layer, decay rate and the maximum number of iterations are the other hyperparameters of ANN modeling. Ghatak (2017) states that a detailed search in the hyperparameter space is critical for the successful implementation of ANN models and he suggests two heuristics in addition to a grid search for estimating the hyperparameters of a model. In the literature (Adamowski et al., 2012; Bougadis et al., 2005; Ghiassi et al., 2008; Guo et al., 2018), ANN and deep learning are used to estimate short term urban water demand. In these models, usually different model architectures are considered together with an extensive grid search on hyperparameter space.

By comparing ANN with regression models, Adamowski and Karapataki (2010) extended this research stream. They utilize a large set of regression and ANN models to weekly water demand forecasting problem of Cyprus using six years of consumption data. They find that ANN models generate more accurate results compared to conventional regression models.

### 2.3. MCDM literature on water management

In water resources literature, MCDM has been widely implemented as a major component of decision-support systems (Amorocho-Daza et al., 2019; Fassio et al., 2005; Hajkowicz and Higgins, 2008; Hämäläinen et al., 2001; Jaber and Mohsen, 2001; Maia and Schumann, 2007; Makropoulos et al., 2008; Qureshi and Harrison, 2001). It has been used for a range of water resource problems, such as river basin planning (Raju et al., 2000; Weng et al., 2010), water supply/allocation and reservoir operation (Flug et al., 2000; Golfam et al., 2019a, 2019b; Mahmoud and Garcia, 2000; Srdjevic et al., 2004), urban water management (De Marchi et al., 2000; Joubert et al., 2003; Zarghami et al., 2008), design of monitoring networks (Nguyen et al., 2019), wastewater treatment alternatives (Khalil et al., 2005; Kholghi, 2001; Piadeh et al., 2018a), water quality (Shourian et al., 2017), groundwater management (Pietersen, 2006), flood control (Shariat et al., 2019), and irrigation planning (Karleuša et al., 2019).

Over 300 MCDM studies published between 1980 and 2012, including 68 water resource management implementations, are reviewed by Kabir et al. (2014). From the methodological perspective, this research stream includes with ELECTRE (Govindan and Jepsen, 2016; Haider et al., 2015; Trojan and Morais, 2012), MAUT (Monte and de Almeida-Filho, 2016; Scholten et al., 2015), Analytical Hierarchy Procedure (AHP) (Benitez et al., 2011; Cabrera et al., 2011; Freitas and Magrini, 2013; Piadeh et al., 2018b; Zamarrón-Mieza et al., 2017; Zyoud et al., 2016), compromise programming (Abrishamchi et al., 2005; Fattahi and Fayyaz, 2010; Shiau and Lee, 2005; Zarghami et al., 2008), TOPSIS and PROMETHEE.

TOPSIS is a common MCDM method that considers the distance of each alternative to the best and the worst ones with respect to a set of decision making criteria (Noureddine and Ristic, 2019; Petrovic and Kankaras, 2020). It is particularly suitable for water management issues as it does not require criteria preferences to be independent (Blanco-Mesa et al., 2017; Moghadas et al., 2019). In the water management and hydrology literature, TOPSIS is used to determine the preference relation between inter-basin water transfer projects (Afshar et al., 2011; Zarghaami et al., 2007), wastewater treatment methods (Gómez-López et al., 2009; Srdjevic et al., 2004), irrigation scheduling techniques (Wang et al., 2011). Behzadian et al. (2012) provide a review of these studies. We extend TOPSIS with fuzzy numbers in order to address randomness in expert opinions using specific distributions.

PROMETHEE is an outranking method for ranking alternatives with respect to conflicting criteria. The most popular application area of the method is environmental problems, such as waste management, environmental impact assessment, life cycle assessment (Behzadian et al., 2010). In the context of water management and hydrology, PROMETHEE is considered by Simon et al. (2006, 2005, 2004) to evaluate water management strategies. Raju et al. (2000) utilize PROMETHEE for ranking different water irrigation systems with respect to environmental, economic and social criteria. Kodikara et al. (2010) developed a PROMETHEE approach for determining the best alternative operating rules for municipal water supply reservoir systems in Melbourne, Australia. Behzadian et al. (2010) review these studies together with other applications of PROMETHEE to environmental problems. We extend PROMETHEE with fuzzy numbers to address variability in expert judgements in the study.

Fuzzy-based systems are commonly used in the literature to model linguistic ratings of experts on alternatives with respect to qualitative criteria, airline service quality (Tsaur et al., 2002). Since its foundation, fuzzy set theory has been applied to various research problems and combined with different analytical methods (Simić et al., 2017). Specifically, fuzzy sets are combined with MCDM, mathematical programming, statistics and artificial intelligence methods. Different fuzzy-MCDM approaches are applied to various problems such as supplier selection (Kahraman, 2008), product design (Liu, 2011) and personnel selection (Karsak, 2001). Simić et al. (2017) review 54 papers including fuzzy mathematical models such as, linear programming (Amid et al., 2006; Guneri et al., 2009; Lin, 2012) and integer programming (Amid et al., 2009). Also, fuzzy set theory is combined with statistics (Bottani and Rizzi, 2008) and artificial intelligence methods (Jain et al., 2004; Kuo et al., 2010). Our study belongs to the literature stream combining fuzzy sets and MCDM methods to solve a decision making problem.

By combining fuzzy sets with TOPSIS and PROMETHEE methods, we incorporate qualitative evaluations of experts on water management into the decision making process. As solution alternatives of water management problems include social and qualitative features, such as water quality and ease of operation, linguistic ratings are important for reaching a conclusive decision using experts' judgements. In addition to fuzzy sets, we assess the impact of linguistic ratings using different techniques for the same MCDM problem. This way, we are able to verify our results from different perspectives. Our verification is extended with our sensitivity analysis in Appendix E.

### 2.4. Our contribution

The closest studies to this paper are Coban et al. (2018) and Hajkowicz and Higgins (2008). The former considers the solid waste management problem in Istanbul by evaluating different solutions with PROMETHEE 1 and PROMETHEE 2. The latter considers only PROMETHEE 2 for water management issues, however, their results are not compared or verified with another methodology.

From the methodological perspective, our contributions to the literature are fivefold: First, to the best of our knowledge, this study is the first one combining forecasting with MCDM methods in the literature. Although multi-criteria decision making problems are widely being used for investment decisions that affect the future, none of the studies in the literature consider conducting a forecasting study and sharing its results with experts in the literature before. Second, our review of the MCDM literature reveals that F-TOPSIS and F-PROMETHEE methods have never been compared before in spite of the large body of literature on these methods. Third, we apply the PROMETHEE GDSS, suggested for the group decision making process by Brans and De Smet (2016), to our problem to obtain a graphical representation of the extent of agreement and consensus between the experts. Fourth, the sufficiency of the number of experts in MCDM studies has never been addressed thoroughly. In this study, we conduct Monte Carlo simulations to determine the sufficient number of experts that guarantee consensus on the ranking of the alternatives. Fifth, to the best of our knowledge, this is the first MCDM study on water management of Istanbul. Our results indicate the best alternative for the water management issue in Istanbul. These results are subjected to sensitivity analysis in using sensitivity simulations (Appendix E).

## 3. Material and methods

The methodology utilized in this study consists of two main parts: Water demand forecasting and MCDM. An overview of the entire methodology of the study is depicted in Fig. 1. The forecasting part of the study starts with obtaining water consumption data from the Istanbul Metropolitan Municipality (IMM). By comparing three different models from the literature, we generate forecasts for Istanbul's water demand for the next year. These forecasts are used as inputs to the MCDM study.

Our MCDM study is initiated with the definition of alternatives and their evaluation criteria which are followed by the design of evaluation forms and scale. In the evaluation forms (Appendix C) we include demand forecasts and ask experts to evaluate water supply alternatives accordingly. This link between the forecasting and MCDM parts of the study is indicated with red dashed lines in Fig. 1. Using these forms, we collect data from a different expert group, consisting of top managers from governmental institutions responsible for water management, respected academics of hydrology and water management, and managers of private sector companies. Collected evaluations are processed with two different MCDM methods, TOPSIS and PROMETHEE, both of which are extended with fuzzy sets to obtain preference rankings of alternatives with respect to evaluation criteria. In the following subsections, both forecasting and MCDM parts are discussed in detail.

### 3.1. Forecasting water consumption of Istanbul

Modeling monthly water consumption starts with trend and

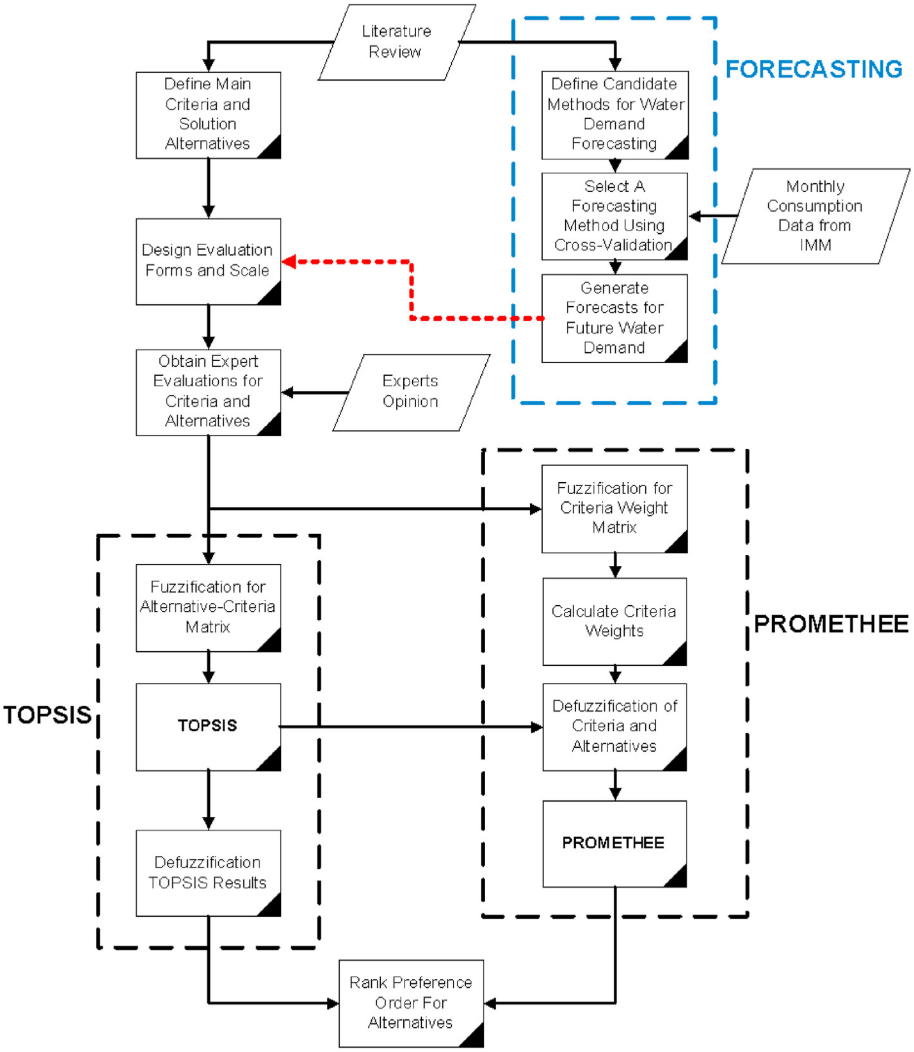

**Fig. 1.** Overview of the study.

seasonality analysis on data. To this end, we decompose monthly consumption data into seasonal and trend components using the Loess model (Cleveland et al., 1990), which is applied to our problem by means of a built-in routine (Ripley, 2002) in R Gui, an open-source statistical programming language. In this model, we assume additive trend and seasonality components for monthly water consumption data. The results (Figs. 2 and 3) indicate that monthly water demand has a linear growth between 2009 and 2020 (5% per year) and demand reaches its peak between May and August whereas the lowest water consumption occurs in February.

These findings motivate us to consider forecasting models that can address both trend and seasonality in data. To this end, we utilize Holt-Winters (HW), Seasonal Autoregressive Integrated Moving Average (S-ARIMA) and feedforward Artificial Neural Network (ANN) for the projection of water consumption in Istanbul.

In Holt-Winters models, the model parameters are updated with new observations after they are corrected by learning parameters, which are optimized to minimize forecasting error. For parameter estimation of the Holt-Winters model, we utilize the *Holt-Winters* routine in R Gui which uses numerical optimization routines based on conjugate gradients (Fletcher and Reeves, 1964). Calculated learning (smoothing) parameters are given in Table 4 and coefficients for trend and months of a year are presented in Table 5.

S-ARIMA is the second method considered for our water demand forecasting. We run *auto.arima,* a built-in routine in R Gui, to automatically search the hyperparameter space of the model and to compare different model structures with respect to Akaike Information Criterion (Hyndman et al., 2007). Calculated parameters of the S-ARIMA model for monthly water consumption in Istanbul are given in Table 6 in Section 4.

As the third forecasting method, we utilize a set of ANN models including different number of nodes in a single hidden layer. In all models, year, month and previous months' consumption are considered as independent variables. In addition to the different sets of inputs, we run a grid search for the decay rate and maximum iteration parameters. The best combination of hyperparameters selected in this search is given in Table 7. For this model, the values of 57 model parameters are given in Table A.1 in Appendix A.

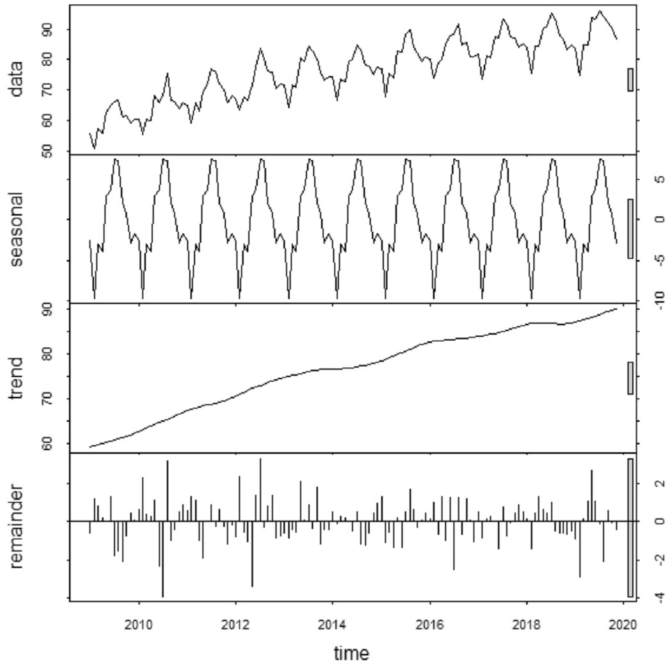

**Fig. 2.** Loess decomposition of water consumption data of Istanbul.

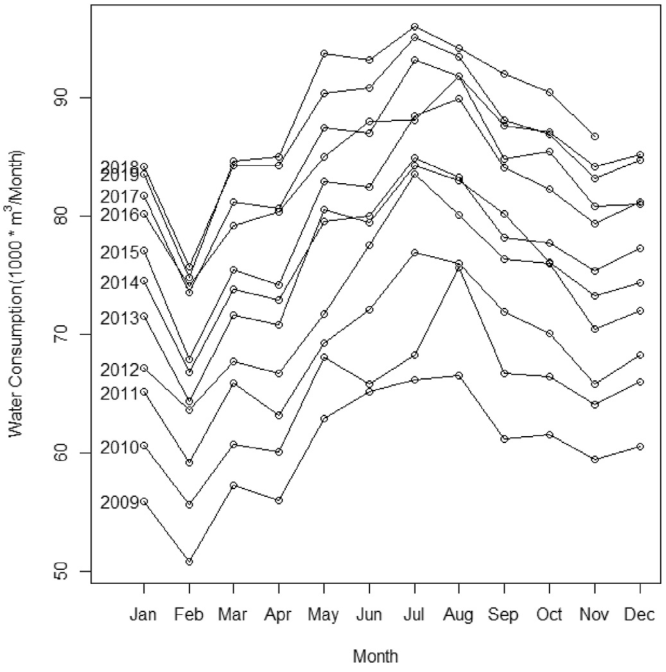

**Fig. 3.** Monthly representation of water consumption between 2009 and 2019.

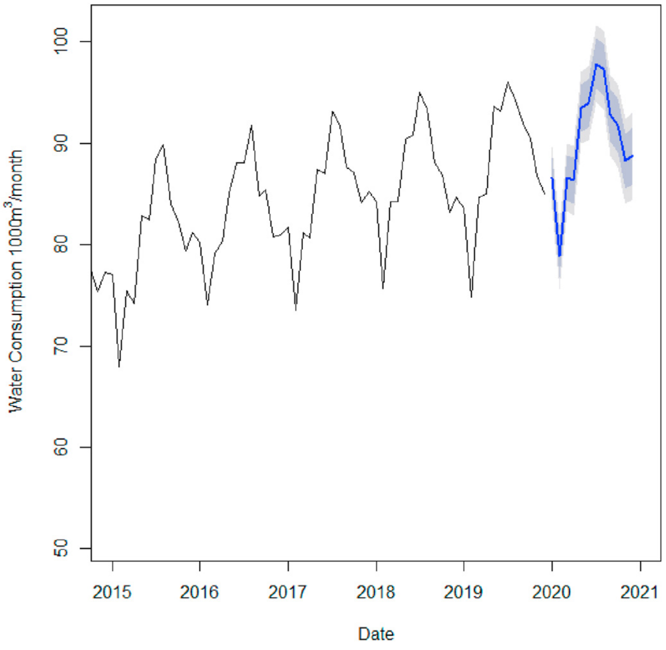

**Fig. 4.** Water consumption forecast for 12 Month in Istanbul.

The performance of forecasting models is verified and compared using k-fold cross-validation, which is executed in a rolling horizon fashion. In this procedure, we divide the time series of water consumption into training and test sets. The test set includes the last $h_{max}$ periods of the data whereas the rest is used as training set, which is split $k$, $k \leq N/h_{max}$ distinct periods. Then we consider the first part and use it to forecast $h$, $h = 1, 2, 3, \ldots, h_{max}$periods ahead. Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and

**Table 2**
Criteria for evaluating alternative solutions of water supply issue.

| Criteria Class | Code | Decision Making Criteria | References |
|---|---|---|---|
| **Economic** | C1 | Initial investment cost | Coban et al. (2018); Fontana et al. (2011); Yilmaz and Harmancioglu (2010) |
| | C2 | Operation and Maintenance Cost | Coban et al. (2018); Fontana et al. (2011) |
| **Environmental** | C3 | Negative impact on the environment during the construction and operation of the activity. | Köksalan and Zionts (2012); Kumar et al. (2017) |
| | C4 | Negative impact on the ecosystem (aquatic and/or coastal) during the operational phase of the activity. | Diaz-Sarachaga et al. (2017); Köksalan and Zionts (2012); Kumar et al. (2017) |
| **Technological** | C5 | Ease of operation | Cambrainha and Fontana (2018); Ilaya-Ayza et al. (2017) |
| **Technical** | C6 | Infrastructure requirements | Garfi and Ferrer-Marti (2011) |
| **Social-Political** | C7 | Evaluation/acceptance by the public/end users | Garfi and Ferrer-Marti (2011); Scholten et al. (2015) |

**Table 3**
Linguistic rating scale for criteria and alternatives evaluations (Chen et al., 2006; Cinar and Ahiska, 2010).

| Linguistic Rating | Criteria | | | Alternatives | | |
|---|---|---|---|---|---|---|
| | $n_1$ | $n_2$ | $n_3$ | $n_1$ | $n_2$ | $n_3$ |
| Very Good (VG) | 0.80 | 1.00 | 1.00 | 8 | 10 | 10 |
| Good (G) | 0.70 | 0.80 | 0.90 | 7 | 8 | 9 |
| Medium Good (MG) | 0.50 | 0.65 | 0.80 | 5 | 6.5 | 8 |
| Medium (M) | 0.40 | 0.50 | 0.60 | 4 | 5 | 6 |
| Medium Low (ML) | 0.20 | 0.35 | 0.50 | 2 | 3.5 | 5 |
| Low (L) | 0.10 | 0.20 | 0.30 | 1 | 2 | 3 |
| Very Low (VL) | 0.00 | 0.00 | 0.20 | 0 | 0 | 2 |

**Table 4**
Learning parameters of holt-winters.

| $\alpha$ | $\beta$ | $\gamma$ |
|---|---|---|
| 0.26121670 | 0.0295383 | 039414580 |

**Table 5**
Coefficients of holt winters.

| Trend Coefficients | |
|---|---|
| Intercept = 90.284 | Slope = 0.1994 |
| **Month Coefficients** | |
| s1 = −2,5161 | s7 = 3.1320 |
| s2 = −3.2597 | s8 = 6.7604 |
| s3 = −11.2980 | s9 = 5.8329 |
| s4 = −3.1539 | s10 = 1.5407 |
| s5 = −3.5596 | s11 = 0.1994 |
| s6 = 3.3026 | s12 = −3.5606 |

**Table 6**
Model parameters of S-ARIMA.

| ARIMA MODEL: (0,1,1)(0,1,1)[12] | | |
|---|---|---|
| | Moving Average 1 (ma1) | Seasonal Moving Average 1 (sma1) |
| **Coef. Estimate** | −0.70000 | −0.77610 |

**Table 7**
Hyperparameters of ANN model.

| Autoregressive Terms | Hidden Neurons | Total Parameters |
|---|---|---|
| 3 | 8 | 57 |
| **Decay** | **Maximum Number of Iteration** | |
| 1E-02 | 100 | |

Mean Absolute Percent Error (MAPE) are calculated for these forecasted periods. Then we apply the same procedure for considering the first and the second periods together and take their averages. The results of the cross-validation tests are given in Table 8 for $h_{max} = 12$ and $k = 6$. Based on the results in Table 8, we selected the S-ARIMA model and used it for generating water demand forecasts of Istanbul for 12 months (Fig. 4).

These short term forecasts of water demand are shared with academics and experts from public and private sectors during our data collection stage to provide a better projection for the water supply problem and to reach a more consistent and realistic solution to the problem. Experts' opinions are evaluated using two distinct MCDM models. The details of this procedure are given in the next section.

### 3.2. MCDM models for water supply issue

MCDM studies consist of multiple phases; development of alternatives, determination of criteria, data collection, and data processing (Fig. 1). In this study, we also complement our analysis with two respective sensitivity analysis studies. All of these phases are explained below in the respective subsections.

#### 3.2.1. Development of alternatives

In 1995, Istanbul suffered from a water shortage and various alternatives are evaluated for providing additional water supply to the city by several authors (Akgul et al., 2008; Eroglu and Sarıkaya, 1998; Yuksel et al., 2004). Scholars state that it is necessary to implement "Management Optimization" for efficiency of such a large water supply and distribution systems. In this study, we consider the following alternatives, which is an extended version of the ones considered by Yuksel et al. (2004).

1. Inter-basin water transfer (artificially moving water from any basin to another by a pipeline or channel)
2. Rainwater harvesting (capturing, storing and reusing rainwater)
3. Greywater (reusing wastewater from baths, sinks and washing machines) Reuse
4. Desalination (converting seawater or brackish water into fresh water)
5. Irrigation with reused water (using wastewater for irrigating gardens, parks, and recreational areas)

**Table 8**
Results of cross-validation tests.

| | MAPE | MSE | RMSE |
|---|---|---|---|
| **Holt-Winters** | 0.0217 | 5.0809 | 2.1113 |
| **S-ARIMA** | 0.0192 | 3.9662 | 1.8570 |
| **ANN** | 0.3156 | 10.7222 | 2.9801 |

Various plans are in place to meet the increasing demand for water in Istanbul, most of which is focused on inter-basin water transfers from rivers to neighboring drainage basins. Six of the major drinking water reservoirs and their watersheds, Terkos, Büyükcekmece, Ömerli, Alibey, Sazlıdere, Elmalı, and Darlık, are within the municipal boundaries; and the others, the Kazandere and Papucdere Reservoirs, (the reservoirs of the Istranca Creeks System), the Yeşilçay and the Melen System, are in nearby watersheds. The Melen Watershed has the highest water potential (1.5 billion $m^3$/year) among the others and it provides almost 45% of the total water resources (Cuceloglu et al., 2017) Therefore, the Melen project was planned to draw water from the Melen River ($1.19 \times 10^9$ $m^3$/year) located at 185 km east of Istanbul in Düzce province, situated in the Black Sea region. Due to its high water capacity and comparatively better water quality, water transfer from Melen Watershed was considered to be the most feasible and reliable water supply to Istanbul. However, no resource is unlimited, and excess exploitation may have adverse effects on the environment and natural resources.

Rainwater harvesting and greywater reuse are widely known applications both for water supply and water end-use optimization. Harvested rainwater is used mainly for irrigation and toilet flushing (Benham et al., 2016) which can lead to a significant reduction in municipal water consumption. Rainwater systems require the implementation of some treatment and filtration before storage as rainwater is clean as it falls but contaminated by its touchpoint on the ground.

To evaluate the potential benefit of a rainwater system investment, precipitation and evaporation rates must be taken into account. In Istanbul average annual rainfall is (687.5 mm) suitable for rainwater harvesting (Harmancioglu and Altinbilek, 2020; Kantaroglu, 2009). In fact, rainwater harvesting has always been a viable water supply alternative throughout the history as one of the world's largest rainwater tanks, Yerebatan Sarayı, was constructed with a storage capacity of 80,000 $m^3$ of water during the rule of Caesar Justinian (A.D. 527–565).

The utilization of greywater is a promising alternative resource in water-stressed areas. Household consumption takes the largest share of total water demand in Istanbul, which means a considerable amount of greywater is produced. Despite the significant and untapped potential of greywater reuse, the method has not been of much interest in the city due to additional costs of constructing separate sewer pipes in new buildings and inconvenience (and difficulty) of renovation to build extra pipes to old ones. However, proper treatment and reuse of greywater can reduce the pressure of increasing water demand whilst reducing the cost of water transfer. The successful implementation of a greywater reuse system can be a good contribution to developing a sustainable water management scheme in the region.

Another viable alternative of drinking water production is to treat groundwater or seawater as the area is close to the sea (Aydin and Sarptas, 2020). Only a limited number of studies consider multiple desalination technologies, with regard to total costs and environmental effects, for different geographic locations in Turkey (Aydin and Sarptas, 2020; Aydiner et al., 2017; Hamut et al., 2014). Akgul et al. (2008) evaluate seawater samples from the Mediterranean Sea, the Marmara Sea, and the Black Sea with respect to return on capital, operating and total production costs criteria together with the basic parameters of cost analysis, which are capacity, recovery, membrane life, energy, chemical costs and flux. Relying on their results, we include seawater desalination into the water supply alternatives for Istanbul.

Turkey has started to apply wastewater reuse with the "Notification for Wastewater Treatment Plant Technical Procedures" (Nas et al., 2020). In the seventh chapter of the notification, there are regulations concerning wastewater reclamation and reuse. The chemical quality criteria for treated wastewater to be reused in irrigation, and the maximum acceptable heavy metal and toxic element concentrations for irrigation waters were established (Nas et al., 2020). The use of treated wastewater to irrigate green areas is called Purple network. Istanbul Pasaköy wastewater treatment plant provides reclaimed water for various purposes with a flow rate of 75,000 $m^3$/day. After the sedimentation tank, treated wastewater passes through sand filters and then it goes through UV disinfection. The disinfected effluent is used by tannery industries in Tuzla and for irrigation purposes.

### 3.2.2. *Development of criteria*

In this study, the abovementioned five water management scenarios are evaluated via seven criteria. For the selection of decision making criteria, we first conducted an extensive literature review on water management planning. Then, we finalize our criteria set with one-to-one surveys with the experts from the field. Our investigations lead us to five criteria classes to analyze water supply alternatives. In these classes, there are seven decision making criteria given in Table 2 together with the references from the literature.

Initial investment and operational costs are common criteria for the evaluation of any infrastructure investment (Coban et al., 2018; Fontana et al., 2011; Yilmaz and Harmancioglu, 2010). Negative impact on the ecosystem might be caused directly by the construction or during the operational phases of the activity. Potential threats to the environment can include land occupation, waste production, and ecosystem (aquatic and/or coastal) destruction (Diaz-Sarachaga et al., 2017; Köksalan and Zionts, 2012; Kumar et al., 2017). Hence any solution alternative should be assessed with its damage together with its benefits. Ease of operation is critical for sustainable and reliable operation of water supply solutions as too much operational complexity might stimulate a higher rate of human error in addition to increased maintenance costs and potentially longer failure downtimes (Cambrainha and Fontana, 2018; Ilaya-Ayza et al., 2017). Infrastructure requirements refer to the compatibility of a water supply alternative with the existing urban water management system (Garfi and Ferrer-Marti, 2011). The requirement of additional infrastructure investment might cripple the economic feasibility and operational sustainability of a water supply system. Successful water management requires the evaluation of water issues with both the physical and social aspects. As community, stakeholder, and agency engagement is essential in water management, institutions need to develop social and political recognition and answers to controversies and conflicts (Garfi and Ferrer-Marti, 2011; Scholten et al., 2015).

Note that some of our criteria include costs whereas others refer to benefit and public welfare. To address this heterogeneity in our criteria set, we slightly alter TOPSIS and PROMETHEE methods. Specifically, we use minimization for costs and maximization for benefits while finding calculating alternative rankings. Therefore, the possible negative effects of using conflicting criteria set on our results are deterred.

### 3.2.3. *Calculation of criteria weights*

Once criteria and solution alternatives are developed, data collection forms (Appendix C), including water demand forecasts in Section 3.1, are distributed to 9 different experts from academia, public, and private sectors. Using the collected responses, the sufficiency of the number of experts to be consulted in total is determined by means of Monte Carlo simulations explained in Appendix B, in which we also provide a mathematical construction of a sufficiency condition to reach a consensus for a given number of experts.

In the data collection process, we asked water management experts to evaluate the importance of criteria and alternatives qualitatively by selecting a linguistic rating from the set of $LR = (very\ high,\ high,\ medium\ high,\ medium,\ medium\ low,\ low,\ very\ low)$. These linguistic ratings are used to calculate criteria weights and alternative ranking scores.

Criteria weights are obtained with the F-TOPSIS method using the criteria set in Table 2. Specifically, we calculate the parameters of a triangular distribution for fuzzification. These fuzzy parameters are used as criteria weights to calculate the importance score of each alternative in both MCDM methods. Different methods, e.g. AHP, Full Consistency Method (FUCOM), Best Worst Method (BWM), are suggested for criteria weight calculation in the literature. It is recognized that AHP can require too much data with pairwise comparisons especially when it is combined with Fuzzy sets (Önüt et al., 2010). FUCOM is reported to be more advantageous compared to BWM and AHP (Mukhametzyanov and Pamucar, 2018). Our method differs from the literature with respect to the required amount of data as it processes linguistic rankings instead of pairwise comparisons to calculate criteria weights. Details of our criteria weight calculations are given in Appendix D (Step1-3).

In the following subsections, we provide a summary F-TOPSIS and F-PROMETHEE used for the importance score of each alternative. Detailed mathematical notation and formulations are given in Appendix D.

### 3.2.4. Fuzzy TOPSIS

F-TOPSIS starts with the transformation of linguistic ratings for each criterion into the parameters of the triangular distribution from Table 3 (Chen et al., 2006). These distribution parameters are generalized to overall ratings for each criterion. The calculated values of these generalized distribution parameters are given in Table 9. Similarly, experts' evaluations for each alternative with respect to each criterion are transformed into numeric values using Table 3. The weighted average of these distribution parameters is calculated and normalized using calculated criteria weights. These normalized parameters are utilized to obtain the best and the worst ideal solutions from which each alternative's distances are calculated. These distances are used to calculate closeness coefficients leading to preference rankings.

### 3.2.5. Fuzzy PROMETHEE

F-PROMETHEE starts with taking the expectation of triangular distribution for each evaluation which we call defuzzification. Then the preference values of each alternative pair with respect to each criterion are calculated assuming a Gaussian preference function for each criterion. This Gaussian preference function maps the difference between alternatives to [0,1] interval and leads to the preference values (Behzadian et al., 2010; Dagdeviren, 2008). Importantly, in the Gaussian preference function we utilize maximum in the exponent for positive criteria, e.g. C5 and C7. Next, we calculate a global preference index by taking the weighted average of each preference value using the criteria weights, which are the expectation of the triangular distribution of each criteria evaluation in F-TOPSIS. The last two steps of F-PROMETHEE is the calculation of positive and negative ranking flows, whose difference leads to the net outranking flow that leads to the preference rankings (Dagdeviren, 2008, Eq. 8). Positive and negative ranking flows are denoted with $\varphi^+$ and $\varphi^-$ whereas the net outranking flow is given with $\varphi$ in Table 10.

### 3.2.6. GAIA plane

In the PROMETHEE method, relative positions of criteria and alternatives can be expressed in an |A|-dimensional space where |A| represents the number of alternatives. To express all alternatives and criteria in a two-dimensional space we form a criteria-alternative matrix which consists of the average differences of the preferences values. Applying Principal Component Analysis (PCA), which relies on eigenvalue decomposition, on this matrix allows expression of the information in column vectors (criteria vectors) in smaller dimensions. Specifically, we consider the first two columns of PCA output to obtain the GAIA plane. Importantly, $\frac{\lambda_1+\lambda_2}{\sum_i^{|J|}\lambda_i}$ ratio conveys the amount of variability explained by the first two columns of the output of PCA, where $\lambda_i$ is the $i$-th eigenvalue of the criteria-alternative matrix and $|J|$ stands for the total amount of criteria. The resulting GAIA plane that we obtain using our dataset is given in Fig. 5. For further details of the visualization method and PCA refer to Hayez et al. (2009).

Furthermore, a slightly modified version of this procedure is applied to obtain another GAIA plane depicting the consensus between experts. Details of this procedure is given in Appendix D. The GAIA plane indicating the extent of consensus between experts is presented in Fig. 6.

## 3.3. Sensitivity analysis

In this study, we collect evaluations of 9 experts to obtain a ranking of solution alternatives. Based on this data set, we conduct two different sensitivity analysis on the results of our MCDM methods. First, we add some perturbations to experts' evaluations and measure the sufficient number of experts to reach a consensus on the results. We find that the required number of experts is moderately sensitive to the variations in experts' evaluations for obtaining a consensus on the results. Our literature review indicates that the size of the expert group changes significantly among different studies in the literature and there is no well-constructed measure for the sufficient number of experts required to reach a consensus. Second, we add white noise to experts' evaluations in a controlled experimental setup, as suggested by Mukhametzyanov and Pamucar (2018). In these simulations, we find that the alternative rankings are fairly insensitive to variations in experts' evaluations. Also, we find that among the two MCDM methods, F-TOPSIS generates more robust solutions compared to F-PROMETHEE.

**Table 9**
Criteria weights obtained from F-TOPSIS.

| Criteria | Code | Lower Bound ($\overline{\overline{C}}_{1j}$) | Mode ($\overline{\overline{C}}_{2j}$) | Upper Bound ($\overline{\overline{C}}_{3j}$) |
|---|---|---|---|---|
| Initial investment cost | C1 | 0.70 | 0.91 | 1.00 |
| Operation and Maintenance Cost | C2 | 0.70 | 0.91 | 1.00 |
| Negative impact on the environment during the construction and operation of the activity | C3 | 0.20 | 0.86 | 1.00 |
| Negative impact on the ecosystem (aquatic and/or shore) during the operational phase of the activity. | C4 | 0.10 | 0.79 | 1.00 |
| Ease of operation | C5 | 0.10 | 0.67 | 1.00 |
| Infrastructure requirements | C6 | 0.20 | 0.78 | 1.00 |
| Evaluation/acceptance by the public/end users | C7 | 0.10 | 0.54 | 1.00 |

**Table 10**
Results of F-TOPSIS and F-PROMETHEE for alternatives.

| | | F-TOPSIS | | | | F-PROMETHEE | | | |
|---|---|---|---|---|---|---|---|---|---|
| Description | Code | $d^*$ | $d^-$ | Score (*CCI*) | Ranking | $\varphi^+$ | $\varphi^-$ | $\varphi$ | Ranking |
| Inter-basin water transfer | A1 | 5.13 | 3.60 | 0.413 | 4 | 0.865 | 1.555 | −0.690 | 4 |
| Rainwater harvesting | A2 | 4.79 | 3.85 | 0.446 | 3 | 1.539 | 0.361 | 1.178 | 2 |
| Greywater Reuse | A3 | 4.71 | 4.36 | 0.481 | 1 | 1.796 | 0.242 | 1.554 | 1 |
| Desalination | A4 | 5.38 | 2.98 | 0.356 | 5 | 0.523 | 2.650 | −2.126 | 5 |
| Irrigation with reused water | A5 | 4.80 | 4.02 | 0.456 | 2 | 1.089 | 0.700 | 0.389 | 3 |

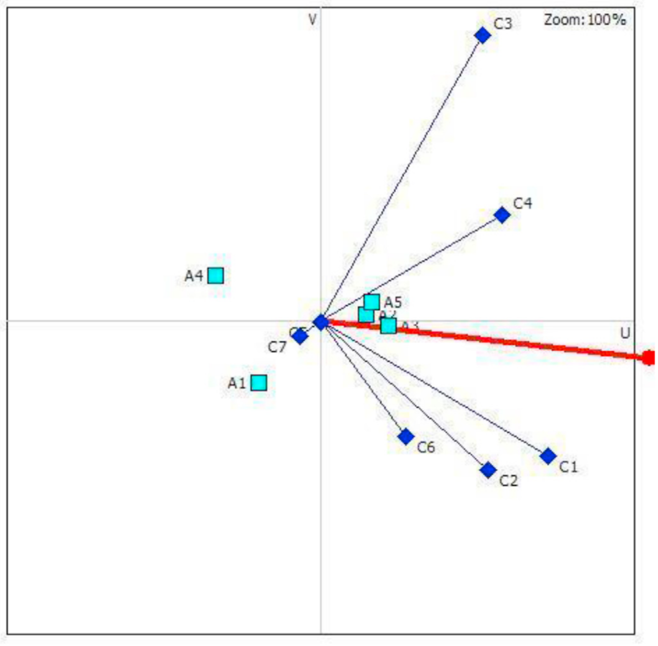

**Fig. 5.** Gaia plane for the results of PROMETHEE

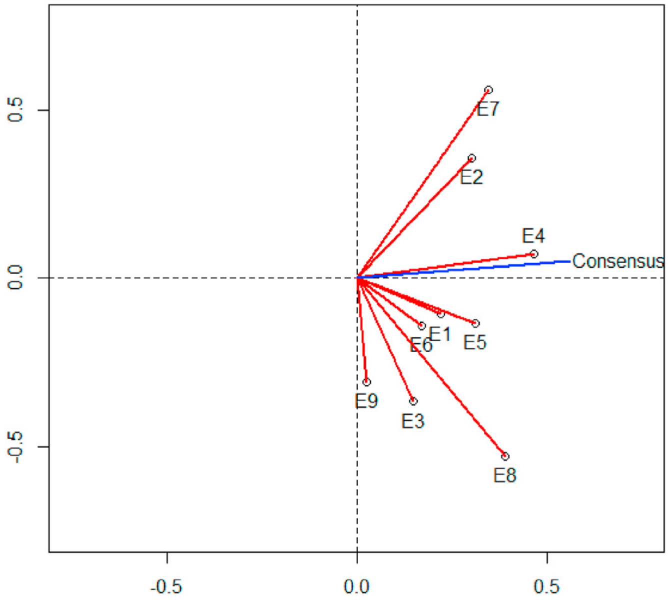

**Fig. 6.** Gaia plane for experts' consensus.

## 4. Results and discussion

### 4.1. Forecasting water demand of Istanbul

To forecast the water consumption of Istanbul for 12 months, we consider Holt-Winters, S-ARIMA, and feedforward ANN. The estimated learning parameters of Holt-Winters, denoted by $\alpha$, $\beta$and $\gamma$, are given in Table 4. These learning rates are utilized to estimate the intercept and the slope of the trend component; and the seasonal coefficients given in Table 5. These parameters indicate that every year between June and November water demand grows significantly due to increasing temperature levels in the region. Also, the positive slope (Table 5) indicates an increasing trend in water demand, after the removal of seasonality, over the years. Further analysis on Holt-Winters parameter estimation reveals that the growth rate of water consumption has been slowing down for the last 10 years which might be an indication for the city's approach to its limits of growth. The limits of urban growth due to various reasons are discussed by Kelley and Williamson (1982) and Meadows et al. (1972).

For the S-ARIMA model, we set the seasonality period to 12 in *auto.arima* routine in R. As a result of the increasing trend, the software includes integration terms to the model (Table 6). In addition, the exclusion of the autoregressive terms indicates the lack of significant autoregression when seasonality is removed from the data.

ANN is the third model considered to forecast water consumption in Istanbul. An extensive search in the hyperparameter space yields that the best-performing model structure includes 8 neurons within a single hidden layer (Table 7). This model includes three autoregressive terms, month and year as input variables and consists of 57 wt given in Table A.1. Also, the best decay rate and the maximum number of the iteration are 0.01 and 100.

The three forecasting models are compared to each other in our 5-fold cross-validation test. Our results in Table 8 indicate that the S-ARIMA model performs the best for this dataset compared to ANN and additive Holt-Winters models. Forecasts of the S-ARIMA model are found to be pretty accurate with a 1.9% absolute error rate on average. Holt-Winters is found to be the second-best whereas ANN has the worst performance. This result is partly consistent with the literature as it is stated that ANN models may fail to address datasets with strong autocorrelation and seasonality (Ghatak, 2017).

Using the S-ARIMA model we forecast water consumption of Istanbul for 12 months with a 95% prediction interval. In Fig. 4, the mean water demand forecast is given by a bold blue line whereas the prediction interval is provided with the shaded area around the mean. Our predictions indicate that water consumption of Istanbul may rise up to 100,000 $m^3$ during the summer season and it will be between 64,000 and 78,000 $m^3$in February with a 95% probability.

### 4.2. Evaluation of water supply alternatives

The projected water consumption is shared with experts to indicate the importance of water management issues in Istanbul. Expert opinion on different solutions for water issues is evaluated using two distinct MCDM techniques.

Experts of the study have an implicit agreement on the importance of initial investment and operational costs criteria whereas weights assigned to other criteria have larger variances. Particularly, we find that expert opinion varies significantly for the importance of C7, which is about the public opinion and acceptance.

Results of MCDM models are given in Table 10. For both models, greywater reuse is found to be the best alternative among others due to its cost advantage and implementability. Similarly, desalination is the least attractive alternative for both models, partly due to its high initial investment and operating costs as well as low applicability. The main difference between the two alternatives is the rank of *A2*, irrigation with reused water. F-TOPSIS suggests this alternative in rank four whereas it is the second-best option according to the results of F-PROMETHEE. This stems from the methodological difference between F-TOPSIS and F-PROMETHEE.

Results of PROMETHEE are expressed in the GAIA plane in Fig. 5. The proximity of greywater reuse (A3) and rainwater harvesting (A2) to the decision stick (bold red line), which is a weighted average of different criteria, $C_i,\ i = 1, 2, \ldots, 7$, explains why they are the best two alternatives among others. Similarly, inter-basin water transfer (A1) and desalination (A4) have the largest distance to the decision stick which is consistent with the fact they are the least favorable ones in Table 10. Fig. 5 also indicates the similarity of alternatives from the perspectives of stakeholders and experts consulted in the study. Negative impact on the environment (C3) and negative impact on ecosystem (C4) are found to be close to each other (Fig. 5) in the evaluations of experts while investment cost (C1), operational costs (C2) and as infrastructure requirements (C6) are found to be similar in our results. Public acceptance by end-users is found to be the most different criteria by our experts. These results indicate the consistency of the expert evaluations used in the study. As discussed in Section 3.2.5, the GAIA plane is constructed using the first two primary axes from the Principal Component Analysis (PCA) on a $(5 \times 7)$ matrix $\Phi = [\varphi_1, \varphi_2, \ldots, \varphi_7]$, where $\varphi_j$ is the net flow vector of the criterion *j*. The ratio of eigenvalues shows that the GAIA plane (Fig. 5) explains 87.3% of the total variance in the expert judgements.

Furthermore, using the PROMETHEE analysis for each expert evaluation, we formed a $(5 \times 9)$ matrix $\Phi = [\tilde{\varphi}_1, \tilde{\varphi}_2, \ldots, \tilde{\varphi}_9]$, where $\tilde{\varphi}_i$ is the netflow vector for expert *i*. By using PCA on this matrix, we obtained a GAIA plane (Fig. 6) summarizing experts' opinion in the data. Results indicate that E2 and E7 (Expert 2 and Expert 7) have similar perspectives on the water supply issue of Istanbul with respect to our decision making criteria. Similarly, E1, E5, E6, E9, E3, and E8 have similar evaluations on the alternatives. Interestingly E4, which is an academic in a higher education institute on water management, gives responses very close to the group consensus (blue line in Fig. 6), which is the final netflow vector (Column $\varphi$ in Table 10). These results indicate that our study is successful in combining the opinions of experts and stakeholders with different perspectives on the water supply issue of Istanbul.

## 5. Conclusion

Making an informed decision among different alternatives of water supply and demand management approaches requires an evaluation with objective (and quantitative) methods with respect to qualitative and quantitative, possibly conflicting criteria such as environmental friendliness, public acceptance and cost. Such decision making problems are difficult not only because a large variety of stakeholders with different perspectives are affected by the outcomes, also consequences of inadequate decisions might be very costly and unpleasant for the entire community.

In this study, we consider a water management issue for Istanbul, a large metropolitan city has been experiencing a rapid population increase (with an annual growth rate of 3.45%) for the last 50 years. Such a high rate of population growth leads to significant infrastructure problems threatening the water supply of the city in the near future. To address the risk of water supply issues, we first conduct a forecasting study indicating the growing water demand of the city together with its seasonal cycles due to different reasons. These demand forecasts are shared with water management experts and different stakeholders who are asked to provide their evaluations of various solution alternatives with respect to multiple criteria. For the analysis of the collected data, we employed two different MCDM models, F-TOPSIS and F-PROMETHEE, to evaluate five alternative solutions with respect to seven distinct criteria by addressing randomness in input data due to subjective judgements and potential misunderstandings in the data collection process.

Sustainable water supply with internationally accepted quality standards is a big challenge for Istanbul where water demand is increasingly difficult to be met under the pressure of population growth. Current infrastructure and management practices indicate that the city has applied water supply management for centuries with its large-scale inter-basin water transfer projects and it has a strong potential to face water scarcity in the future especially due to the increasing pressure of climate change and rapid urbanization. Therefore, the city needs to adopt demand management and reuse management policies as soon as possible, as both policies take time to achieve their full potentials.

Our analysis reveals that the two alternatives of reuse management, reuse of greywater and irrigation with reclaimed, treated water, are the most preferred whereas the two alternatives of water supply management, inter-basin water transfer and desalination, are the least attractive solutions for the city. Especially inter-basin water transfer has been applied as a part of large-scale construction projects (Section 2.1), which we think due to political reasons in addition to lack of awareness of the potential of reuse management. On the other hand, our results indicate that there exists a consensus among experts from academia, public and private sectors for a required shift of focus towards water demand management instead of water transfer projects increasing in numbers and sizes (new reservoirs or inter-basin water transfer). We conjecture that this awareness can be attributed to the efforts and initiatives of non-profit institutes and inter-governmental organizations such as European Union's strategic plan for reuse of greywater and irrigation of green areas with water from treatment plants. Also, we find evidence that stakeholders of water management decisions in the city are cognizant of increasing costs and environmental bargain of sustained application of water supply management. Although this indicates a promising change in perception, the city still has a long way to go to achieve significant positive effects of reuse management on virgin water resources of the city. To the best of our knowledge, ours is the first MCDM study on water management in Istanbul despite it has been one of the biggest cities of Europe and challenged by chronic water supply issues for centuries.

In addition, we conduct sensitivity simulations and conclude that the number of experts in the study are sufficient for reaching a consensus, for which a mathematical characterization is provided. Further analysis of consensus on water supply alternatives reveals that their perspectives are independent of their sectors and consistent with each other. This consistency is examined with a graphical representation of expert opinions in a two-dimensional plane, which is another methodological contribution of this study, and confirmed by respective MCDM analyses on the data. Also, we analyze sensitivity of alternative rankings to variations in experts' evaluations. Our results indicate that rankings are insensitive to perturbations in experts' evaluations. F-TOPSIS generate more stable results compared to F-PROMETHEE.

This study relies on the empirical analysis of quantitative and qualitative data for the evaluation of different alternatives with respect to multiple, conflicting criteria. Although we explicitly conduct simulations, and detect significant evidence for the sufficiency of the number of experts and the existence of a consensus on the subject matter, we admit that our qualitative data are subjective to some extent. To circumvent, more research with a different set of experts and various analysis approaches are required. Furthermore, we combine short-term water demand forecasting with MCDM analysis to evaluate the water supply alternatives for Istanbul. Our method does not address the isolated effect of forecasting on experts' evaluations as we do not include a control group of experts whom we do not share forecasts. This constitutes another limitation which is left to future research.

For future research, we aim to extend our analysis with questionnaires that will be applied to a large number of citizens to evaluate their perceptions on the problem when it is explained without technical details. Also, we are interested in combining water supply simulations with MCDM methods and measure the impact of water supply projections on experts' opinions by using a control group.

## CRediT authorship contribution statement

**Basak Savun-Hekimoğlu:** Conceptualization, Problem definition, Criteria Development, Writing. **Barbaros Erbay:** Methodology, Software. **Mustafa Hekimoğlu:** Writing - review & editing, Supervision. **Selmin Burak:** Supervision, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.125080.

## References

Abrishamchi, A., Ebrahimian, A., Tajrishi, M., Mariño, M.A., 2005. Case study: application of multicriteria decision making to urban water supply. J. Water Resour. Plann. Manag. 131, 326–335.

Adamowski, J., Fung Chan, H., Prasher, S.O., Ozga-Zielinski, B., Sliusarieva, A., 2012. Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. Water Resour. Res. 48.

Adamowski, J., Karapataki, C., 2010. Comparison of multivariate regression and artificial neural networks for peak urban water-demand forecasting: evaluation of different ANN learning algorithms. J. Hydrol. Eng. 15, 729–743.

Afshar, A., Mariño, M.A., Saadatpour, M., Afshar, A., 2011. Fuzzy TOPSIS multi-criteria decision analysis applied to Karun reservoirs system. Water Resour. Manag. 25, 545–563.

Akgul, D., Çakmakci, M., Kayaalp, N., Koyuncu, I., 2008. Cost analysis of seawater desalination with reverse osmosis in Turkey. Desalination 220, 123–131.

Alpaydin, E., 2014. Introduction to Machine Learning. MIT press.

Amid, A., Ghodsypour, S.H., O'Brien, C., 2009. A weighted additive fuzzy multiobjective model for the supplier selection problem under price breaks in a supply chain. Int. J. Prod. Econ. 121, 323–332.

Amid, A., Ghodsypour, S.H., O'Brien, C., 2006. Fuzzy multiobjective linear model for supplier selection in a supply chain. Int. J. Prod. Econ. 104, 394–407.

Amorocho-Daza, H., Cabrales, S., Santos, R., Saldarriaga, J., 2019. A new multi-Criteria decision analysis methodology for the selection of new water supply infrastructure. Water (Switzerland) 11, 1–23.

Antucheviciene, J., Zavadskas, E.K., Zakarevicius, A., 2012. Ranking redevelopment decisions of derelict buildings and analysis of ranking results. Econ. Comput. Econ. Cybern. Stud. Res. 46, 37–62.

Aydin, F., Sarptas, H., 2020. Spatial assessment of site suitability for solar desalination plants: a case study of the coastal regions of Turkey. Clean Technol. Environ. Policy 22, 309–323.

Aydiner, C., Imer, D.Y.K., Oncel, S., Dogan, E.C., Narci, A.O., Cakmak, S., Yilmaz, T.N., Celebi, E.E., Tilki, Y.M., 2017. Marmara seawater desalination by membrane distillation—direct consumption assessment of produced drinking water. In: Desalination. InTech E-Publishing Inc. Rijeka, pp. 99–126.

Behzadian, M., Kazemzadeh, R.B., Albadvi, A., Aghdasi, M., 2010. PROMETHEE: a comprehensive literature review on methodologies and applications. Eur. J. Oper. Res. 200, 198–215.

Behzadian, M., Otaghsara, S.K., Yazdani, M., Ignatius, J., 2012. A state-of the-art survey of TOPSIS applications. Expert Syst. Appl. 39, 13051–13069.

Benitez, J., Delgado-Galván, X., Izquierdo, J., Pérez-Garcia, R., 2011. Achieving matrix consistency in AHP through linearization. Appl. Math. Model. 35, 4449–4457.

Benham, B., Ling, E., Ziegler, P., Krometis, L.A., 2016. What's in your water? Development and evaluation of the Virginia household water quality program and Virginia master well owner network. J. Hum. Sci. Ext. 4.

Blanco-Mesa, F., Merigó, J.M., Gil-Lafuente, A.M., 2017. Fuzzy decision making: a bibliometric-based review. J. Intell. Fuzzy Syst. 32, 2033–2050.

Bottani, E., Rizzi, A., 2008. An adapted multi-criteria approach to suppliers and products selection—an application oriented to lead-time reduction. Int. J. Prod. Econ. 111, 763–781.

Bougadis, J., Adamowski, K., Diduch, R., 2005. Short-term municipal water demand forecasting. Hydrol. Process. An Int. J. 19, 137–148.

Box, G.E., Jenkins, G.M., Reinsel, G.C., Ljung, G.M., 2015. Time Series Analysis: Forecasting and Control. Hoboken, NJ 07030-5774.

Brans, J.-P., De Smet, Y., 2016. PROMETHEE methods. In: Multiple Criteria Decision Analysis. Springer, pp. 187–219.

Burak, S., Bilge, A., Dernek, D., 2017. A network model simulation proposal for river basin management plans (RBMPs) in Turkey. In: 10th World Congress on Water Resources and Environment "Panta Rhei", pp. 5–9. Athens, Greece.

Burak, S., Demir, V., 2016. Land-based Pollution in the Sea of Marmara and Assessment of Pollution Abatement Strategies. The Sea of Marmara Marine Biodiversity, Fisheries, Conservation and Governance. Turkish Marine Research Foundation (TUDAV), Istanbul.

Burak, S., Margat, J., 2016. Water management in the Mediterranean region: concepts and policies. Water Resour. Manag. 30, 5779–5797.

Burak, S., Mat, H., 2020. Urban and industrial water uses. In: Water Resources of Turkey. Springer, pp. 341–398.

Cabrera Jr., E., Cobacho, R., Estruch, V., Aznar, J., 2011. Analytical hierarchical process (AHP) as a decision support tool in water resources management. J. Water Supply Res. Technol. 60, 343–351.

Caiado, J., 2010. Performance of combined double seasonal univariate time series models for forecasting water demand. J. Hydrol. Eng. 15, 215–222.

Cambrainha, G.M., Fontana, M.E., 2018. A multi-criteria decision making approach to balance water supply-demand strategies in water supply systems. Production 28.

Chen, C.-T., Lin, C.-T., Huang, S.-F., 2006. A fuzzy approach for supplier evaluation and selection in supply chain management. Int. J. Prod. Econ. 102, 289–301.

Cinar, N., Ahiska, S.S., 2010. A decision support model for bank branch location selection. Int. J. Hum. Soc. Sci. 5, 846–851.

Cleveland, R.B., Cleveland, W.S., McRae, J.E., Terpenning, I., 1990. STL: a seasonal-trend decomposition. J. Off. Stat. 6, 3–73.

Coban, A., Ertis, I.F., Cavdaroglu, N.A., 2018. Municipal solid waste management via multi-criteria decision making methods: a case study in Istanbul, Turkey. J. Clean. Prod. 180, 159–167.

Cuceloglu, G., Abbaspour, K.C., Ozturk, I., 2017. Assessing the water-resources potential of Istanbul by using a soil and water assessment tool (SWAT) hydrological model. Water 9, 814.

Dagdeviren, M., 2008. Decision making in equipment selection: an integrated approach with AHP and PROMETHEE. J. Intell. Manuf. 19, 397–406.

De Marchi, B., Funtowicz, S.O., Cascio, S. Lo, Munda, G., 2000. Combining participative and institutional approaches with multicriteria evaluation. An empirical study for water issues in Troina, Sicily. Ecol. Econ. 34, 267–282.

Diaz-Sarachaga, J.M., Jato-Espino, D., Castro-Fresno, D., 2017. Methodology for the development of a new sustainable infrastructure rating system for developing countries (SIRSDEC). Environ. Sci. Pol. 69, 65–72.

Donkor, E.A., Mazzuchi, T.A., Soyer, R., Alan Roberson, J., 2014. Urban water demand

forecasting: review of methods and models. J. Water Resour. Plann. Manag. 140, 146–159.
Eroglu, V., Sarıkaya, H.Z., 1998. Achievements towards better water supply and wastewater disposal in Istanbul. In: Proceedings of the International Symposium on Water Supply and Treatment. Organized by Istanbul Water and Sewerage Administration, pp. 22–27.
Fassio, A., Giupponi, C., Hiederer, R., Simota, C., 2005. A decision support tool for simulating the effects of alternative policies affecting water resources: an application at the European scale. J. Hydrol. 304, 462–476.
Fattahi, P., Fayyaz, S., 2010. A compromise programming model to integrated urban water management. Water Resour. Manag. 24, 1211–1227.
Fletcher, R., Reeves, C.M., 1964. Function minimization by conjugate gradients. Comput. J. 7, 149–154.
Flug, M., Seitz, H.L.H., Scott, J.F., 2000. Multicriteria decision analysis applied to glen canyon dam. J. Water Resour. Plann. Manag. 126, 270–276.
Fontana, M.E., Morais, D.C., de Almeida, A.T., 2011. A MCDM model for urban water conservation strategies adapting simos procedure for evaluating alternatives intra-criteria. In: International Conference on Evolutionary Multi-Criterion Optimization, pp. 564–578.
Freitas, A.H.A., Magrini, A., 2013. Multi-criteria decision-making to support sustainable water management in a mining complex in Brazil. J. Clean. Prod. 47, 118–128.
Froukh, M.L., 2001. Decision-support system for domestic water demand forecasting and management. Water Resour. Manag. 15, 363–382.
Garfi, M., Ferrer-Marti, L., 2011. Decision-making criteria and indicators for water and sanitation projects in developing countries. Water Sci. Technol. 64, 83–101.
Ghatak, A., 2017. Machine Learning with R. Springer.
Ghiassi, M., Zimbra, D.K., Saidane, H., 2008. Urban water demand forecasting with a dynamic artificial neural network model. J. Water Resour. Plann. Manag. 134, 138–146.
Gohari, A., Eslamian, S., Mirchi, A., Abedi-Koupaei, J., Bavani, A.M., Madani, K., 2013. Water transfer as a solution to water shortage: a fix that can backfire. J. Hydrol. 491, 23–39.
Golfam, P., Ashofteh, P.-S., Loáiciga, H.A., 2019a. Evaluation of the VIKOR and FOWA multi-criteria decision making methods for climate-change adaptation of agricultural water supply. Water Resour. Manag. 33, 2867–2884.
Golfam, P., Ashofteh, P.-S., Rajaee, T., Chu, X., 2019b. Prioritization of water allocation for adaptation to climate change using multi-criteria decision making (MCDM). Water Resour. Manag. 33, 3401–3416.
Gómez-López, M.D., Bayo, J., Garcia-Cascales, M.S., Angosto, J.M., 2009. Decision support in disinfection technologies for treated wastewater reuse. J. Clean. Prod. 17, 1504–1511.
Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning. MIT press.
Govindan, K., Jepsen, M.B., 2016. ELECTRE: a comprehensive literature review on methodologies and applications. Eur. J. Oper. Res. 250, 1–29.
Guneri, A.F., Yucel, A., Ayyildiz, G., 2009. An integrated fuzzy-lp approach for a supplier selection problem in supply chain management. Expert Syst. Appl. 36, 9223–9228.
Guo, G., Liu, S., Wu, Y., Li, J., Zhou, R., Zhu, X., 2018. Short-term water demand forecast based on deep learning method. J. Water Resour. Plann. Manag. 144, 4018076.
Haider, H., Sadiq, R., Tesfamariam, S., 2015. Selecting performance indicators for small and medium sized water utilities: multi-criteria analysis using ELECTRE method. Urban Water J. 12, 305–327.
Hajkowicz, S., Higgins, A., 2008. A comparison of multiple criteria analysis techniques for water resource management. Eur. J. Oper. Res. 184, 255–265.
Hämäläinen, R., Kettunen, E., Marttunen, M., Ehtamo, H., 2001. Evaluating a framework for multi-stakeholder decision support in water resources management. Group Decis. Negot. 10, 331–353.
Hamut, H.S., Dincer, I., Rosen, M.A., 2014. Assessment of desalination technologies integrated with renewable energy sources in Turkey. In: Progress in Exergy, Energy, and the Environment. Springer, pp. 279–292.
Harmancioglu, N.B., Altinbilek, D., 2020. Water Resources of Turkey. Springer.
Hayez, Q., Mareschal, B., De Smet, Y., 2009. New GAIA visualization methods. In: 2009 13th International Conference Information Visualisation, pp. 247–251.
Holt, C.C., 1957. Forecasting trends and seasonals by exponentially weighted moving averages, ONR Research Memorandum, Carnegie Institute of Technology 52. PR Winters (1960) Forecasting sales by exponentially weighted moving averages. Manag. Sci. 6, 324–342.
Hyndman, R.J., Khandakar, Y., others, 2007. Automatic Time Series for Forecasting: the Forecast Package for R. Monash University, Department of Econometrics and Business Statistics.
Ilaya-Ayza, A.E., Benitez, J., Izquierdo, J., Pérez-Garcia, R., 2017. Multi-criteria optimization of supply schedules in intermittent water supply systems. J. Comput. Appl. Math. 309, 695–703.
Islar, M., Boda, C., 2014. Political ecology of inter-basin water transfers in Turkish water governance. Ecol. Soc. 19.
ISKI, 2019. Activity report of 2019. https://www.iski.gov.tr/web/assets/SayfalarDocs/faaliyetraporlari/faaliyetraporu/pdf/2019-FAAL&Idot;YET-RAPORU.pdf. (Accessed 28 September 2020).
Jaber, J.O., Mohsen, M.S., 2001. Evaluation of non-conventional water resources supply in Jordan. Desalination 136, 83–92.
Jain, V., Tiwari, M.K., Chan, F.T.S., 2004. Evaluation of the supplier performance using an evolutionary fuzzy-based approach. J. Manuf. Technol. Manag. 735–744.
Joubert, A., Stewart, T.J., Eberhard, R., 2003. Evaluation of water supply augmentation and water demand management options for the City of Cape Town. J. Multi-Criteria Decis. Anal. 12, 17–25.
Kabir, G., Sadiq, R., Tesfamariam, S., 2014. A review of multi-criteria decision-making methods for infrastructure management. Struct. Infrastruct. Eng. 10, 1176–1210.
Kahraman, C., 2008. Fuzzy Multi-Criteria Decision Making: Theory and Applications with Recent Developments. Springer Science & Business Media.
Kantaroglu, Ö., 2009. Yagmur Suyu Hasadı Plan Ve Hesaplama Prensipleri.
Karleuša, B., Hajdinger, A., Tadić, L., 2019. The application of multi-criteria analysis methods for the determination of priorities in the implementation of irrigation plans. Water 11, 501.
Karsak, E.E., 2001. Personnel selection using a fuzzy MCDM approach based on ideal and anti-ideal solutions. In: Multiple Criteria Decision Making in the New Millennium. Springer, pp. 393–402.
Kelley, A.C., Williamson, J.G., 1982. The limits to urban growth: suggestions for macromodeling third world economies. Econ. Dev. Cult. Change 30, 595–623.
Khalil, M.I., Schmidhalter, U., Gutser, R., 2005. Turnover of chicken manure in some upland soils of Asia: agricultural and Environmental Perspective. In: Hamburger Berichte, pp. 275–292.
Kholghi, M., 2001. Multi-criterion decision-making tools for wastewater planning management. JAST 281–286.
Kodikara, P.N., Perera, B.J.C., Kularathna, M., 2010. Stakeholder preference elicitation and modelling in multi-criteria decision analysis–A case study on urban water supply. Eur. J. Oper. Res. 206, 209–220.
Köksalan, M., Zionts, S., 2012. In: Multiple Criteria Decision Making in the New Millennium: Proceedings of the Fifteenth International Conference on Multiple Criteria Decision Making (MCDM) Ankara, Turkey. Springer Science & Business Media.
Kumar, A., Sah, B., Singh, A.R., Deng, Y., He, X., Kumar, P., Bansal, R.C., 2017. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renew. Sustain. Energy Rev. 69, 596–609.
Kuo, R.J., Hong, S.Y., Huang, Y., 2010. Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection. Appl. Math. Model. 34, 3976–3990.
Lin, R.-H., 2012. An integrated model for supplier selection under a fuzzy situation. Int. J. Prod. Econ. 138, 55–61.
Liu, H.-T., 2011. Product design and selection using fuzzy QFD and fuzzy MCDM approaches. Appl. Math. Model. 35, 482–496.
Mahmoud, M.R., Garcia, L.A., 2000. Comparison of different multicriteria evaluation methods for the Red Bluff diversion dam. Environ. Model. Software 15, 471–478.
Maia, R., Schumann, A.H., 2007. DSS application to the development of water management strategies in Ribeiras do Algarve River Basin. Water Resour. Manag. 21, 897–907.
Makropoulos, C.K., Natsis, K., Liu, S., Mittas, K., Butler, D., 2008. Decision support for sustainable option selection in integrated urban water management. Environ. Model. Software 23, 1448–1460.
Meadows, D.H., Meadows, D.L., Randers, J., Behrens, W.W., 1972. The Limits to Growth. New York.
Memon, F.A., Butler, D., 2006. Water consumption trends and demand forecasting techniques. Water demand Manag 1–26, 2006.
Moghadas, M., Asadzadeh, A., Vafeidis, A., Fekete, A., Kötter, T., 2019. A multi-criteria approach for assessing urban flood resilience in Tehran, Iran. Int. J. disaster risk Reduct. 35, 101069.
Monte, M.B.S., de Almeida-Filho, A.T., 2016. A multicriteria approach using MAUT to assist the maintenance of a water supply system located in a low-income community. Water Resour. Manag. 30, 3093–3106.
Mousavi-Nasab, S.H., Sotoudeh-Anvari, A., 2017. A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems. Mater. Des. 121, 237–253.
Mukhametzyanov, I., Pamucar, D., 2018. A sensitivity analysis in MCDM problems: a statistical approach. Decis. Mak. Appl. Manag. Eng. 1, 51–80.
Mutailifu, K., 2019. Water and Wastewater Management in the Mega City Istanbul: A General Analysis from a Supply-Demand-Reuse Perspective.
Nas, B., Uyanik, S., Aygün, A., Dogan, S., Erul, G., Nas, K.B., Turgut, S., Cop, M., Dolu, T., 2020. Wastewater reuse in Turkey: from present status to future potential. Water Supply 20, 73–82.
Nguyen, T.H., Helm, B., Hettiarachchi, H., Caucci, S., Krebs, P., 2019. The selection of design methods for river water quality monitoring networks: a review. Environ. Earth Sci. 78, 96.
Noureddine, M., Ristic, M., 2019. Route planning for hazardous materials transportation: multicriteria decision making approach. Decis. Mak. Appl. Manag. Eng. 2, 66–85.
Opricovic, S., Tzeng, G.-H., 2004. Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. Eur. J. Oper. Res. 156, 445–455.
Önüt, S., Efendigil, T., Kara, S.S., 2010. A combined fuzzy MCDM approach for selecting shopping center site: an example from Istanbul, Turkey. Expert Syst. Appl. 37, 1973–1980.
Peng, X., Dai, J., 2018. Approaches to single-valued neutrosophic MADM based on MABAC, TOPSIS and new similarity measure with score function. Neural Comput. Appl. 29, 939–954.
Petrovic, I., Kankaras, M., 2020. A hybridized IT2FS-DEMATEL-AHP-TOPSIS multi-criteria decision making approach: case study of selection and evaluation of criteria for determination of air traffic control radar position. Decis. Mak. Appl.

Manag. Eng. 3, 146–164.

Piadeh, F., Ahmadi, M., Behzadian, K., 2018a. Reliability assessment for hybrid systems of advanced treatment units of industrial wastewater reuse using combined event tree and fuzzy fault tree analyses. J. Clean. Prod. 201, 958–973.

Piadeh, F., Alavi-Moghaddam, M.R., Mardan, S., 2018b. Assessment of sustainability of a hybrid of advanced treatment technologies for recycling industrial wastewater in developing countries: case study of Iranian industrial parks. J. Clean. Prod. 170, 1136–1150.

Pietersen, K., 2006. Multiple criteria decision analysis (MCDA): a tool to support sustainable management of groundwater resources in South Africa. WaterSA 32, 119–128.

Qureshi, M.E., Harrison, S.R., 2001. A decision support process to compare riparian revegetation options in Scheu Creek catchment in North Queensland. J. Environ. Manag. 62, 101–112.

Raju, K.S., Duckstein, L., Arondel, C., 2000. Multicriterion analysis for sustainable water resources planning: a case study in Spain. Water Resour. Manag. 14, 435–456.

Ripley, B.D., 2002. Time series in R 1.5. 0. Newsl. R Proj 2, 2.

Scholten, L., Schuwirth, N., Reichert, P., Lienert, J., 2015. Tackling uncertainty in multi-criteria decision analysis–An application to water supply infrastructure planning. Eur. J. Oper. Res. 242, 243–260.

Shariat, R., Roozbahani, A., Ebrahimian, A., 2019. Risk analysis of urban stormwater infrastructure systems using fuzzy spatial multi-criteria decision making. Sci. Total Environ. 647, 1468–1477.

Shiau, J.T., Lee, H.C., 2005. Derivation of optimal hedging rules for a water-supply reservoir through compromise programming. Water Resour. Manag. 19, 111–132.

Shourian, M., Raoufi, Y., Attari, J., 2017. Interbasin water transfer capacity design by two approaches of simulation-optimization and multicriteria decision making. J. Water Resour. Plann. Manag. 143, 4017054.

Simić, D., Kovačević, I., Svirčević, V., Simić, S., 2017. 50 years of fuzzy set theory and models for supplier assessment and selection: a literature review. J. Appl. Logic 24, 85–96.

Simon, U., Bruggemann, R., Mey, S., Pudenz, S., 2005. METEOR-application of a decision support tool based on discrete mathematics. MATCH Commun. Math. Comput. Chem 54, 623–642.

Simon, U., Brüggemann, R., Behrendt, H., Shulenberger, E., Pudenz, S., 2006. METEOR: a step-by-step procedure to explore effects of indicator aggregation in multi criteria decision aiding–application to water management in Berlin, Germany. Acta Hydrochim. Hydrobiol. 34, 126–136.

Simon, U., Brüggemann, R., Pudenz, S., 2004. Aspects of decision support in water management—example Berlin and Potsdam (Germany) I—spatially differentiated evaluation. Water Res. 38, 1809–1816.

Srdjevic, B., Medeiros, Y.D.P., Faria, A.S., 2004. An objective multi-criteria evaluation of water management scenarios. Water Resour. Manag. 18, 35–54.

Su, L., Wang, T., Li, H., Chao, Y., Wang, L., 2020. Multi-criteria decision making for identification of unbalanced bidding. J. Civ. Eng. Manag. 26, 43–52.

Trojan, F., Morais, D.C., 2012. Using Electre TRI to support maintenance of water distribution networks. Pesqui. Oper. 32, 423–442.

Tsaur, S.-H., Chang, T.-Y., Yen, C.-H., 2002. The evaluation of airline service quality by fuzzy MCDM. Tourism Manag. 23, 107–115.

Wang, F., Kang, S., Du, T., Li, F., Qiu, R., 2011. Determination of comprehensive quality index for tomato and its response to different irrigation treatments. Agric. Water Manag. 98, 1228–1238.

Weng, S.Q., Huang, G.H., Li, Y.P., 2010. An integrated scenario-based multi-criteria decision support system for water resources management and planning–A case study in the Haihe River Basin. Expert Syst. Appl. 37, 8242–8254.

Yilmaz, B., Harmancioglu, N., 2010. Multi-criteria decision making for water resource management: a case study of the Gediz River Basin. WaterSA 36. Turkey.

Yuksel, E., Eroglu, V., Sarikaya, H.Z., Koyuncu, I., 2004. Current and future strategies for water and wastewater management of Istanbul City. Environ. Manage. 33, 186–195.

Zamarrón-Mieza, I., Yepes, V., Moreno-Jiménez, J.M., 2017. A systematic review of application of multi-criteria decision analysis for aging-dam management. J. Clean. Prod. 147, 217–230.

Zarghaami, M., Ardakanian, R., Memariani, A., 2007. Fuzzy multiple attribute decision making on water resources projects case study: ranking water transfers to Zayanderud basin in Iran. Water Int. 32, 280–293.

Zarghami, M., Abrishamchi, A., Ardakanian, R., 2008. Multi-criteria decision making for integrated urban water management. Water Resour. Manag. 22, 1017–1029.

Zyoud, S.H., Kaufmann, L.G., Shaheen, H., Samhan, S., Fuchs-Hanusch, D., 2016. A framework for water loss management in developing countries under fuzzy environment: integration of Fuzzy AHP with Fuzzy TOPSIS. Expert Syst. Appl. 61, 86–105.