A fuzzy multi-stakeholder socio-optimal model for water and waste load allocation

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Abstract This study proposes a fuzzy multi-stakeholder socio-optimal methodology for joint water and waste load allocation (WWLA) in river systems while addressing upstream flow uncertainty and different social choice rules (SCRs). QUAL2Kw, as the numerical river water quality model, is executed for various scenarios of water and waste loads to construct a comprehensive dataset of plausible settings, which is in turn used to train a meta-model in the form of multivariate linear regressions. The river upstream flow as the main uncertain parameter is assessed by fuzzy transformation method (FTM). Then, for different confidence levels of fuzzy uncertain input, the meta-model is linked with the non-dominated sorting genetic algorithm (NSGA-II) multi-objective optimization model to generate trade-off curves among the stakeholders' utility functions. Subsequently, five SCRs are utilized at each confidence level to determine the fuzzy interval solutions for each objective. Next, the possibility degree method is applied to rank the fuzzy interval solutions in each α-cut level. Finally, considering the priorities of all stakeholders, the fallback bargaining method is used to specify the most appropriate SCR in each confidence level. Application of the proposed methodology in Kor River, Iran, shows its efficacy to realize the socio-optimal WWLA scenario(s) among different stakeholders.

Keywords Fuzzy transformation method · NSGA-II · Social choice rules (SCRs) · Fallback bargaining method

Introduction

River systems are an integral part of the sustainable development in different communities (Sadegh et al. 2010). Over the past few decades, joint water and waste load allocation (WWLA) has become a serious challenge in integrated river management (Karamouz et al. 2003; Nikoo et al. 2013). This is mainly due to agricultural and industrial expansion, population growth, and consequently excessive water pollution (Tavakoli et al. 2014; Sadegh and Kerachian 2011), exacerbated by climate change (Mallakpour et al. 2018). This is more pressing at the presence of numerous stakeholders with conflicting interests in the river basin (Karamouz et al. 2008; Nikoo et al. 2012a, b). Therefore, the decision makers were prompted to adopt allocation policies that are compatible with water equity, efficiency, and sustainability (Nikoo et al. 2012a). Social acceptance of the joint WWLA plans in river systems, however, is overlooked in the literature, and lack of socio-optimal plans is tangible. This research proposes multi-stakeholder socio-optimal solutions for joint WWLA based on the priorities of all involved stakeholders given the underlying uncertainties.

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There are different studies in the literature that consider water quality or waste allocation as a constraint in single or multi-objective optimization models (Cao 2005; Karamouz et al. 2008; Kerachian and Karamouz 2007; Karamouz et al. 2009; de Moraes et al. 2010; Paredes-Arquiola et al. 2010; Hakimi-Asiabar et al. 2010; Mahjouri and Ardestani 2011; Nikoo et al. 2016; Yao et al. 2016; Afshar and Masoumi 2016; Allam et al. 2016a; Xu et al. 2016; Xu et al. 2017; Saberi and Niksokhan 2017; Afshar et al. 2018; Moridi 2019; Saadatpour et al. 2019; Jamshidi et al. 2019; Aghasian et al. 2019) or as an integral component in water management systems (Mousavi et al. 2004; Labadie 2004; Ghosh and Mujumdar 2010; Nikoo et al. 2013; Estalaki et al. 2015; Mahjouri and Abbasi 2015; Farhadi et al. 2016; Meng et al. 2017; Saberi and Niksokhan 2017; Xia et al. 2017; Xu et al. 2017; Huang et al. 2018; Yu and Lu 2018). In these studies, water quality is taken into consideration as a static condition, which does not replicate the dynamic nature of the water quantity (Zhang et al. 2010). Moreover, studies that have directly performed joint WWLA in a river system are limited in number (Dai and Labadie 2001; Zhang et al. 2010; Nikoo et al. 2012b; Nikoo et al. 2013; Liu et al. 2014; Tavakoli et al. 2014; Soltani and Kerachian 2018), neither of which has considered socio-optimal conflict resolution. Models like social choice rules (SCRs) and fallback bargaining method can modify the solutions provided by the joint WWLA methods, which are explored in this study.

Planning under uncertainty is another significant issue for decision makers (Zhang et al. 2010). An integrated optimization model for joint WWLA should be able to handle the underlying uncertainties both in methodology and in boundary condition (Zhang et al. 2010; Shojaeezadeh et al. 2018). Considering the parameters' uncertainties in WWLA models, similar to any other modeling practice, can markedly improve the reliability of the results (e.g., Sadegh et al. 2018). Source of uncertainty is the defining factor in selecting the analysis methods. Classical stochastic models have a high computational burden and application of probabilistic distributions in large-scale problems may not be specifically useful (Ghosh and Mujumdar 2010; Naeini et al. 2018). Fuzzy set theory is a powerful tool when data is sparse and incomplete, or when data inaccuracy is the source of uncertainty, in which case, it is more appropriate to consider uncertain parameter as intervals (Tavakoli et al. 2014; Sadegh and Kerachian 2011). Uncertainty

analysis in the field of water or waste load allocation in the form of randomness or fuzziness of parameters has been considered in the literature (Singh et al. 2007; Li et al. 2008; Qin et al. 2009; Mesbah et al. 2009; Niksokhan et al. 2009; Sadegh and Kerachian 2011; Poorsepahy-Samian et al. 2012; Nikoo et al. 2012a, b; Mahjouri and Abbasi 2015; Zolfagharipoor and Ahmadi 2016; Xu et al. 2017; Nafarzadegan et al. 2018; Sedghamiz et al. 2018; Jamshidi et al. 2019). However, uncertainty analysis of joint WWLA is only proposed in Nikoo et al. 2013, in a single objective optimization problem, to the best of authors' knowledge. Due to involvement of many influential factors such as interaction of stakeholders, variations of assimilative capacity throughout the river, and water flow dynamics in joint WWLA problems, it is inevitable to utilize a multi-objective optimization model (Zhang et al. 2010; Nikoo et al. 2012a, b; Liu et al. 2014). Hence, this research proposes a fuzzy multi-objective WWLA model that generates intervals of objectives in each fuzzy degree and utilizes the possibility degree method to rank the fuzzy intervals in each confidence level.

Need for a comprehensive study that considers different aspects of an integrated allocation plan in a unified framework for joint WWLA is clear. These aspects include numerical river water quality model, multi-objective optimization of WWLA, and more importantly, finding the multi-stakeholders socio-optimal solutions based on the priorities of all involved stakeholders. In this study, to bridge these scientific gaps, a non-linear multi-stakeholder socio-optimal methodology is proposed for joint optimization of WWLA in river systems that accounts for the upstream flow uncertainty. Accordingly, the water quality model of the river system was developed and calibrated using QUAL2Kw model. The validated model was executed for various water and waste load scenarios to construct a comprehensive dataset of plausible environmental situations, which is in turn used to train a substitute meta-model in the form of multivariate linear regressions. Then, the upstream flow as the most substantial uncertain parameter in the river was analyzed by fuzzy transformation method (FTM). The meta-model was linked with the non-dominated sorting genetic algorithm (NSGA-II) multi-objective optimization model at different confidence levels (α-cuts) of the fuzzy uncertain parameter to (i) maximize the allocated water and waste load allocation to different stakeholders, and (ii) minimize the deviation of water quality variables from the standard levels. The

NSGA-II model provides trade-off curves among stake-holders' utility functions for different α-cut levels. Next, at each confidence level, five SCRs were utilized to determine the fuzzy intervals for each objective. Subsequently, the possibility degree method was applied to rank the resulted fuzzy intervals in each α-cuts level. Finally, according to the priorities of stakeholders, the fallback bargaining method specifies the most appropriate SCRs in each α-cuts level. The proposed methodology considers the quantity of discharged waste, allocated water to different users, and river water quality. The water quality variables are 5-day biochemical oxygen demand (BOD_5), total suspended solid (TSS), and dissolved oxygen (DO), which were assessed at five checkpoints.

Novelty of this study lies in incorporating social choice rules to achieve a socio-optimal solution, which is agreed among multi-stockholders, in joint WWLA problems. This study also further states the knowledge by addressing uncertainty of environmental factors (river upstream flow) in joint WWLA problems and implementing the possibility degree method to rank the fuzzy interval solutions in each confidence level. Furthermore, this study establishes a quantitative framework for considering the uncertainty in joint WWLA by a fuzzy multi-objective model and initiates the first step to thoroughly examine the application of SCRs and fallback bargaining method to achieve a socio-optimal plan in joint WWLA. The efficiency and applicability of the proposed methodology were assessed in the Kor River system, southwest of Iran. This study is presented in five sections. Following the methodology in the next section, the case study is presented in the "Case study" section. The results and discussions are reported in the "Results" section, which is followed by the conclusions in the "Summary and conclusion" section.

Methodology

The proposed methodology consists of five main steps (Fig. 1). First, essential information including hydrological and geometrical parameters of the Kor river system was collected based on the Fars Regional Water Authority's (FRWA) reports, and main pollution sources and water users throughout the river path were determined. Accordingly, the main objective functions and relative constraints were defined to construct the optimization framework. Second, the QUAL2Kw model was

parameterized to develop the multi-index river water quality model. To reduce the runtime and couple with the multi-objective water and waste load allocation (WWLA) model, the QUAL2Kw model was run for different allocated water and waste load scenarios and a comprehensive input-output dataset was obtained, which was in turn used to train a substitute meta-model in the form of multivariate linear regressions. In addition, upstream river flow, water depth, amount of waste load (BOD_5 and TSS) discharge, temperature, and conductivity in river water, which represent various geometric, hydraulic, and environmental variables, were assessed in sensitivity analysis of the QUAL2Kw model. Accordingly, the upstream flow in the river was detected as the most important stochastic parameter of the river. In this study, the main source of uncertainty is related to the inexactness of upstream flow in the river, which is partly because of lack of observation and missing data, and partly due to the ambiguity or imprecision in measured data. Thus, in the third step, general fuzzy transform method (FTM) was utilized to determine the fuzzy form of upstream flow in different confidence levels. Next, the fuzzy multi-objective WWLA model was developed by coupling the water quality meta-model and the NSGA-II model to optimize objective functions in different confidence levels. Fuzzy NSGA-II multi-objective WWLA model for each α-cut level returns a series of Pareto fronts among various objectives. Finally, five SCRs were utilized to determine the fuzzy intervals for each objective in each confidence level. This stage continued by using the possibility degree method to rank the fuzzy intervals in each α-cut level. Based on the priorities of all stakeholders, the fallback bargaining method specified the most desirable SCRs in each confidence level.

QUAL2Kw model and substitute meta-model

QUAL2Kw is a flexible and precise model to simulate fate and transport of pollutants in the watershed (Pelletier et al. 2006) and has been widely used in river water quality management (Ning et al. 2001; Pelletier et al. 2006; Cho and Ha 2010; Zhang et al. 2012; Shojaei et al. 2015; Zhu et al. 2015; Allam et al. 2016a, 2016b; Chaudhary et al. 2018). This model considers the dispersion and advection transport in the longitudinal direction of the river stream. The geometric, hydraulic, and environmental data of the river system are required to develop the QUAL2Kw model. In order to develop the QUAL2Kw model, the river has to be divided into
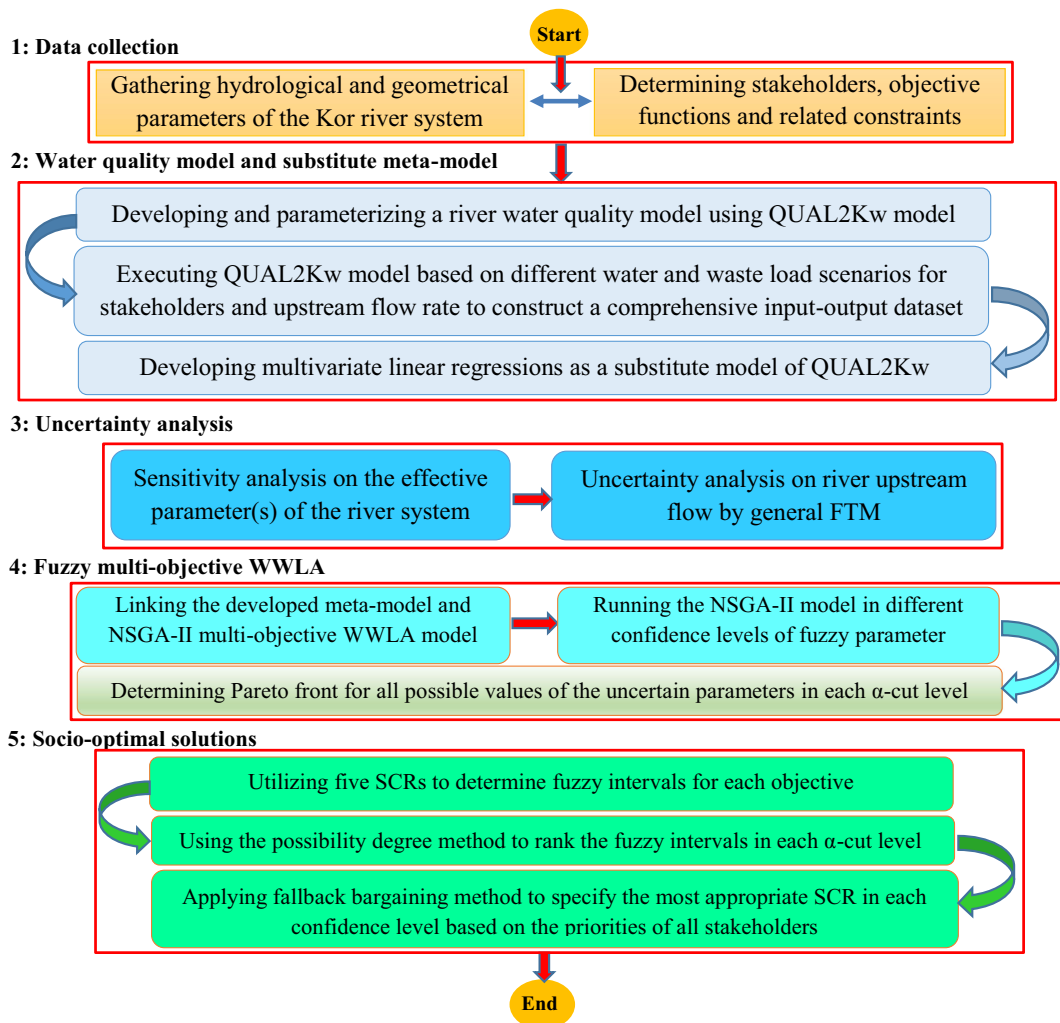
1: Data collection

Start

Gathering hydrological and geometrical parameters of the Kor river system

Determining stakeholders, objective functions and related constraints

2: Water quality model and substitute meta-model

Developing and parameterizing a river water quality model using QUAL2Kw model

Executing QUAL2Kw model based on different water and waste load scenarios for stakeholders and upstream flow rate to construct a comprehensive input-output dataset

Developing multivariate linear regressions as a substitute model of QUAL2Kw

3: Uncertainty analysis

Sensitivity analysis on the effective parameter(s) of the river system

Uncertainty analysis on river upstream flow by general FTM

4: Fuzzy multi-objective WWLA

Linking the developed meta-model and NSGA-II multi-objective WWLA model

Running the NSGA-II model in different confidence levels of fuzzy parameter

Determining Pareto front for all possible values of the uncertain parameters in each α-cut level

5: Socio-optimal solutions

Utilizing five SCRs to determine fuzzy intervals for each objective

Using the possibility degree method to rank the fuzzy intervals in each α-cut level

Applying fallback bargaining method to specify the most appropriate SCR in each confidence level based on the priorities of all stakeholders

End

Fig. 1 Proposed methodology to achieve socio-optimal WWLA in the river system. WWLA, water and waste load allocation; SCR, social choice rule; FTM, fuzzy transform model

several intervals with similar geometric, hydraulic, and qualitative characteristics. In this model, flow rate, depth, temperature, amount and location of waste load discharge, concentration of river water quality variables such as DO and BOD_5, alkalinity, pH, pathogens, phytoplankton, organic and inorganic phosphorus (SRP), nitrogen, and inorganic solids are the input data (forcing).

The model was calibrated by tuning the parameters associated with the river quality including DO, BOD_5, and TSS. Model calibration was performed to minimize the difference between the simulated and measured values of river water quality variables. Next, a range of probable changes in the allocated water and waste load to different stakeholders were determined and input variables were perturbed with white noise to mimic the

stochasticity of the system. The QUAL2Kw model was executed to estimate the concentration of the river water quality variables in the five checkpoints along the river path. The resulted dataset is recorded to create a substitute model for the QUAL2Kw model in the form of multivariate linear regressions. The obtained meta-model can readily explain the relationship between the allocated water and waste load, upstream flow rate, and the concentration of river water quality variables at each checkpoint.

Uncertainty analysis

There are the different uncertain parameter(s) in the spatio-temporal simulation of river water quality. In order

to determine the most influential uncertain input, a sensitivity analysis was performed and the river upstream flow was selected as the most influential uncertain variable in the current WWLA problem. FTM (Hanss 2003; Hanss and Klimke 2004) as an advanced fuzzy arithmetic method has a great potential to evaluate a range of uncertain data in the non-linear and non-monotonic models, such as QUAL2Kw, and can effectively improve the applicability and reliability of uncertain models (Ghosh and Mujumdar 2010; Nikoo et al. 2013; Alizadeh et al. 2017). Hence, given the non-monotonic and non-linear nature of WWLA in a river system, the general FTM model was applied to address the uncertainty of upstream river flow. Accordingly, based on the membership functions of the fuzzy parameter, all possible values of the uncertain parameter in each confidence level (α-cut level) were characterized. For more details and applications of FTM, refer to Hanss (2003), Nikoo et al. (2013), and Alizadeh et al. (2017).

Fuzzy multi-objective WWLA model

There are many stakeholders with numerous priorities and sometimes conflicting utilities involved in a WWLA problem. Accordingly, to achieve an agreement based on the utilities of all stakeholders, a multi-objective WWLA model is required (Nikoo et al. 2013). Such a model was developed herein by coupling the multivariate linear regression (water quality surrogate model) and the NSGA-II models. NSGA-II (Deb et al. 2000) is a multi-objective optimization algorithm that provides a trade-off curve (Pareto front) among the objectives. The Pareto front in turn provides compromise solutions for the optimization problem (Deb et al. 2000; Nikoo et al. 2014). The multi-objective WWLA model was executed for each possible value of the fuzzy parameter in all α-cut levels to account for the underlying uncertainties. Subsequently, for each specific α-cut level, trade-off curves were derived. In this study, the fuzzy multi-objective WWLA model maximizes the allocated water to three main water users along the river. Also, to use the river's self-purification capacity, the optimization model maximizes the allocated waste load to four different dischargers, while minimizing the deviation of water quality variables from the standard threshold. The main utility functions of different involved stakeholders in joint WWLA problem are described as follows:

$$\text{Max } h_1 = \left(\sum_{i=1}^{nwu} x_i \right) \quad i = 1, 2, ..., nwu \quad (1)$$

$$\text{Max } h_2 = \left(\sum_{j=1}^{nwl} y_j \right) \quad j = 1, 2 ..., nwl \quad (2)$$

$$\begin{aligned}\text{Min } h_3 = &\ W_{\text{DO}} \times (V_{\text{DO}}/\text{DO}_{\text{Max}}) + W_{\text{BOD}} \\ &\times (V_{\text{BOD}}/\text{BOD}_{\text{Max}}) \\ &+ W_{\text{TSS}} \times (V_{\text{TSS}}/\text{TSS}_{\text{Max}})\end{aligned} \quad (3)$$

$$-\sum_{i=1}^{4} x_i + \sum_{j=1}^{3} y_j \leq q_{\text{up}} - \text{E}_\text{d} \quad (4)$$

$$-\sum_{i=1}^{3} x_i + y_j \leq q_{\text{up}} \quad j = 1 \quad i = 1, 2, 3 \quad (5)$$

$$-\sum_{i=1}^{3} x_i + \sum_{j=1}^{2} y_j \leq q_{\text{up}} \quad (6)$$

$$-\sum_{i=1}^{4} x_i + \sum_{j=1}^{2} y_j \leq q_{\text{up}} \quad (7)$$

$$C_{c,\text{DO}} = R\left(\sum_{i=1}^{i-1} x_i, \sum_{j=1}^{j-1} y_j, q_{\text{up}}, C_{\text{up,DO}} \right) \geq C_{S,\text{DO}} \quad \forall \text{c} = 1, 2, ..., 5 \quad (8)$$

$$C_{c,\text{TSS}} = g\left(\sum_{i=1}^{i-1} x_i, \sum_{j=1}^{j-1} y_j, q_{\text{up}}, C_{\text{up,TSS}} \right) \leq C_{S,\text{TSS}} \quad \forall \text{c} = 1, 2, ..., 5 \quad (9)$$

$$C_{c,\text{BOD}} = f\left(\sum_{i=1}^{i-1} x_i, \sum_{j=1}^{j-1} y_j, q_{\text{up}}, C_{\text{up,BOD}} \right) \leq C_{S,\text{BOD}} \quad \forall \text{c} = 1, 2, ..., 5 \quad (10)$$

where h signifies objective function in the optimization model. In this case, h_1 is the total amount of waste load discharged to the river system, which is considered as the first objective, h_2 is the total amount of allocated water to different users as the second objective, and h_3 is the deviation of water quality variables from standard (third

objective). The Fars Environmental Organization (FEO) as the local authority enforcing river water quality is considered as the third stakeholder, corresponding to third objective. x_i and y_j indicate the amount of discharged waste load by ith discharger and the amount of water allocated to the jth water user, respectively. In this study, there are four waste load dischargers (j) and three water users (i). W_{DO}, W_{BOD}, and W_{TSS} define the weights of the three river water quality variables in the third objective, and V shows the variation of water quality variable from the standard. DO_{Max}, BOD_{Max} and TSS_{Max} show the maximum values of DO, BOD_5, and TSS in the river path. q_{up} is the daily upstream flow rate in the river system and E_d is the river ecological demand. In fact, Eq. 4 dictates that after all waste load dischargers and water users supply their needs, the river flow should hold the capability to meet the ecological needs of the downstream. C_c and C_{up} show the concentration in the $c$thcheckpoint and upstream, respectively, and C_s is their standard level.

Socio-optimal solution(s)

There are different practical methods to resolve the conflicts among all involved stakeholders in a river system including social choice rules (SCRs) and fall-back bargaining method (Sheikhmohammady and Madani 2008; Raei et al. 2017; Alizadeh et al. 2017). The social choice theory is a powerful tool in facilitating agreement among stakeholders when they have various preferences on available alternatives. This approach prefers to satisfy the priorities of all stakeholders in the form of compromised solutions instead of prioritizing each individual. The socio-optimal solutions are acceptable by all stakeholders, while solutions might or not be their first priority. The social choice theory is an effective method for decision-making in the social, economic, and political fields (Sheikhmohammady and Madani 2008; Sheikhmohammady et al. 2010; Madani et al. 2014a). Hence, in this study, five SCRs including Condorcet's practical method (CPM), Condorcet choice (CC), Borda scoring (BS), plurality rule (PR), and median voting rule (MVR) were employed to gain socio-optimal fuzzy intervals for each objective in different α-cut levels. Due to the different criteria for each SCR, the socio-optimal solution by each rule may differ. The resulted fuzzy intervals indicate the bounds (lower and upper) of each objective. The main concept behind the mentioned SCRs is presented herein.

- Condorcet's practical method (CPM): Based on pairwise comparisons of the alternatives, CPM selects an alternative as socio-optimal that obtains the majority of reliance on the first priority level. If such an alternative does not exist, the one with the highest reliance (which may not be the majority reliance) on the second priority level is the CPM solution, and so on (Nurmi 1999; Brams and Kilgour 2001).
- Condorcet choice (CC): For each alternative, this rule evaluates how many times it is preferred in all priority levels. The winner alternative is, hence, preferred by a majority of participants.
- Borda scoring (BS): Each stakeholder allocates the score $s - i$ to his ith most preferred alternative while s defines the number of alternatives. The score of ith alternative is equal to the number of all alternatives that i was preferred against. The alternative(s) that has (have) the highest total score is (are) selected as the Borda choice set (Sheikhmohammady and Madani 2008; Mahjouri and Bizhani-Manzar 2013).
- Plurality rule (PR): This rule focuses on the first level of priority, regardless of any other quality levels, and selects the alternative that has the highest number of selection as the socio-optimum choice (Reynolds et al. 2008).
- Median voting rule (MVR): After ranking the alternatives by stakeholders, the number of times that alternatives are preferred in each quality level is calculated. Then, at the highest possible quality, the first alternative associated with the majority of support is defined as the MVR choice (Bassett and Persky 1999; Alizadeh et al. 2017).

Due to using five SCRs to achieve socio-optimal solutions, all stakeholders bargain on their priorities and should compromise on an individual SCR. To serve this purpose, given the fuzzy nature of the proposed methodology, the obtained fuzzy interval in each α-cut level was ranked and prioritized through possibility degree method. Then, unanimity fallback bargaining (UFB) method (Brams and Kilgour 2001) was applied to find the SCR that is capable to maximize the stakeholder's minimum satisfaction. Consequently, a bargaining agreement is found (the compromise solution). For more details and applications of SCRs, possibility degree method and UFB refer to Brams and Kilgour (2001), Sheikhmohammady and Madani (2008), Sheikhmohammady et al. (2010), Madani et al. (2014a), Nikoo et al. (2016), Raei et al. (2017), and Alizadeh et al. (2017).
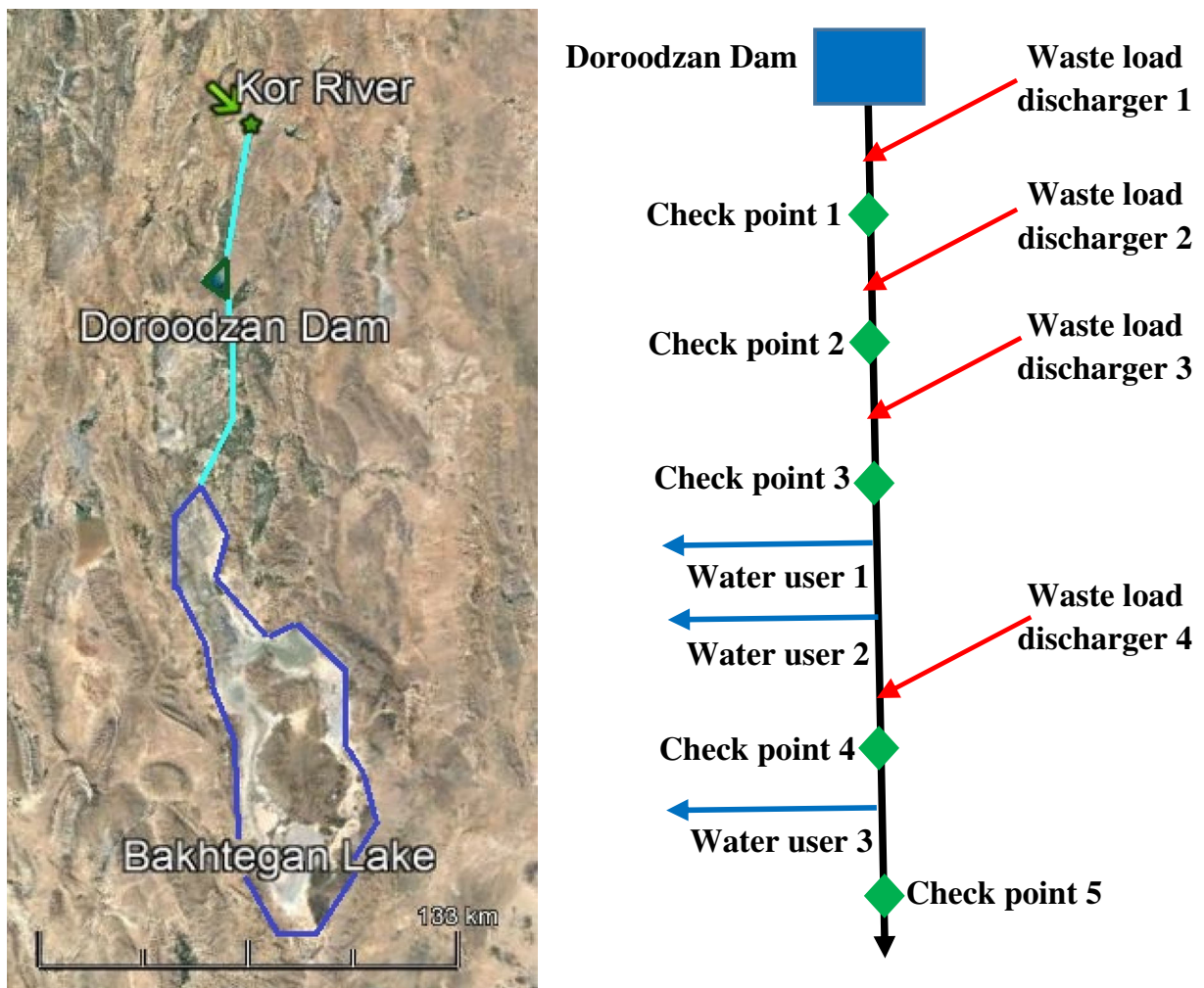
Fig. 2 The schematic view of the considered section of the Kor River system

Table 1 The multivariate linear regressions for DO concentration as the meta-model

Checkpoint number	Multivariate linear regression
1	$DO_{C_1} = 6.6062 + (-0.0833 \times O_1)$
2	$DO_{C_2} = 8.564 + (-0.228 \times O_2) + (-0.306 \times DO_{C_1})$
3	$DO_{C_3} = -4.401 + (-0.171 \times O_3) + (1.625 \times DO_{C_2})$
4	$DO_{C_4} = -0.163 + (0.144 \times O_5) + (1.0204 \times DO_{C_3})$
5	$DO_{C_5} = -23.771 + (-0.346 \times O_7) + (4.534 \times DO_{C_4})$

DO_{C_i} and O_i: the DO concentration at the ith checkpoint and ith water user/waste load discharger

Case study

The efficacy of the proposed methodology was evaluated in a part of the Kor River system in Fars Province, Iran. The Kor River system with the total area of 9650 m^2 originates from the Zagros mountain range and discharges to the Bakhtegan Lake in Fars Province, Iran. This river passes through different cities including Sivand, Marvdasht, Kenareh, Seidan, Ghaderabad, Sourian, and Safashahr. It is considered as the most important river of the Fars Province due to its vital role in agriculture and supplying ecological demand of the Bakhtegan and Tashk lakes. This river is regulated by the Doroodzan Reservoir Dam and irrigates a large agricultural sector. The Kor River receives various types of pollution from the urban, industrial, and agricultural sources. Based on FRWA's report, the pollution from
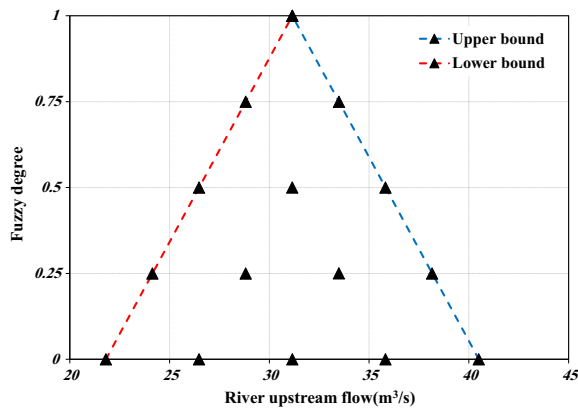
Fig. 3 The fuzzy degree of river's upstream flow rate

agricultural activities accounts for about 42% of the total pollution discharged to this river and is the highest percentage in the Kor River contamination budget, followed by urban and industrial sectors with 34% and 18% of the total budget, respectively. The study area is constrained to 74.3 km of the Kor River system, located between two large drainages of Sabz Mountain and Ahoochar, which consists of three water users (the first stakeholder) and four waste load dischargers (the second stakeholder). The FEO as the third stakeholder enforces the river water quality. The schematic positions of the water users and waste load dischargers are presented in Fig. 2.

Results

In this study, the QUAL2Kw model was developed and calibrated based on the geometry and velocity of the Kor River at different sections provided in the Fars Regional Water Authority's (FRWA) report. The considered length of the river was 73.4 km, which was divided into 12 segments throughout the Kor River flow path. Also, as part of the boundary conditions for the model (headwater), average annual flow, average annual

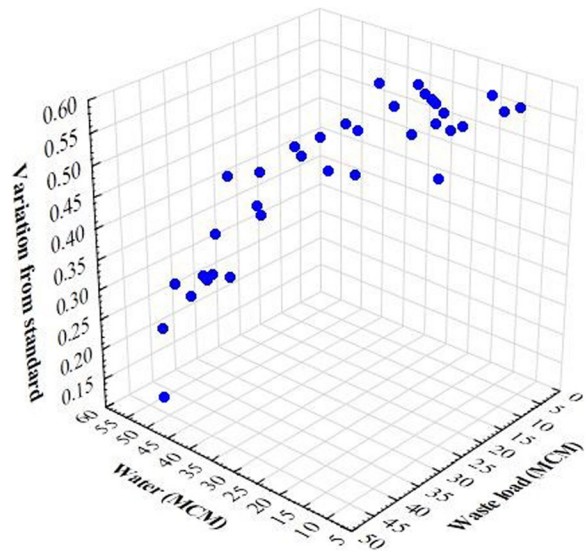

Fig. 4 Pareto front of optimal solutions in α-cut level of 0 and river's upstream flow of 31.153 m³/s

temperature, and pH were set to 31.153 m³/s, 18 °C, and 7, respectively. The solution methods for integration and pH were set to Euler and Newton-Raphson, respectively. Using different potential forcing for the WWLA for various stakeholders, the outputs of the QUAL2Kw model were determined and utilized to construct a substitute meta-model in the form of multivariate linear regressions. The meta-model determines the values of three river water quality variables namely DO, BOD_5, and TSS in five consequent checkpoints along the river path. To summarize, these multivariate linear regressions are presented for DO in Table 1.

In this table, DO_{C_i} is the DO concentration at the ith checkpoint and O_i is the DO concentration at the $i$thwater user/waste load discharger location along the Kor River path (Fig. 2). The substitute meta-model is readily coupled with the multi-objective WWLA model. Note that sensitivity analysis indicated that the river's upstream flow rate is the most influential uncertain

Table 2 The fuzzy form of river's upstream flow rate for different fuzzy degrees

Fuzzy degree	Array number (l)				
	$l = 1$	$l = 2$	$l = 3$	$l = 4$	$l = 5$
0	21.81	26.48	31.15	35.83	40.50
0.25	24.14	28.82	33.49	38.16	–
0.50	26.48	31.15	35.83	–	–
0.75	28.82	33.49	–	–	–
1	31.15	–	–	–	–

parameter. Hence, a symmetric triangular fuzzy membership function was applied for uncertainty analysis according to its maximum, average, and minimum possible values. In this study, the average value for the minimum recorded flow rate of 7 consecutive days with a return period of 10 years ($7Q_{10}$) was considered as the river's upstream flow rate. Using the variation of observed data over the years 2008–2018 and engineering judgment, the maximum and minimum values of the uncertain parameter were determined in the range of ± 30% of the average value. Accordingly, the lower and upper bounds of the uncertain parameter for five different α-cut levels (0, 0.25, 0.5, 0.75, and 1) were determined by general fuzzy transform method (FTM), which considers all possible values of the uncertain parameter at different confidence levels. The set of fuzzy

points in each α-cut level is demonstrated in Fig. 3. In this way, an interval of upstream flow rate with a confidence level of α was simulated in each α-cut level, which in turn was utilized in the fuzzy multi-objective WWLA model. As shown, the points on the red (the left side) and blue (right side) lines show the lower and upper bounds of each fuzzy degree, respectively. Also, the values of the upstream flow rate in each fuzzy degree are presented in Table 2.

Considering three objectives including maximizing the allocated water and waste load to stakeholders and minimizing the deviation of water quality variables from maximum allowable thresholds, the NSGA-II multi-objective WWLA model explored the feasible space to find the optimal solutions. The corresponding weights of the river water quality variables (W_{DO}, W_{BOD}, and W_{TSS})

Table 3 Lower and upper bounds of stakeholders' utility functions in each α-cut level by social choice rules (SCRs)

Method	α-cut level	Objective 1*	Objective 2**	Objective 3***
CPM[1]	0	[20.663, 53.657]	[28.186, 63.283]	[0.237, 0.877]
	0.25	[20.663, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.5	[42.066, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.75	[42.792, 53.657]	[28.186, 63.283]	[0.304, 0.877]
	1	53.657	63.283	0.877
CC[2]	0	[33.545, 53.657]	[28.186, 63.283]	[0.237, 0.877]
	0.25	[35.748, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.5	[42.066, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.75	[42.792, 53.657]	[28.186, 63.283]	[0.304, 0.877]
	1	53.657	63.283	0.877
BS[3]	0	[33.545, 53.657]	[28.186, 63.283]	[0.237, 0.877]
	0.25	[35.748, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.5	[42.066, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.75	[42.792, 53.657]	[28.186, 63.283]	[0.304, 0.877]
	1	53.657	63.283	0.877
PR[4]	0	[20.663, 53.657]	[28.186, 63.283]	[0.237, 0.877]
	0.25	[20.663, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.5	[42.066, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.75	[42.792, 53.657]	[28.186, 63.283]	[0.304, 0.877]
	1	53.657	63.283	0.877
	0	[20.663, 53.657]	[28.186, 63.283]	[0.237, 0.877]
	0.25	[20.663, 53.657]	[28.186, 63.283]	[0.259, 0.877]
MVR[5]	0.5	[42.066, 53.657]	[28.186, 63.283]	[0.259, 0.877]
	0.75	[42.792, 53.657]	[28.186, 63.283]	[0.304, 0.877]
	1	53.657	63.283	0.877

[1] Condorcet's practical method, [2] Condorcet choice, [3] Borda scoring, [4] Plurality rule, [5] Median voting rule

Objective 1*: water allocation (stakeholder 1); objective 2**: waste load allocation (stakeholder 2); objective 3***: deviation of water quality variables from the standard (stakeholder 3)

were considered 0.5, 0.3, and 0.2, respectively (Eq. 3). In the NSGA-II optimization model, based on trial and error analysis, the population size and the number of generations were set to 70 and 100, respectively. To develop a fuzzy multi-objective WWLA model, the values of the uncertain parameter in each α-cut level were considered as forcing data. In other words, the NSGA-II model was executed for all possible values of upstream flow rates, obtained from the general FTM, and 15 trade-off curves were obtained among stakeholders' utility functions. The

fuzzy multi-objective WWLA model provided a set of optimal solutions (Pareto front) that are the best match on the mentioned objectives in each α-cut level. The Pareto front space corresponding to each value of the river's upstream flow rate consists of 35 optimal solutions, which cannot be dominated by any other point in the feasible space. As an example, the Pareto front of the fuzzy multi-objective WWLA model for α-cut level of 0 and for river's upstream flow of 31.153 m^3/s is presented in Fig. 4.

(a) First objective

(b) Second objective
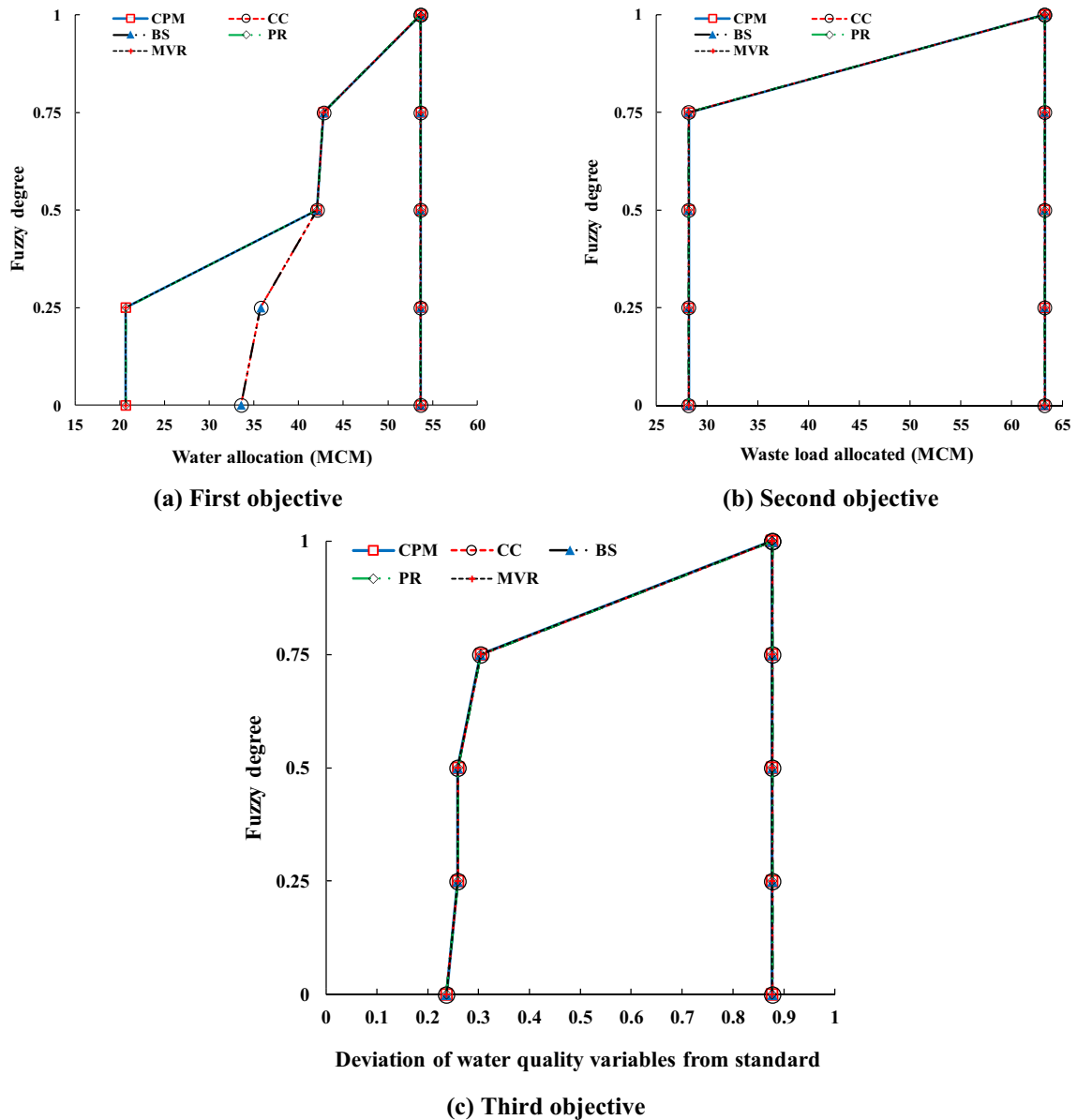
(c) Third objective

Fig. 5 Fuzzy membership functions for water allocation (stakeholder 1) (**a**), waste load allocation (stakeholder 2) (**b**), and deviation of water quality variables from standard levels (stakeholder 3) (**c**) through different SCRs

Table 4 Ranking of interval numbers through the possibility degree method for α-cut level 0

Objectives

Water users (objective 1)		Waste load dischargers (objective 2)		Water quality deviation (objective 3)	
Pairwise comparison	Possibility degree ($P_{A>B}$)	Pairwise comparison	Possibility degree ($P_{A>B}$)	Pairwise comparison	Possibility degree ($P_{A>B}$)
A B		A B		A B	
CC - PR	0.695	CC - PR	0.500	CC - PR	0.500
CC - MVR	0.695	CC - MVR	0.500	CC - MVR	0.500
BS - PR	0.695	BS - PR	0.500	BS - PR	0.500
BS - MVR	0.695	BS - MVR	0.500	BS - MVR	0.500
CPM - PR	0.500	CPM - PR	0.500	CPM - PR	0.500
CPM - MVR	0.500	CPM - MVR	0.500	CPM - MVR	0.500
CC - BS	0.500	CC - BS	0.500	CC - BS	0.500
PR-MVR	0.500	PR-MVR	0.500	PR-MVR	0.500
CPM - CC	0.179	CPM - CC	0.500	CPM - CC	0.500
CPM - BS	0.179	CPM - BS	0.500	CPM - BS	0.500

In order to find the socio-optimal solutions, which are acceptable by all involved stakeholders, five social choice rules (SCRs) were applied. These rules select the compromise solutions on the Pareto front in each α-cut level. Subsequently, the lower and upper bounds

of the three objectives were determined by each SCR in each α-cut level (Table 3). For the first objective (stakeholder 1), the Borda scoring (BS) and Condorcet choice (CC) methods select the same solutions on the Pareto front for all α-cut levels and Condorcet's practical

Table 5 Preference matrix of three objectives for different α-cut levels

α-cut level	Objective	Preference level (ranking)				
		1st	2nd	3rd	4th	5th
0	1*	CC, BS	CPM, PR	MVR	–	–
	2**	Identical#	–	–	–	–
	3***	Identical	–	–	–	–
0.25	1	CC, BS	CPM, PR	MVR	–	–
	2	Identical	–	–	–	–
	3	Identical	–	–	–	–
0.5	1	Identical	–	–	–	–
	2	Identical	–	–	–	–
	3	Identical	–	–	–	–
0.75	1	Identical	–	–	–	–
	2	Identical	–	–	–	–
	3	Identical	–	–	–	–
1	1	Identical	–	–	–	–
	2	Identical	–	–	–	–
	3	Identical	–	–	–	–

1*: water allocation; 2**: waste load allocation; 3***: variation of water quality variables from the standard. Identical# means that all SCRs have the same priority for this situation.

Table 6 The most appropriate SCRs in various α-cut levels based on UFB

α-cut level	0	0.25	0.5	0.75	1
Selected SCRs	BS, CC	BS, CC	Identical[#]	Identical	Identical

UFB, unanimity fallback bargaining. Identical[#] means that all SCRs have the same priority for this situation

method (CPM), plurality rule (PR), and median voting rule (MVR) yield an identical alternative as their result. Furthermore, for the second and third objectives (stakeholders 2 and 3), all SCRs determined the same alternative in each α-cut level and consequently, the fuzzy ranges of stakeholders' utility function are similar.

For more clarification, fuzzy membership functions of the involved stakeholders derived by different SCRs in the uncertain environment are presented in Fig. 5. For the second and third objectives (stakeholders 2 and 3), similar socially optimal solutions were selected on all Pareto fronts using different SCRs. This issue, in turn, returns identical values of the fuzzy membership function. On the other hand, for the first objective (stakeholder 1), there are different solutions in α-cut levels 0 and 0.25. It is notable that the range of variation for stakeholders' utility functions derived by CPM, PR, and MVR is wider than those selected by CC and BS methods.

The results presented in Table 3 and Fig. 5 indicate that, in terms of the first objective, widely different solutions are found based on the stakeholders' preference functions. Therefore, it is necessary to find one SCR, as the most appropriate method for all involved stakeholders, to determine the compromise solution. In this process, ranking the resulted interval numbers from SCRs is an integral part of the negotiation process. Possibility degree method was used herein to rank interval numbers for each stakeholder and in each α-cut level. As an example, for α-cut level 0, possibility degree of different interval numbers in ascending or descending orders is presented in Table 4. It should be noted that only unique pairwise comparison obtained by the possibility degree method, in which $P_{A > B} = 1 - P_{B > A}$, are presented here. However, all possible pairwise comparisons among interval numbers were computed.

Objectives of this study may advocate conflicting solutions, with the first two objectives (maximizing the WWLA) preferring the interval numbers with more possibility degree and the third objective (minimizing the deviation of water quality variables from standard levels) preferring less possibility degree. Accordingly, interval numbers based on the values of possibility degree were sorted

in descending order given the first two objectives and in ascending order corresponding to the third objective. For instance, from the first objective point of view, $P_{CC > PR} = P_{CC > MVR} = P_{BS > PR} = P_{BS > MVR} = 0.695$, which shows that the possibility of interval numbers obtained by CC and BS rules is larger than those obtained by PR and MVR with the possibility degree of 0.695. The possibility degree of 0.5 for the second and third objectives in each α-cut level expresses that the possibility of interval numbers obtained by all SCRs in those levels is identical, and they were ranked similarly. This means that all SCRs select the same alternative in the α-cut levels of 0.5, 0.75, and 1. The final ranking or preference matrix of different SCRs based on the priority of objectives for each α-cut level is listed in Table 5. For example, from the first objective's point of view, in the first and second α-cut levels (0 and 0.25), CC and BS were located in the first preference, followed by CPM and PR as the second preference and MVR as the third desired social choice rule.

Finally, it is necessary to find the most appropriate SCR for all stakeholders, which is determined by the bargaining process. In this study, the unanimity fallback bargaining (UFB) method was utilized in various confidence levels to determine the best rule for selecting the socio-optimal solution. The minimum satisfaction of all involved bargainers is maximized by UFB method with sufficient support of stakeholders. This ensures that the results are at the middle of the ranking list or above for all stakeholders. Table 6 shows the compromise set of UFB method in different α-cut levels, which are the common agreement among stakeholders. As listed in Table 6, Borda scoring (BS) and Condorcet choice (CC) were suggested by UFB method in the α-cut levels of 0 and 0.25. For the rest of α-cuts (0.5, 0.75, and 1), all SCRs are identical in terms of priority.

Summary and conclusion

In this study, a novel methodology was proposed for optimization of water and waste load allocation (WWLA) in river systems. This non-linear multi-

stakeholder socio-optimal methodology considers the upstream flow uncertainty in the optimization process. The QUAL2Kw model was used in this framework to develop and calibrate the river water quality model. The QUAL2Kw model was then executed for various water and waste load scenarios, the results of which were used to train a set of multivariate linear regressions as the substitute meta-model for QUAL2Kw. To consider the parameter uncertainty, the upstream flow was analyzed through general fuzzy transform method (FTM). Considering three objectives and various confidence levels (α-cuts) of the fuzzy uncertain parameter, the fuzzy multi-objective WWLA model was developed by coupling the meta-model and NSGA-II. Due to the fuzzy nature of the developed simulation-optimization model, the developed optimization model was executed for all possible values of the uncertain parameter and optimal solutions on the Pareto front were determined. In order to achieve the socio-optimal solution on each α-cut level, five social choice rules (SCRs) were utilized. Subsequently, the fuzzy intervals for each objective were determined. Next, the possibility degree method was applied to rank the fuzzy interval results in each α-cut level, and the preference matrix was derived. Finally, based on the simultaneous preference of all involved stakeholders, the unanimity fallback bargaining (UFB) method specified the most appropriate SCR for each α-cut level. The proposed methodology optimized water and waste load allocation to different users, while considering the river water quality in a unified framework. The results showed that for the first two first α-cut levels (0, 0.25), stakeholders agreed on Borda scoring and Condorcet choice methods for optimal WWLA in the Kor River system. For the rest of α-cut levels (0.5, 0.75, and 1), based on the results of possibility degree method, all SCRs were identical in the bargaining process among all stakeholders through UFB method.

The novelty of this study lies in the application of the social choice rules and fallback bargaining method in river water quality management, while considering the uncertainty of environmental factors in joint WWLA. Moreover, this study contributes to the body of knowledge by applying social choice rules in the context of joint WWLA and employing an array of technical tools (e.g., possibility degree method, fallback bargaining method) to solve a complex system. In the future works, this methodology can be extended by applying bankruptcy methods for resolving conflicts in WWLA (Madani et al. 2014b). In addition, using agent-based models and water quality

indices to investigate the effect of water users' behavior in the upstream on the reservoir water quality and releases can be a great contribution in the context of the herein proposed framework (e.g., Nikoo et al. 2011; Farhadi et al. 2016). Furthermore, main uncertainties (water demands and inflow's water quality variables) can be addressed using either fuzzy set theory or Bayesian analysis (e.g., Sadegh et al. 2017; Sadegh et al. 2018b). Finally, using the concept of trading discharge permits in rivers along with the optimized WWLA is an interesting idea for the future studies (e.g., Mesbah et al. 2009; Nikoo et al. 2016).

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