Multi-objective multi-pollutant waste load allocation model for rivers using coupled archived simulated annealing algorithm with QUAL2Kw

Motahareh Saadatpour, Abbas Afshar and Helaleh Khoshkam

ABSTRACT

A simulation-optimization approach is a suitable tool in waste load allocation problems when considering competing objectives and complex pollutant fate and transport processes in water bodies. Here, an archived multi-objective simulated annealing (AMOSA) algorithm is developed to determine various decision variables related to multi-pollutant waste load allocation (MPWLA) problems. The developed AMOSA algorithm has been coupled to QUAL2Kw in order to derive optimal MPWLA programs in Gheshlagh River, Kordestan, Iran. Minimizing wastewater treatment plant (WWTP) costs, improving the *EquityMeasure*, and enhancing water quality index (WQI) of the river have been considered as objective functions of MPWLA problems. The applied WQI integrates various water quality parameters (biochemical oxygen demand (BOD), dissolved oxygen (DO), NH_4-N, NO_3-N, PO_4-P, total suspended solids (TSS), and Coliform) in monitoring stations along the river. Results show in the scenario with the best *EquityMeasure*, higher pollutant removal rates have been allocated to Sanandaj WWTP effluent and pollutant point source No. 7 (creek of landfill leachate) due to their greater contributions to Gheshlagh River contamination. Owing to high pollutant load effluents and unsuitable background conditions in Gheshlagh River, more specific studies show that the water quality index may not be improved over 0.22, no matter how much cost is incurred or equity is sacrificed.

Key words | archived multi-objective simulated annealing algorithm, CapdetWorks, Gheshlagh River, multi-pollutant waste load allocation, QUAL2Kw, water quality index

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INTRODUCTION

Water quality protection is an essential component of sustainable water resource management. During the last few decades, due to ever-increasing population and extensive development of agricultural and industrial activities, water resources have been under threat from various pollutant dischargers. As a result, rivers as receiving water bodies, have been polluted extensively mainly due to easy access. A wide variety of contaminants containing organic and/or inorganic pollutants are often discharged into rivers through municipal and industrial sewage units. Timing, spacing, and mass of pollutant discharge to the rivers could be managed by optimizing waste load allocation (WLA) at a number of point sources. In an optimal WLA program, the optimal pollutant removal rates are determined, which yield acceptable water quality responses in various monitoring stations along the river considering economic and/or equity aspects (Burn & Yulianti 2001; Yandamuri *et al.* 2006).

In a systematic approach, a WLA model incorporates a water quality simulation model coupled with an optimization algorithm. The mathematical framework of a WLA model consists of goals, objectives, and constraints of a water quality management problem. The spatial and temporal distribution of water quality constituents in a river system is often presented as a numerical and/or analytical

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water quality simulation model (Mujumdar & Saxena 2004; Mujumdar & Vemula 2004; Saadatpour & Afshar 2007; Nikoo et al. 2012). WLA problem is inherently multi-objective in nature, as it incorporates water quality aspects, economic objectives, and *EquityMeasure*. Equity has been illustrated as waste allocation fee according to treatment costs, absolute or relative equal waste load allocation among pollutant dischargers, and waste load allocation proportional to the discharged waste load rate (Park 2010). Various multi-objective optimization algorithms such as Non-dominated Sorting GA-II (Yandamuri et al. 2006; Rathnayake & Tanyimboh 2015; Allam et al. 2016; Saberi & Niksokhan 2017), Non-dominated Archiving Multi-Colony Ant Algorithm (Mostafavi & Afshar 2011), Weighted Multi-Objective Simulated Annealing (MOSA) (De Andrade et al. 2013), and Multi-Objective Particle Swarm Optimization (Ashtiani et al. 2015) have been applied in WLA problems. Also, multi-objective optimization algorithms with deterministic and fuzzy objectives have been successfully employed to solve WLA problems (Ghosh & Mujumdar 2010; Nikoo et al. 2012). Minimizing wastewater treatment costs, water quality standard violations, and waste removal inequity measures more frequently have been considered as objective functions in multi-objective optimization WLA models (Yandamuri et al. 2006; Hosseinzadeh et al. 2010).

As outlined, most of the cited works have dealt with single pollutant WLA problems. In fact, multiple pollutants in WLA models have not received as much attention as deserved. Multiple pollutants seem to be important from both the Pollutant Control Agency (PCA) and discharger points of view. Natural systems, however, are subjected to combinations of different pollutants with various concentrations from diverse sources. Therefore, a multiple pollutant waste load allocation (MPWLA) model may address the environmental issues in a receiving water body more realistically. Different dischargers with various pollutants as well as existence of variant treatment strategies with quite diverse costs make the decision-making process a real challenge.

This paper presents a simulation-optimization (S-O) model to tackle the challenging multiple pollutant multi-objective waste load allocation problem. The S-O model employs QUAL2Kw to simulate the fate and transport of multiple pollutants in a water body and Pareto domination-based multi-objective simulated annealing (PDMOSA) as an efficient optimization tool to solve the resulting multi-objective problems. In order to assess the quality of the water at different checkpoints along the river, an improved water quality index that integrates nitrate (NO_3-N), ammonium (NH_4-N), phosphate (PO_4-P), biochemical oxygen demand (BOD), Coliform, and dissolved oxygen (DO) concentrations as water quality indicators has been employed. From the diverse sets of predefined treatment strategies, the model selects the best treatment strategies for each discharger with various rates of removal for each pollutant to satisfy the acceptable values of water quality index at each control point. Since the model handles more than one objective, the ultimate results are in the form of a Pareto front which integrates a combination of the best solutions, trading off one objective against the others.

Coupled PDMOSA algorithm and QUAL2Kw have been applied to derive optimal MPWLA in Gheshlagh River, Kordestan, Iran. The construction, operation, and maintenance costs of wastewater treatment plants (pollutant removal cost) have been extracted from CapdetWorks 2.5d software (Hydromantis 2003) and studies on pollutant monitoring and analysis in the Gheshlagh River (Iran DoE 2006). The proposed methodology represents an effective and efficient technique for optimal MPWLA in any contaminated waterway, supports different management objectives to preserve and protect water quality in various meteorological, hydrological and man-made environments.

METHODS AND PROCEDURES

Study area

Gheshlagh River is the main stem of the Sirvan watershed in Kordestan province in the west of Iran. The river supplies municipal, agricultural, and industrial water for people in the adjacent area, including the city of Sanandaj. The geographic location of Gheshlagh River is presented in Figure 1.

Due to rapid municipal, agricultural, and industrial development in Gheshlagh River basin, large volumes of untreated or partially treated sewage are, either directly or through urban sewers, being discharged into the Gheshlagh River. As a result, the Gheshlagh River became seriously

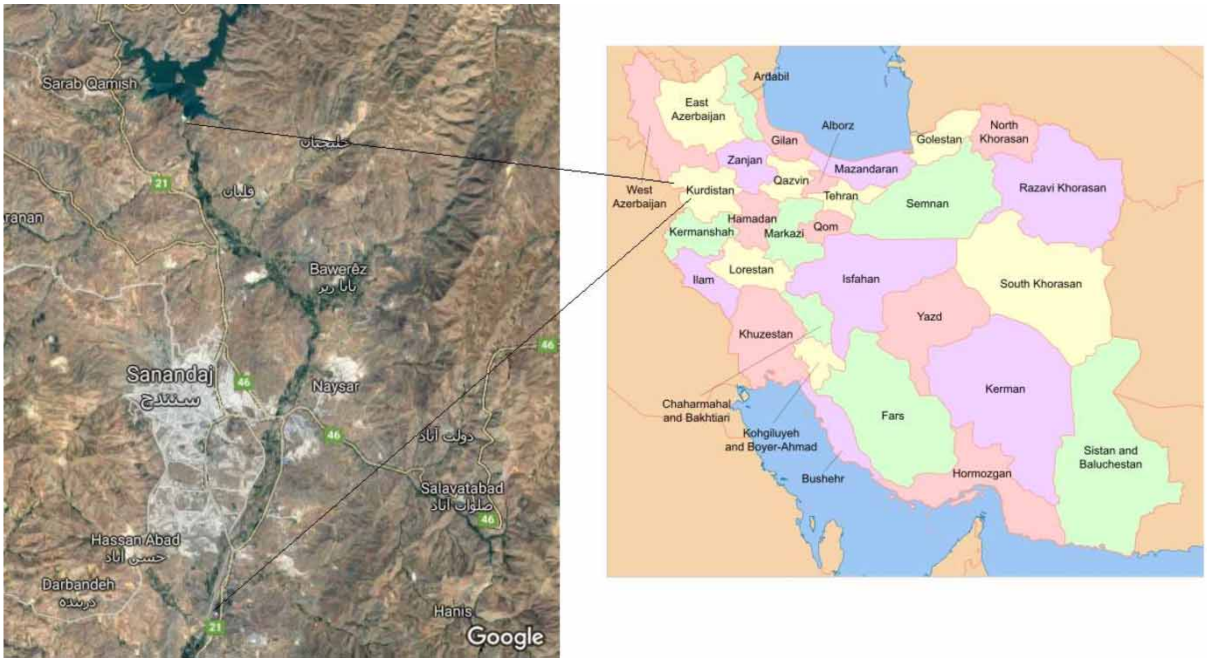

Figure 1 | Geographic location and detailed boundaries of the study area.

polluted (Khaledian & Nikkami 2017). Since 2000, Iran Department of Environment (Iran DoE) and Ministry of Energy have given specific attention to pollution control in the Gheshlagh River basin. Therefore, environmental legislation and standards were stipulated for ambient water quality and effluent, and monitoring institutions for enforcement have been activated. Although waste dischargers have been encouraged to install and/or upgrade their treatment plants, any improved treatment technology requires significant financial resources.

Part of the Gheshlagh River with altitude and longitudinal position of reaches, point sources, and monitoring stations (checkpoints) are presented in Figure 2. The geometry and hydraulic data of the study area are presented in Table 1. In this research, the studied branch of the Gheshlagh River is bounded to Gheshlagh reservoir in the upstream section and therefore, the hydrological pattern of the river system is affected by reservoir operations. The studies on the hydrological regime in Gheshlagh River indicates there are no meaningful seasonal variations in the

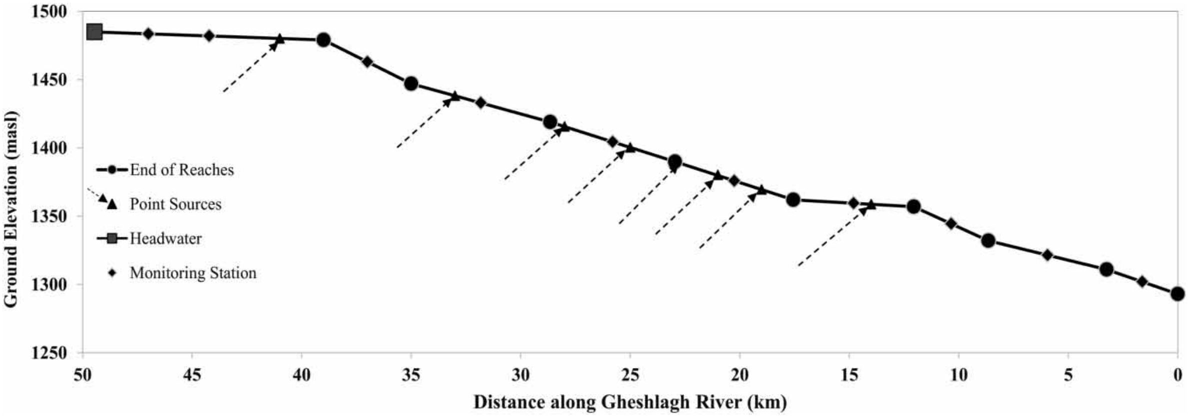

Figure 2 | Geometrical position of pollutant point sources and monitoring stations along the Gheshlagh River.

Table 1 | Geometry and hydraulic characteristics of reaches in Gheshlagh River (Asheghmoala et al. 2014)

Reach names	Distance from downstream (km)	Manning roughness coefficient	River bed width (m)	Bed slope	Side slope
Headwater	49.45	0.09	4	0.003	0.03
Reach 1 – Downstream of Gheshlagh Dam	39	0.09	5.5	0.003	0.02
Reach 2 – Salavat-Abad	35	0.08	7.5	0.007	0.025
Reach 3 – Baharan	28.56	0.06	10	0.005	0.02
Reach 4 – Sanandaj sewage	22.95	0.055	10	0.005	0.015
Reach 5 – Landfill leachate	17.55	0.055	12.5	0.001	0.01
Reach 6 – Par chicken slaughter	12.05	0.05	12.5	0.005	0.01

stream flow after dam construction (Aria et al. 2013). At the distance between the downstream of Gheshlagh (Vahdat) dam to the end of Gheshlagh River, eight municipal and industrial pollutant point sources are located. The chemical and biological parameters of each municipal and industrial pollution source are presented in Table 2. Municipal and rural pollutions, pollutant units No. 1 and 5, are equipped with wastewater treatment plants and their effluents are directly discharged into the Gheshlagh River. The remaining pollutant dischargers are industrial units.

QUAL2Kw

QUAL2Kw as a 1D non-uniform steady-state hydraulic and water quality simulation model depicts the flow and kinetics of advective systems. The model has the ability to simulate the fate and transport of constituents such as temperature, nutrients (BOD, PO_4-P, NO_3-N, NH_4-N, etc.), pH, sediment, pathogens, organic matter, algae, DO, carbonaceous BOD, and so on. Meteorological, hydrological, hydraulic, geometry, and water quality data are considered as the main input data of this model. The model is able to simulate point and non-point source pollution and/or water abstraction along the waterbody. The model solves flow, heat, and mass conservation equations in each segment of water body. The genetic algorithm is included in QUAL2Kw modules to facilitate the calibration processes in application to particular waterbodies. QUAL2Kw is implemented within Microsoft Excel and it is programmed in Visual Basic (VBA) environment (Pelletier & Chapra 2008).

Archived multi-objective simulated annealing

Simulated annealing (SA) is a probabilistic single-solution based search algorithm. It originated from the annealing process in metallurgy. Annealing is a physical process of

Table 2 | Characteristics of pollutant point sources in Gheshlagh River (Asheghmoala et al. 2014)

Name of pollution discharge unit	Reach number	BOD	COD	PO_4	NH_4	NO_3	Coliform	TSS	Wastewater flow rate (MGD)
Nanleh wastewater	1	✓		✓	✓	✓	✓		2.28
Industrial park	3	✓	✓					✓	0.23
Sanandaj livestock slaughter	3	✓	✓					✓	0.07
Fajr concrete foundation	4	✓	✓					✓	0.09
Treatment plant outflow	4			✓	✓	✓	✓		31.95
Asphalt and grain recycling and production	5	✓	✓					✓	0.07
Creek of landfill leachate	5	✓	✓					✓	0.68
Poultry slaughter	6	✓	✓					✓	0.05

MGD = million gallons per day (1 MGD is equal to 0.043813 cubic meters per second).

slowly cooling a metal until its structure is eventually frozen at a minimum energy configuration. SA is basically composed of two stochastic processes. Trial solutions are generated in the first process and checked for acceptance in the second process. Solutions by SA are independent of initial conditions and near optimal, depending on computational time. SA also tries to improve solutions on a greedy local search by taking a risk of accepting a worse solution during the process (Teegavarapu & Simonovic 2002; Du & Swamy 2016).

In multi-objective optimization, the members of the Pareto-optimal set are non-dominated and equally important solutions. The Pareto optimal set allows the decision maker to view options before making a decision. These optimization techniques incorporate *a posteriori* articulation of preferences, particularly where expressing an explicit approximation of the preference function is difficult for a decision maker (Marier & Arora 2004; Cao 2017). MOSA algorithm has recently been adapted and used by many researchers (e.g. Suman 2003; Bandyopadhyay *et al.* 2008; Antunes *et al.* 2011; Tian *et al.* 2017). In many recent Pareto-domination-based MOSA algorithms, the acceptance criterion between the current and a new solution has been defined in terms of the difference in the number of solutions that they dominate or the amount by which this domination occurs (Bandyopadhyay *et al.* 2008). In this research, archived multi-objective simulated annealing (AMOSA), introduced by Bandyopadhyay *et al.* (2008), has been developed to derive optimal MPWLA programs in rivers. The proposed algorithm measures the levels of domination to determine the acceptance criteria of a new solution.

The AMOSA algorithm, used in this study, identifies the non-dominated optimal solutions and stores them in an archive. At a given temperature, T, a new state, s, can be selected with a probability, P_{qs}, where q is the current state and $E(s, T)$ and $E(q, T)$ are the corresponding energy values of s and q, respectively (Bandyopadhyay *et al.* 2008):

$$P_{qs} = \frac{1}{1 + e^{\frac{-(E(q,T) - E(s,T))}{T}}} \tag{1}$$

Based on Equation (1), the new state (s) will be available if P_{qs} is greater than a random number generated from uniform distribution in the range [0,1]. Otherwise, the current state (q) will be retained. The general formulation of P_{qs} in Equation (1) has been rewritten as '*Exp*' function of 'Δdom' in various cases as presented in the Pseud code of AMOSA algorithm (Appendix A, available with the online version of this paper). A measure of domination for solutions a and b, $\Delta dom_{a,b}$, is proposed as (Bandyopadhyay *et al.* 2008):

$$\Delta dom_{a,b} = \prod_{i=1; f_i(a) \neq f_i(b)}^{M} \frac{|f_i(a) - f_i(b)|}{R_i} \tag{2}$$

where M and R_i are the number of objectives and the maximum bonding value of the i^{th} objective, respectively. To bring the measure of domination for all solutions (Equation (2)) into the range [0,1], the feature scaling approach is used. To do so, the measure of domination is divided by the maximum bonding value of the same objective (R_i).

In many cases, including this case, R_i may not be known *a priori*. In this research, R_i is set equal to the maximum value of the i^{th} objective function among the whole generated solutions. In this research, the upper bonding value of the i^{th} objective function (R_i), in MPWLA problem, is set equal to 200×10^6, 36, and 0.26 for cost, equity measure, and WQI, respectively. This domination measure, $\Delta dom_{a,b}$, is used to decide whether the new non-dominated solution enters the archive.

Similar to other EAs, in the first step of AMOSA, random solutions are generated according to variables' bounds. Then a routine for selecting the non-dominated solutions is called to build up the *Archive* of the AMOSA algorithm. In the second step, new solutions are generated from the initial random solutions by defining feasible moves transforming function. The solution in iteration *iter* and *iter* + 1 is defined as *current-pt* and *new-pt*, respectively. The domination status of *new-pt* is checked with respect to the *current-pt* and the archive is updated. The Pseudo-code of AMOSA is presented in Appendix A.

In this research, the *Archive* is sized so as to control the loss of diversity while archiving a limited number of well distributed non-dominated solutions. When the number of non-dominated solutions exceeds the *Archive* size, distance measure is calculated between the non-dominated solutions and then the suitable distributed solutions are selected and stored in the *Archive*.

Water quality index

The physical, chemical, and biological characteristics of a water resource determine its suitability for an intended use. To describe water quality, it is useful to employ an index that aggregates various sub-indices representing different water quality variables.

The nature of sub-indices depends on the type of water quality variables studied. Considering the different behaviors of the quality variables, the sub-indices were divided into uniformly decreasing sub-indices, non-uniformly decreasing sub-indices, and uni-modal sub-indices. Equation (3) describes the variations of uniformly decreasing sub-indices (Swamee & Tyagi 2000):

$$s = \left(1 + \frac{q}{q_c}\right)^{-m} \tag{3}$$

where q, q_c, and m are quality variable, characteristic value of q, and a positive number, respectively. m and q_c are constant values, which are obtained based on fitted values of various water quality parameters. Coliform, nitrate, phosphate, turbidity, and BOD belong to uniformly decreasing sub-indices. The following function form (Equation (4)) represents the variation of non-uniformly decreasing sub-indices (Swamee & Tyagi 2000):

$$s = \frac{1 + \left(\frac{q}{q_T}\right)^4}{1 + 3\left(\frac{q}{q_T}\right)^4 + 3\left(\frac{q}{q_T}\right)^8} \tag{4}$$

q_T is a threshold concentration which decreases and it is a constant value of non-uniformly decreasing sub-indices. Aluminum, arsenic, cadmium, chromium, copper, cyanide, iron, lead, manganese, mercury, selenium, and zinc belong to this group. DO, pH, fluoride, temperature, and total solids belong to uni-modal sub-indices. The behaviors of these water quality parameters are presented as Equation (5).

$$s = \frac{pr + (n+p)(1-r)\left(\frac{q}{q*}\right)^n}{p + n(1-r)\left(\frac{q}{q_T}\right)^{n+p}} \tag{5}$$

The constant values of n, p, r, and q_* for each water quality parameters belong to uni-modal sub-indices and are found in valid references. To aggregate various sub-indices, Swamee & Tyagi (2000) proposed an aggregative index as below:

$$I = \left(1 - N + \sum_{i=1}^{N} s_i^{-1/k}\right)^{-k} \tag{6}$$

where k is a positive constant, which is sensitive to the variation of sub-indices. The value of 0.4 is recommended for k. The proposed water quality index as an assessment method involves different numbers of quality variables. In this study, BOD, DO, total suspended solids (TDS), NO_3-N, NH_4-N, PO_4-P, Coliform, as water quality parameters, have been transformed to sub-indices according to the corresponding equations (Equations (3)–(5)). Then the index formulated in Equation (6), has been applied to aggregate various sub-indices. The aforementioned WQI will vary between zero and one, in which the higher the value, the better.

CapdetWorks: a wastewater treatment design tool

CapdetWorks is a tool which provides suitable and rapid preliminary design and can provide cost estimates for wastewater treatment plant (WWTP) construction projects. This software may be used for preliminary evaluation of various design alternatives in WWTPs. CapdetWorks designs each unit process of WWTP based on the characteristic of the influent to the process and then estimates the economic costs of the selected design (Hydromantis 2003). Numerous unique features have been included in CapdetWorks, which make it a suitable and useful tool in WWTP design and preliminary cost estimations. Choice of over 60 treatment processes covering all WWTPs, including biological nutrient removal, is included in the model's capabilities. In addition, the design of the required unit process dimensions and equipment is performed automatically (Hydromantis 2003).

The unit processes to build a WWTP, the influent and the desired effluent quality are defined by the planner. CapdetWorks will then automatically estimate the plant design and calculate construction, operation, and maintenance costs of the equipment and facility in the WWTP. Designs are selected based on the rate of influent and many physical-chemical and biological characteristics of the wastewater being treated. The interactive sensitivity analysis helps us identify and focus on the most effective parameters on WWTP cost (Hydromantis 2003; Sasani 2007).

CapdetWorks is set up for each pollutant discharge unit (Table 2) to design and calculate the cost of a new WWTP. The CapdetWorks tool has been used to derive the required process units, equipment, and their capacities. 'Sensitivity analysis' option in the Cost Estimation Toolbar of CapdetWorks has been implemented to focus on the most effective water quality parameters on WWTP cost. The unit cost techniques are included in the CapdetWorks tool to derive WWTP costs versus concentration of various quality parameters in the influent. Studies show that BOD and TSS concentrations have the most significant effects on municipal and industrial WWTP costs, respectively. Based on laboratory measurements, dissolution and/or suspension ratio of various water quality parameters, as well as the interactions between BOD and TSS with other water quality parameters (Iran DoE 2006), and the treatment plant costs for municipal and industrial wastewater have been estimated as Equations (7) and (8), respectively (Hydromantis 2003; Iran DoE 2006). Here, suspension ratio is defined as the percentage of a given water quality indicator (i.e. BOD, COD) which is in suspension form. The dissolution ratio refers to the percentage which is dissolved in the effluent.

$$Cost_{i=1,5} = f(C_{BOD_i}, C_{NO3_i}, C_{NH4_i}, C_{PO4_i}, C_{Coliform_i}, x_{BOD_i}, x_{NO3_i}, x_{NH4_i}, x_{PO4_i}, x_{Coliform_i}, Q_i) \quad (7)$$

$$Cost_{i=2,3,4,6,7,8} = f(C_{BOD_i}, C_{COD_i}, C_{TSS_i}, x_{BOD_i}, x_{COD_i}, x_{TSS_i}, Q_i) \quad (8)$$

in which C and x stand for concentration and removal rate of special pollutant, respectively. Dischargers numbered 1 and 5 address the municipal and rural waste dischargers, respectively, and dischargers numbered 2, 3, 4, 6, 7, and 8 refer to the industrial waste dischargers. The sum of construction, operation, and maintenance costs of WWTP in eight pollutant units along Gheshlagh River is defined as the economic objective function in this study.

MPWLA problem formulation in Gheshlagh River

The proposed multi-objective, multi-pollutant waste load allocation model considers three different objectives, simultaneously. The first objective (Equation (9)) aims to reduce the treatment costs addressed by the construction, operation, and maintenance costs for various WWTPs. The sum of construction, maintenance, and operation costs of eight WWTPs along Gheshlagh River represent the economic measure of the design problem. The second objective aims to attain proper equity by reducing the inequity measure among all the waste dischargers (Equation (10)). The third objective (Equation (11)) attempts to improve water quality indices in checkpoints along the river (ten checkpoints/monitoring stations). Maximizing the average water quality index (Equation (11)) in various checkpoints is considered as environmental criteria to protect and/or enhance Gheshlagh River water quality. The constraints, minimum and maximum allowable removal rates in various WWTPs and for each pollutant, are defined in this MPWLA problem (Equation (12)). The multi-objective MPWLA model may be formulated as:

$$Min \quad Cost = \sum_{i=1}^{8} Cost_i \,(Construction, Operation, Maintenance) \quad (9)$$

$$Min \quad EquityMeasure = \sum_{i=1}^{8}\sum_{j=1}^{7}\left|\frac{X_{ij}}{\bar{X}_j} - \frac{W_{ij}}{\bar{W}_j}\right| \quad (10)$$

$$Max \quad aveWQI = \frac{1}{10}\sum_{k=1}^{10} I_k \quad (11)$$

$$\text{St.} \quad X_{min} < X_{ij} \leq X_{max} \quad \forall i = 1, 2, \ldots, 8 \quad \forall j = 1, 2, \ldots, 7 \quad (12)$$

$$I_k = f(Q, X, W, Meteorology, RiverGeometry, RiverBedMaterial) \quad (13)$$

where X_{ij}, $\bar{X}_j$, W_{ij}, and $\bar{W}_j$ are removal rate of pollutant j in WWTP i, average removal rate of pollutant j, influent mass rate of pollutant j to WWTP i, and average influent mass rate of pollutant j, respectively. i and j stand for pollutant unit and pollutant type, respectively, according to Table 2. $Cost_i$ and $aveWQI$ are total treatment cost (including construction, operation, and maintenance cost) for discharge unit i and the average WQI in ten checkpoints along the river, respectively. X_{min} and X_{max} are minimum and maximum achievable removal rates in WWTPs, which are set according to technological and economic limits. In this research, these values have been set as zero and 0.9, respectively. I_k is WQI in checkpoint k calculated according to Equation (6). This WQI is a function of hydrological, pollutant removal rate, pollutant mass rate discharged into the river, meteorological, river geometry, and river bed material (Equation (13)). WQI is determined based on the results of the water quality simulation model. QUAL2Kw as water quality simulation model depicts Gheshlagh River responses according to various MPWLA scenarios. The simulated water quality responses in each checkpoint are aggregated according to Equation (6) and then, the average of WQI in checkpoints is considered as a description of water quality responses in Gheshlagh River, which should be improved.

As stated, Equation (10) addresses the equity objective. There are various equity measures in WLA problems such as sum deviation equity measure (SDEM), range equity measure (REM), maximum efficiency equity measure (MEEM), etc. (Burn & Yulianti 2001). The principle behind the aforementioned equity measures is to distribute the treatment costs among the pollutant dischargers in such a way that the treatment cost for each unit is as close to an overall average treatment cost as possible. These equity measures are appropriate when there is not much difference between pollution units in terms of discharged mass rate. However, when the difference among pollutant dischargers is large (i.e. small and large scale industry or municipal units beside each other discharge pollutant to the river), the use of SDEM or REM equity measures may not be advantageous for small polluters. In cases when the overall treatment cost of a system is largely dependent on some pollutant dischargers, it is suitable to implement equity measure based on the principle that the treatment cost for a pollution unit should be proportional to its waste contribution. This equity measure is based on the concept that a pollution unit must be penalized according to the share of its waste load (Park 2010). The equity measure defined in the presented study is based on the fact that higher waste load should undergo a higher level of treatment (Equation (10)).

RESULTS AND DISCUSSION

The large amount of domestic sewage and/or industrial effluents (Table 2) discharging into Gheshlagh River greatly exceeds the river's natural capacity to attenuate pollutants. These lead to water quality standard violations and gradual deterioration of the river as a valuable water body. Therefore, developing a MPWLA program is urgently required in Gheshlagh River to implement necessary environmental conservation actions and achieve the desired water quality standards.

To develop a tradeoff between the objectives, the MPWLA model is set up and applied to Gheshlagh River. QUAL2Kw, as a 1D numerical hydraulic and water quality simulation model, has been calibrated and verified according to data collected in a monitoring program of Gheshlagh River. The relative error never exceeded 11% for all modeled water quality parameters in this study, which may be considered as satisfactory performance of the QUAL2Kw model in predicting the water body's responses to various MPWLA scenarios. The comparisons between the field data and QUAL2Kw model results for some water quality parameters in Gheshlagh River have been presented in Figure 3.

The AMOSA algorithm applied in this research, determines an entire Pareto optimal solution set in MPWLA problem. The Pareto optimal set allows the decision maker to view various MPWLA programs before making a decision. Selection of MPWLA program can be done in terms of the design space (pollutant removal rate) or in terms of the criterion space (objective function). One does not consider which objective function (economic cost, equity measure, and WQI) is more or less important; one only considers which solution (pollutant removal rate and/or treatment technology) is most appealing, most accessible, and/or most practical (Marier & Arora 2004; Cao 2017).

More specific study of the objective values describes the possible performance tradeoffs. Figure 4 presents the tradeoff between water quality index and total cost for different classes of *EquityMeasures*. To simplify the presentation, *EquityMeasure* is categorized into eight classes. In class 1 as the best case, the *EquityMeasure* is assumed to vary from 4 to 8, whereas for the worst case (class 8), it ranges from 32 to 36. As presented, the *EquityMeasure* in range 28–32 (class 7) has the highest frequency in various water quality–cost management scenarios. As an example, for WQI of 0.1 and *EquityMeasure* in class 7, various scenarios

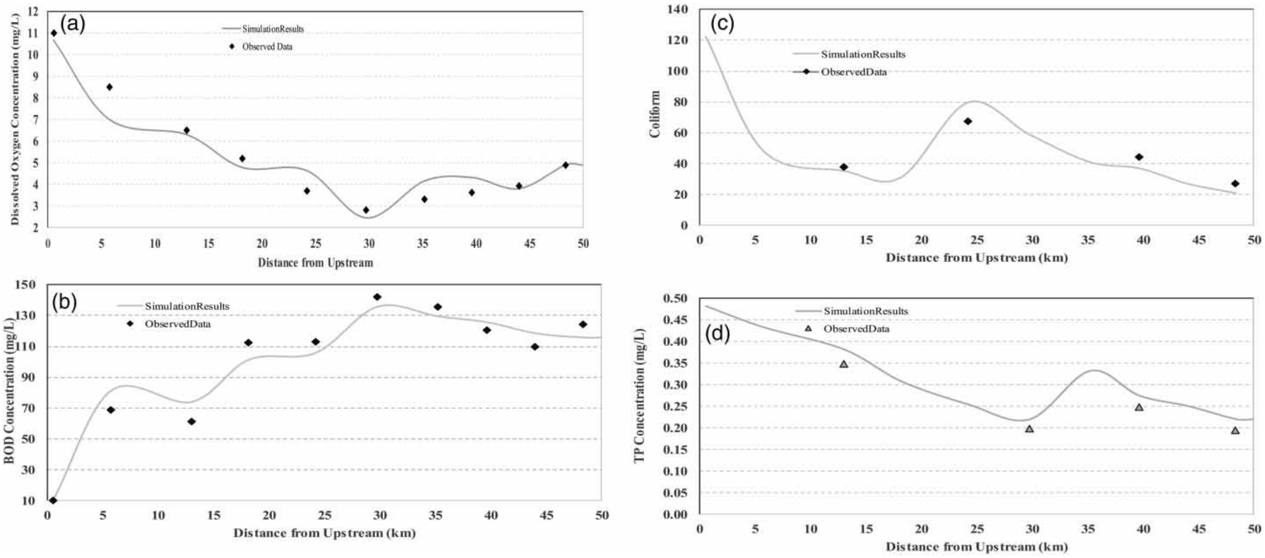

Figure 3 | The comparison results between observed data and QUAL2Kw model results in Gheshlagh River: (a) dissolved oxygen, (b) BOD, (c) Coliform, and (d) total phosphorus (TP).

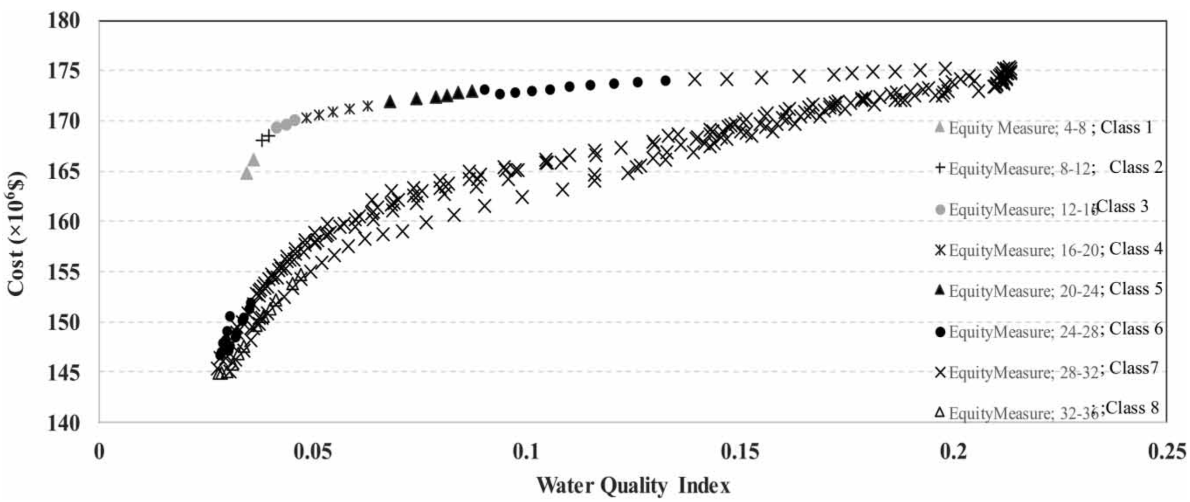

Figure 4 | Cost-water quality index tradeoff in deriving optimal MPWLA program.

are available where the total cost may range from 162 to 165 million dollars. For the best *EquityMeasure* (class 1) limited number of feasible solutions within the policy zone have been identified. These solutions are limited to low water quality index and/or high cost. As class of *EquityMeasure* increases, the number of non-dominated solutions increases. As another point of interest, for *EquityMeasure* in the range 24–28 (class 6), ten numbers of the non-dominated solutions are identified where water quality index and total cost are in the ranges 0.09–0.13 and 172.5–174, respectively. In addition, results show that the average WQI in Gheshlagh River may not be improved over 0.22, no matter how much cost is incurred or equity is sacrificed. This is because of high influent rates, background condition in river and existing sediments in the river bed. As expected, the earlier improvement in quality index demands higher cost per unit of quality index improvement due to economy of scale. For a water quality index exceeding 0.17, the rate of treatment cost remains almost constant. According to the results presented in Figure 4, for total cost of 160 million dollars or less, the WQI may not exceed 0.06 for *EquityMeasure* ranging from 28 to 36. The results indicate that with 15 million dollar increases in total cost (from 160 to 175), the WQI may be enhanced greatly. In fact, construction of WWTP with least removal rate capabilities (minimum cost scenario) would result in insignificant river water quality improvements compared with current condition. The results clearly show that providing desirable water quality conditions in Gheshlagh River in an equitable manner is rarely accessible.

Figure 5(a) depicts the multi-pollutant removal rates of municipal/rural WWTP units in the scenarios with the best criteria values (extreme scenarios) of an optimal MPWLA problem. In the extreme scenarios, the scenario with the best *EquityMeasure* refers to a scenario with the least *EquityMeasure* value. In this option, pollutant removal rates for all dischargers are proportional to their waste mass effluents. As an extreme scenario, this solution is achieved without any concern on WQI and economic measure. The extreme scenario with the best water quality measure (Maximum WQI), where enhancement in water quality is the only objective of concern, and the best economic scenario is the alternative with the least economic costs in which the low pollutant removal rates are allocated to the discharge units without focusing on *EquityMeasure* and/or WQI.

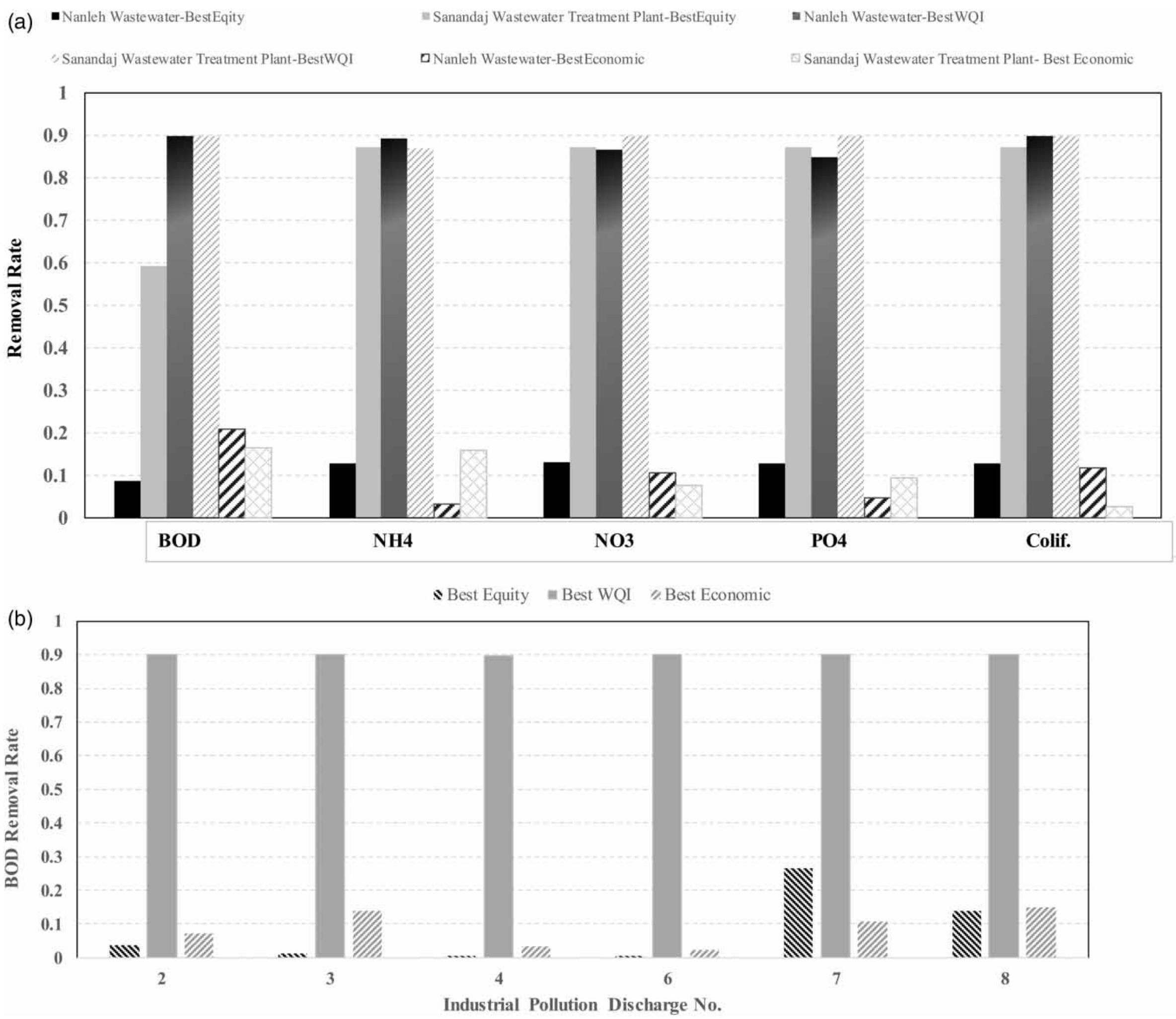

Figure 5 | (a) Multi-pollutant removal rates in municipal/rural WWTP; (b) BOD removal rates of industrial pollutant units in the extreme scenarios of optimal MPWLA program in Gheshlagh River.

The results indicate that in the scenario with the best *EquityMeasure*, higher waste removal rates have been allocated to Sanandaj WWTP effluent compared with Nanleh WWTP. This is due to the greater effects of Sanandaj WWTP effluent on Gheshlagh River pollution through its higher waste load contributions. In contrast, in the best economic scenario lower removal rates have often been allocated to Sanandaj WWTP effluent compared with Nanleh WWTP and the limited exceptions are due to PO_4 and NH_4 ignorable concentrations in municipal sewages. In the scenario with the best WQI value, the multi-pollutant removal rates have often been adjusted to the corresponding upper bounds in order to reduce the waste influents of various point sources as much as possible. The removal rates of BOD in various industrial pollutant units along Gheshlagh River are presented in Figure 5(b). The greater contribution of pollutant point source No. 7 in river contamination resulted in more BOD removal allocation to this source in the scenario with the best *EquityMeasure*. More detailed study on the water quality model and data indicates that pollutant units No. 4 and 6 have slight contributions on Gheshlagh River contamination compared with other pollutant point sources.

Variation of WQI along Gheshlagh River at various monitoring stations is presented in Figure 6. As presented, for the current scenario, the WQI decreases along the river with a minimum of 0.0015 at monitoring station No. 5. This quality deterioration is clearly attributed to the existing background condition and pollutant loads received from the upstream parts of the river. In the scenario with the best WQI value, the highest WQI value of 0.26 is observed at station No. 4. For this scenario, the WQI ranges from 0.13 to 0.26. Spatial variations of the WQI for the economic scenario are also presented in Figure 6. As expected, this does not significantly enhance the water quality of the river, however, minor improvement is achieved. For the best water quality scenario selected from the set of identified non-dominated solutions, improvement in WQI in downstream is more pronounced compared with upstream sections. This is due to increase in the flow rates of WWTP in Km 25, increase in the river velocity, pollutant transportations, and higher pollutant removals in the upstream sections of Gheshlagh River through enhancing the treatment processes in WWTP. The results (Figure 6) indicate that water quality status has been improved in the optimal MPWLA scenarios (members of Pareto front) in comparison with the current scenario in the river. Figure 6 illustrates the Pareto front of the MPWLA problem lead to water quality responses between the best WQI scenario and the least cost and/or best *EquityMeasure* scenarios. In the other words, the water quality responses of Gheshlagh River in the selected MPWLA program (scenario defined based on selected member of Pareto front) is more favorable than the economic and/or equitable MPWLA program, and less suitable compared with the best WQI scenario.

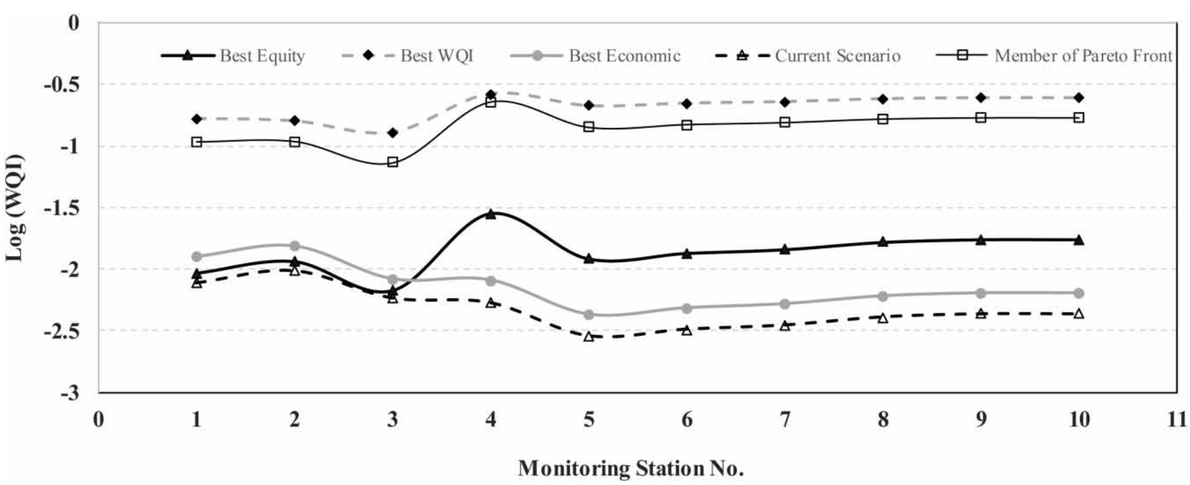

Figure 6 | Log (WQI) values along Gheshlagh River in the extreme desirable scenarios and scenario according to the random selected member of Pareto front compared with the existing condition.

Higher pollutant removal allocations to the pollutant sources with higher contributions in Gheshlagh River contamination processes in the best *EquityMeasure* scenario lead to water quality enhancement in downstream river sections particularly when compared with the current scenario (Figure 6).

Figure 7 compares the DO concentrations along Gheshlagh River in scenarios with the best value in each objective value (management scenarios) and a member of Pareto front with that of the existing condition. DO concentration for the solution with the best WQI from the set of non-dominated solutions shows significant improvement compared wih the initial existing condition. As expected, the DO concentration in the scenario corresponding to the selected member of the Pareto front ranges between the water quality responses of the best WQI scenario and the least cost and/or the best *EquityMeasure* scenarios. Similar results are available from the corresponding author for other water quality parameters such as BOD, NO_3-N, NH_4-N, PO-P, Coliform, TSS, and COD in various management scenarios.

CONCLUDING REMARKS

To obtain useful, equal, and sustainable water management, it is necessary to consider water quality alongside water quantity. WLA program, in general, is a water quality management approach addressing economic, social, and environmental criteria. In this study, optimal MPWLA programs have been developed in S-O framework. QUAL2Kw was coupled to AMOSA optimization algorithm to derive optimal removal of various pollutants in eight discharge units along Gheshlagh River, Kordestan, Iran. Pollutants such as BOD, COD, TSS, NH_4-N, NO_3-N, PO_4-P, and Coliform have been considered in WWTP design and cost estimation in CapdetWorks software. Minimizing construction, operating and maintenance costs of WWTP, minimizing inequity measure, and maximizing the average of WQI in ten monitoring stations along Gheshlagh River have been defined as objective functions in the MPWLA problem. WQI integrates various water quality parameters such as BOD, DO, TSS, NH_4-N, NO_3-N, PO_4-P, and Coliform in each checkpoint along the river. The results have demonstrated that the developed AMOSA algorithm coupled with QUAL2Kw could efficiently incorporate the expectations and conflicting objectives, and provide various suitable solutions to support decision makers.

To continue research in this area in future, it is necessary to consider non-point source pollutions (agriculture drainages, urban runoff, etc.) along with the point source pollution in deriving optimal MPWLA programs. Furthermore, deriving optimal MPWLA programs for other water bodies such as wetlands, reservoir, and/or the combinations of different water bodies (river-reservoir (-river), river-wetland, etc.) could be the subject of future research. Also, the use of multi-criteria decision-making techniques or game theories can assist managers and decision makers involved in the water quality management field in selecting

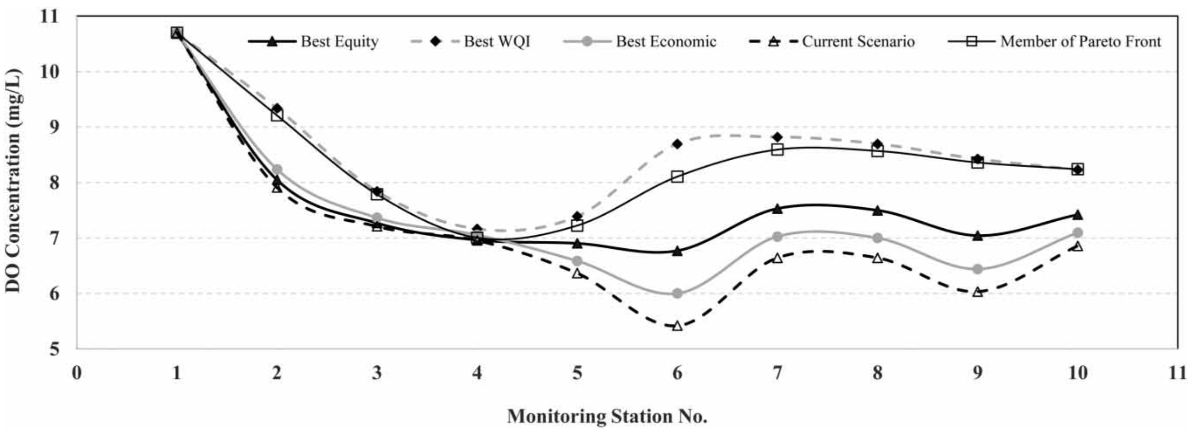

Figure 7 | DO concentration along Gheshlagh River in the existing scenario, the extreme desirable scenarios, and scenario according to the random selected member of Pareto front of MPWLA problem.

the preferred alternative in the Pareto front derived with the AMOSA algorithm. The studies on the uncertainties due to water quality model parameters and/or natural variables (Maier *et al.* 2001) caused by the climate change and/or change in reservoir operating policies could be suggested for further future research. The uncertainty analysis on indices such as reliability, vulnerability, and resilience of the developed MPWLA program can provide proper insights for environmental managers, decision makers, and policy makers. The comprehensive studies on the interactions between various water quality parameters in wastewater treatment processes in each pollutant unit are recommended for further studies.

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