Optimal utilization of groundwater resources and artificial recharge system of Shahriar Plain aquifer, Iran

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Abstract

Developments in agriculture, industry, population growth and climate change lead to increased exploitation of groundwater resources and cause qualitative and quantitative problems in aquifers. Accordingly, the objective of this study was to investigate the impact of optimal groundwater utilization and artificial recharge systems on the Shahriar Plain aquifer. In our study, a multi-objective modeling platform was developed that included two independent simulator-optimizer models. In the first model, the artificial neural network (ANN) was used to simulate the changes of groundwater level (GWL) and its quality as a function of the TDS index in the Shahriar Plain aquifer. The regression was then used to predict groundwater quality. Finally, the multi-objective genetic algorithm (NSGA-II) was used to optimize groundwater resources harvesting. The second model simulated the flood storage volume in the reservoirs of the artificial recharge system (ARS) using ANN and then optimized utilization of the artificial recharge system using (NSGA-II). The results of the first model showed that the optimal volume of water withdrawn from the aquifer and the optimal TDS value of the aquifer decreased by 29 and 18%, respectively, while the changes of the optimal groundwater level increased by 28 m. Furthermore, based on the second model results, the total volume of optimal recharge will increase by 119% in the studied period due to the artificial recharge system, followed by a 14% increase in the changes of the optimal groundwater level. Overall, it can be concluded that the multi-objective modeling platform method can support multiple factors simultaneously.

Introduction

Domestic water, industry, and agriculture have always depended on groundwater. Due to environmental conditions, these resources are generally of good quality and in certain cases form the basis for meeting water needs. In addition, floods irreparably damage the environment, but by collecting runoff water, this temporary water supply can be properly utilized. Due to excessive use of groundwater today, this resource is declining and becoming limited to an extent that continues to have unfortunate consequences. For the development and rehabilitation of groundwater resources, flood control and utilization can be effective solutions. In addition, an artificial recharge system reduces environmental problems in the related areas (Zahng et al., 2015). Arid regions with high rainfall intensity and low infiltration and groundwater recharge are generally suitable for the introduction of artificial recharge systems (Makkawi 2015; Xu et al., 2014). In light of this, modeling studies have been conducted to determine the surface runoff volume for artificial recharge systems and to identify the most suitable locations for project implementation (Ringleb et al., 2016).

Therefore, it is necessary to ensure efficient planning and appropriate management to maximize the water potential of the plains and artificial recharge systems. Also, it seems essential to simulate and optimize groundwater levels, groundwater quality, and artificial recharge systems in the plains. While physical and mathematical models are useful for understanding hydrogeologic variables and processes in a system, they have cost and time constraints. Thereby, in some cases, it is necessary to use intelligent and nonlinear models instead of numerical and physical models (Rajaee et al., 2019). Artificial neural

networks can be used to understand weak hydrological relationships. In other words, not only are they a powerful and suitable method for data analysis, but they can also recognize patterns and hidden relationships in the data and educate themselves, and by increasing their information, they can make appropriate predictions (Banerjee et al., 2011). In addition, these models can be used in groundwater management strategies because of their high predictive power (Coppola et al.,2005).

Moasheri et al., (2013) used a geostatistical method combined with ANN optimized by a genetic algorithm to estimate the spatial distribution of groundwater quality parameters in the Kashan Plain. The results showed the accurate performance of the combined approach optimized by genetic algorithm to estimate the studied quality parameters such that the values of sodium, calcium, and magnesium were estimated with 99, 99, and 98% coefficients, respectively. Sreekanth and Datta (2010) investigated multi-objective management strategies for saltwater infiltration into coastal aquifers. In this study, an approach based on combining two models of alternative modular neural networks (MNN) and (GP) with the algorithm (NSGA-II) was used. This study found that the GP model is less uncertain than the MNN models. This model (GP) is also more suitable for solving multi-objective optimization problems using the comparative search space. To solve the monthly irrigation water source of Najafabad plain of Isfahan, Safavi and Enteshari (2016) presented a simulator-optimizer model based on artificial neural networks and ant optimization algorithm. According to the results, the simulator model can predict the behavior of the aquifer, and the simulator-optimizer model can determine how much water needs to be extracted. This not only reduces the current water deficit but also improves the condition of the aquifer.

In another study, Safavi and Esmikhani (2013) studied the combined use of surface and groundwater resources using support vector machines and genetic algorithms in the Zayandehrud Basin. They used an integrated model to minimize water scarcity in the four agricultural areas studied. In the southern part of Tehran, Karamouz et al., (2007) studied the combined use of surface and groundwater considering water quality. Genetic algorithms and artificial neural networks were used to obtain an acceptable quality of water consumption, reduce pumping costs, and control changes in groundwater levels as an objective function. The results showed the importance of a comprehensive approach to allocating surface and groundwater resources in the studied area. A surface water-groundwater model (SW-GW) was developed by Dehghanipour et al., (2019) for the Miandoab water plain in the Urmia Basin in northwestern Iran. Simulators (MODFLOW) and (WEAP) were used to implement this model. The results showed that the water demand of the plants could not be met during the drought due to the limited pumping capacity. Also, increased pumping had a relatively strong impact on the water table caused by the low specific efficiency of the aquifer. Alaviani et al., (2018) presented a simulator optimization model using the GMS model and the particle swarm algorithm for the integrated exploitation of surface water, groundwater, and wastewater. Based on the results, the best way to manage water resources to prevent overharvesting is to use all available water sources (surface water, groundwater, and wastewater) in each area. Dehghanipour et al., (2020) developed management strategies for the Miandoab watershed upstream of Lake Andorhik in Urmia using a new simulation-optimization approach (SO). This study demonstrated the usefulness and flexibility of this method to identify a wide range of potential water management strategies in complex Andorhik watersheds, such as Lake Urmia.

Khatiri et al., (2020) used the hydrologic model of SWAT to determine nutrient values and entered them into the MODFLOW model to simulate the quantitative and qualitative characteristics of the studied aquifer. They also used the DREAM (zs) algorithm to check the uncertainty of the model parameters (MODFLOW). Furthermore, they estimated the optimal head and total dissolved solids (TDS) by combining the model and algorithm of MOPSO. It was found that the amount of water extracted from the study area is about 540 (MCM) per year, which reaches 395 (MCM) per year. Chakraei et al., (2021) optimized the criteria of fuzzy stability and normal supply shortage compared to demand using the Water Evaluation and Planning System (WEAP) model and the multi-objective optimization algorithm (NSGA-II). Reservoir stability was increased by 37% and aquifer stability by up to 16%. Elhamian et al., (2021) simulated the Nobandegan aquifer using a model of GMS and an ANN. Then, by combining a valid neural network with a multi-objective optimization model, they determined the optimal Pareto front. According to the results, the annual decline in water level decreased by 68% compared to the similar reductions observed in the plain, while the quality values improved compared to the observed ones. In another study, Ranjbar and Mahjouri (2020) used a simulator optimizator model, a modular evolutionary polynomial regression model, and information gap theory to investigate the robustness of optimization scenarios involving uncertainties in the hydraulic conductivity of heterogeneous aquifers. They concluded that the proposed method can provide a reliable management scenario with a relatively low computational cost. Rezaei et al., (2017) presented a new algorithm called fuzzy multi-purpose particle swarm optimization to improve surface and groundwater management and estimated water demand with almost minimal monthly and cumulative changes in groundwater level. By determining the optimal water demand based on changes in the groundwater table, their research showed that the algorithm is capable of providing a unique optimal solution to facilitate decisions to solve large-scale optimization problems.

Mohammadi and Motaghian (2011) considered reservoir utilization and output hydrograph of the reservoir as a suitable solution to reduce flood damages. In river- reservoir systems of Dez and Bakhtiari dams and simulation of past floods and hydrographs entering the reservoirs with different return periods, the amount of flood damage was calculated by determining its zone using the hydraulic model and determining the uses in the flooded plain. Then, the reservoir hydrograph was optimized by defining flood damage as a damage function in the short-term reservoir utilization model by minimizing the damage downstream. Kawo et al., (2018) presented an optimization-simulation approach to optimize the artificial pumping and charging system for the water supply of Cebu, Philippines. According to the stability condition optimization results, the optimal total harvest rate was 38 m^3 per day, while the artificial charge increased to 29313 m^3 per day. When the overflow height was increased by 1 and 2 m, the results of the transient optimization demonstrated that the average of the total optimal pumping rate increased to 39 and 40 m^3 per day, respectively. Ebrahim et al., (2016) studied the highest recharge and withdrawal rate from the nearshore aquifer in Oman using a simulator (SLP) and a multi-objective genetic algorithm (NSGA-II). According to this model, the total water volume for four months of recharge without return flow in most cases, the total water volume for four months of recharge and eight months of return flow, and the total water yield at return flow were 106× 6 m^3, 106×5.3 m^3, and about 66%, respectively.

To date, there have been numerous studies investigating artificial recharge systems to manage aquifer recharge in different regions, such as the northwestern Himalayas in India (Jasrotia et al., 2019), the Gorbayegan Basin in Iran (Rahimi et al.,, 2014), arid and semi-arid regions in Iran (Hashemi et al.,, 2015), downstream of the Trim River in northwestern China (Liu et al.,, 2021), a region in northern Italy (Masetti et al., 2016), a region in southern India (Aju et al., 2021), Wadi al-Arab Wolfield in Jordan (Alkatib et al., 2021), region in China (Jiang et al.,, 2021), Meymand and Tangriz dams area in southern Iran (Mohammad-Zadeh-Habili & Khalili 2020), Mirzapur region in Uttar Pradesh, India (Dhanaraj, 2021), Ghamrasen region in southern Tunisia (Yahiaoui et al., 2021), Shiraz catchment in Iran (Mokarram et al., 2020), Hamirpour region in northern India (Kumari et al.,, 2021).

All of these researches focused on artificial recharge systems to improve aquifer conditions. Until now, meta-heuristic algorithms and simulation models have been used in various studies to optimize the use of water resources. While, this study aimed to develop a multi-objective modeling platform consisting of two simulator-optimizer models for optimal use of groundwater resources and artificial recharge systems to increase the stability of groundwater resources and reduce quantitative, qualitative, and ecological issues.

Materials And Methods

Study area

The present study was conducted on the Shahriar Plain (50° 22'14"- 51° 22' 02" E and 35° 44' 32"- 35° 02' 25" N), located on the western edge of Tehran with an approximate area of 897 km^2 (Fig. 1). An artificial drainage system was developed in the north of the study area and installed in the alluvial fan. It consisted of five consecutive recharge reservoirs that were located along the longitudinal axis of the river with a capacity of about 3.2 (MCM). In the past, the Karaj River in this area was composed of two tributaries, the Karaj and the Shadchay Rivers. Currently, this river flows from above into the Bilghan Diversion Dam meeting Tehran and Karaj's domestic water supply and agriculture. It then flows into the Shahriar study area. In addition, floodwater flows downstream from the Bilghan Diversion Dam, entering the alluvial fan and artificial recharge system. Surface and groundwater resources are used by agriculture, while only groundwater is used by domestic water supply and industry in the study area. The volume of groundwater resources harvesting was calculated using data from withdrawal wells. In addition, Tables 1 and 2showed the withdrawal volumes from surface and groundwater sources during the desired period. Each survey was based on a monthly period covering the three water years 2014–2016.

Table 1
The volume of the Karaj River flow in the Bilghan diversion dam (MCM)

Condition of Karaj River flow	Water year		
	2014	2015	2016
Sum of Bilghan	581	385	304
Flood of Bilghan	22	13	8
Inflow from Bilghan to Shahriar	78	52	41
Consumption of Tehran and Karaj city	481	320	255

Table 2
Exploitation volume of groundwater resources in the study period (MCM)

Water year	part of consumption			Total
	Agriculture	Domestic	Industry	
2014	502	193	50	745
2015	514	190	48	752
2016	525	208	52	785

In the desired artificial recharge plan, the overflows were built of concrete and rubble with reinforced concrete and ogee weir. Figure 1 illustrated the location of the study area and the artificial recharge system. Due to the location of this system, there are large sand holes downstream, located at the end of the alluvial fan. In this study, a multi-objective modeling platform with two simulator-optimizer models was presented to optimize water use and artificial recharge. Thus, the study provided innovative strategies to improve the use of groundwater resources and to support changes in groundwater quality considering changes of groundwater level in the study area. Based on the defined objectives and constraints, these points can be generalized to other studies. The first model, which uses the multi-objective modeling platform in this study, determined the optimal groundwater resource utilization policy and included ANN, regression, and multi-objective genetic algorithms (ANN-R-NSGA-II). The second model also determined the optimal use of the artificial recharge system that was the same as the first model except that it did not include the regression model and was (ANN-NSGA-II).

Quantitative-qualitative modeling of groundwater using ANN

In the first model, the artificial neural network of Perceptron was used to calculate groundwater level changes. In this way, groundwater inflow and outflow volume data at the boundaries of the study area, surface recharge, and groundwater discharge through withdrawal wells were considered as input variables (MCM), while groundwater level changes were considered as output values (m). Thus, the neural network had four input vectors and one output vector. Since the input of data in primary form

reduces the accuracy and speed of the network, the data were preprocessed when training the network before calculation and analysis. After analyzing the changes in the water table, four layers, including an input layer, two hidden layers, and an output layer, were considered for designing the network. The input layer contained an input data vector, as well as the first hidden layer with 5 neurons, the second hidden layer with 10 neurons, and the output layer with 1 neuron. Moreover, the Tansig transfer function was used for the first and second hidden layers, whereas the Purelin transfer function was used for the output layer. Moreover, the newff network was used to encode the desired neural network in the first model. Then, the data were divided into three categories to assign them to the training, validation, and testing phases. Depending on the question, 70%, 15%, and the remaining 15% were assigned to the training phase, validation phase, the testing phase, respectively. The network was trained using the Levenberg-Marquardt algorithm.

For qualitative modeling using ANN, the changes of groundwater level were used as input, while the TDS value ($mg.L^{-1}$) was considered as output. Since the qualitative values of the aquifer were directly affected by the quantitative values of the aquifer, quantitative data at the input of the neural network were used in this analysis. The neural network quality model was designed similarly to the neural network model for groundwater level changes. In the first model, TDS in groundwater were predicted by regression after the change in groundwater level and its TDS in were simulated by ANN. The qualitative regression model was calculated using SPSS software. Finally, the changes of groundwater level derived from the neural network and the TDS in groundwater derived from the regression were input to the optimization model. In the first model, the optimization objectives included minimizing the average ratio of groundwater level changes to the maximum groundwater level, and also, minimizing the average ratio of groundwater quality (TDS) to maximum groundwater quality (TDS). Domestic, industrial, and agricultural water withdrawal rates were considered an important and effective means of changing groundwater levels and groundwater quality in this model.

Artificial recharge system modeling

The artificial recharge system in the second model included the river and the artificial recharge system. A multilayer perceptron artificial neural network model (ANN-MLP) was used to calculate the flood volume stored in the reservoirs of the artificial enrichment system. The inputs were the floodwater infiltration data into the reservoirs, the inflow and outflow floodwater volume to the recharge system, while the outputs were the volume of floodwater stored in the reservoirs of the artificial recharge system. We estimated one input layer, two hidden layers, and one output layer to design the network. There were 5 neurons in the input hidden layer, 8 neurons in the second hidden layer, and 1 neuron in the output layer. A neural network (newff) was also included in this model. The Tansig transfer function was used for the first and second hidden layers, whereas the Purelin transfer function was used for the output layer. Also, 70% of the data was assigned for the training layer, 20% for the validation layer, and 10% for the testing layer. We investigated the effects of the first simulator-optimizer model on changes in groundwater quality (TDS) by determining the optimal strategy for groundwater resources exploitation.

For the second model, the volume of floodwater storage in the artificial recharge system tanks was input into the algorithm calculations along with other data. The optimization objectives in developing the second model included maximizing the recharge volume of the associated system and minimizing the changes in the level caused by the artificial recharge system. In addition, aquifer remediation and environmental issues of groundwater were considered in this model. In this study, based on the current conditions of the study area, constraints were placed on the allocation of surface water resources for the artificial recharge system, the optimal infiltration volume, and the change in optimal water levels due to artificial recharge. Furthermore, the allocation of surface resources prioritized agricultural supply and agricultural consumption before allocation to the recharge system. This model analyzed the effects of artificial recharge on changes in groundwater levels. Furthermore, the aquifer was extensively estimated to calculate the desired targets. Figure 2 depicted the algorithm for the computational process of the multi-objective modeling platform.

Optimization model structure

Based on equations (1) to (11), we developed the first optimization model (quantitative and qualitative changes of the aquifer). Equations (12) to (26) similarly represent the structure of the second model (modelling of artificial recharge).

$$Z_1 = \text{Minimize}\left(\frac{\sum_t^{nt}(\text{wtct})}{(\Delta L_{MAX} \times m \times y)}\right) + \text{penalty function} \quad (1)$$

$$\text{penalty function} = ((GWQ_{max})^2 \times \alpha) + ((GWQ_{min})^2 \times \beta) + ((WT_{max})^2 \times \gamma) \quad (2)$$

$$GWQ_{max} = \begin{cases} \text{if} & Q - Q_{max} \leq 0 \quad , \quad 0 \\ \text{else} & Q - Q_{max} \end{cases} \quad (3)$$

$$GWQ_{min} = \begin{cases} \text{if} & Q - Q_{min} \geq 0 \quad , \quad 0 \\ \text{else} & Q - Q_{min} \end{cases} \quad (4)$$

$$\text{wtcp} = \frac{Q - Q_P}{A \times S_y} \quad (5)$$

$$\text{wtct} = \begin{cases} \text{if} & \text{wtc} \leq 0 \quad \text{wtcp} < 0 \quad , \quad \text{wtc} + |\text{wtcp}| \\ \text{elseif} & \text{wtc} \leq 0 \quad \text{wtcp} > 0 \quad , \quad \text{wtc} - \text{wtcp} \\ \text{elseif} & \text{wtc} > 0 \quad \text{wtcp} \leq 0 \quad , \quad \text{wtc} + |\text{wtcp}| \\ \text{elseif} & \text{wtc} > 0 \quad \text{wtcp} > 0 \quad , \quad \text{wtc} - \text{wtcp} \end{cases} \quad (6)$$

$$WTmax = \begin{cases} \text{if} & |wtct| - \Delta L_{MAX} \leq 0 \quad , \quad 0 \\ \text{else} & |wtct| - \Delta L_{MAX} \end{cases} \quad (7)$$

$$Z_2 = \text{Minimize } \left(\frac{\sum_t^{nt}(RC)}{(C_{sta} \times m \times y)}\right) + \text{penalty function} \quad (8)$$

$$\text{penalty function} = ((Rqs)^2 \times \omega) \quad (9)$$

$$RC = 243.729 + (6.502 \times Q) \quad (10)$$

$$Rqs = \begin{cases} \text{if} & RC - C_{sta} \leq 0 \quad , \quad 0 \\ \text{else} & RC - C_{sta} \end{cases} \quad (11)$$

$$Z_1 = \text{Maximize } \sum_t^{nt}(R_{rech} - \text{penalty function}) \quad (12)$$

$$R_{rech} = ((Vsa) + (Vrbi) + (Voutput) + (Vri) + (Vinf)) \quad (13)$$

$$\text{penalty function} = \left(\left(V_{shb}\right)^2 \times \alpha\right) + \left(\left(Q_{pm}\right)^2 \times \beta\right) + \left(\left(Q_{bm}\right)^2 \times \gamma\right) \quad (14)$$

$$V_{input} = Vrit - Vri \quad (15)$$

$$V_{output} = V_{input} - (Vinf + Vsa) \quad (16)$$

$$shr = \begin{cases} \text{if} & V_{bar} - V_{sa} < 0 \quad , \quad V_{bar} - V_{sa} \\ \text{else} & V_{bar} - V_{sa} = 0 \quad , \quad 0 \end{cases} \quad (17)$$

$$Qm = \begin{cases} \text{if} & Q_{bi} - Q_{agr} \leq 0 \quad , \quad 0 \\ \text{else} & Q_{bi} - Q_{agr} \end{cases} \quad (18)$$

$$Vrbi = \begin{cases} \text{if} & Q_m - shr \leq 0 \quad , \quad Qm \\ \text{else} & shr \end{cases} \quad (19)$$

$$Vshb = \begin{cases} \text{if} & (Vrbi + Vsa) - Vbar \leq 0 \quad , \quad 0 \\ \text{else} & (Vrbi + Vsa) - Vbar \end{cases} \quad (20)$$

$$Qpm = \begin{cases} \text{if} & Q_m = 0 \quad , \quad Q_{agr} \\ \text{else} & 0 \end{cases} \quad (21)$$

$$Qbm=\begin{cases} \text{if} & Q_m\text{-}Q_{max} \leq 0 \quad , \quad 0 \\ \text{else} & Q_{bi}\text{-}Q_{max} \end{cases} \quad (22)$$

$$Z_2=\text{Minimize } \sum_t^{nt}(\text{wrchb+ Penalty function}) \quad (23)$$

$$\text{wrchb}= \left(\frac{\left((|\text{input-output}|) + \left(R_{ra+}R_{con}+R_{ri}+R_{rech} \right) - (w) \right)}{A \times S_y} \right) \quad (24)$$

$$\text{penalty function} = \left(\left(\text{rchs} \right)^2 \times \lambda \right) \quad (25)$$

$$\text{rchs}=\begin{cases} \text{if} & |\text{wrchb}| - \Delta L_{MAX} \leq 0 \quad , \quad 0 \\ \text{else} & |\text{wrchb}| - \Delta L_{MAX} \end{cases} \quad (26)$$

Calculation of optimal groundwater level changes in the first model

Based on Eq. (1), the first objective function for the first model was defined. Q-value was the volume of groundwater use (MCM) and the decision variable. Also, ΔL_{MAX} was the maximum allowable groundwater level change (m), m and y were the months and years number, respectively. In this study, the maximum allowable groundwater level change ΔL_{MAX} was set at 0.04 m per month based on monthly and annual statistics and data on groundwater level changes and aquifer conditions. Numerous studies have used the maximum allowable groundwater level change as a limiting factor, the amount of which varies depending on the study conditions. Tabari and Yazdi (2014) considered a maximum allowable groundwater level change of 0.05 m per month in a study of the combined use of surface and groundwater resources using an inter-basin water transfer approach. According to Sadeghi-Tabas et al., (2017), they studied sustainable groundwater modeling using single- and multi-objective optimization algorithms considering the maximum change in groundwater level of 0.40 m per year.

In these calculations, Q was the volume of optimal groundwater use in the domestic, industrial, and agricultural sectors, and Q_p was the volume of current groundwater use. In penalty function equations, when the maximum and minimum volume limits (GWQ_{max} and GWQ_{min}) and maximum groundwater level changes (WT_{max}) were not met, their penalty values were calculated by the penalty function and added to the objective function. The maximum groundwater consumption (Q_{max}) was equal to the current level, while the minimum groundwater consumption (Q_{min}) was estimated to be 60% of the current level.

Based on the resources and exploitation of the study area, a minimum volume for harvesting was calculated. The value of WT_{max} was calculated to estimate the optimal groundwater level change (wtct) as the maximum allowable groundwater level change or less than it. Otherwise, a penalty equal to the same difference was imposed according to the WT_{max} equations. To impose fewer penalties, the

algorithm also attempts to estimate the optimal level changes as much as or less than the maximum allowable balance changes.

The optimal water table of wtct was calculated by using the values and sign of the water height equal to the optimal withdrawal volume of wtcp and the changes in water table resulting from the estimation of the neural network of wtc. If the optimal withdrawal amount in the wtcp equation was less, greater that, or equal to the current withdrawal amount, the response of the equation was calculated as negative, positive, or zero, respectively. Moreover, if the changes in the water table calculated from the desired equation were positive, the level changes resulting from the optimal withdrawal quantity also decrease. Whereas, when the value was negative, the level changes increased. Therefore, the changes in the optimal groundwater level under these conditions were calculated according to Eq. (6). The constant coefficients α and β and γ were 10 and 10,000 in the first penalty function.

Determination of the standard concentration of total dissolved solids (TDS)

According to World Health Organization (WHO), the standard TDS concentration for domestic use is 1000 (mg. L^{-1}). Based on the Food and Agriculture Organization (FAO), the same parameter for agricultural use is between 450 and 2000 (mg. L^{-1}), which is suitable for low to moderate restrictions. In addition, according to Iranian standards, the quality of TDS for industrial use should be less than 1000 (mg. L^{-1}), as medium quality. This grade allows its use in industrial processes with the lowest sensitivity, and with or without refining. Therefore, based on the quantitative and qualitative conditions of groundwater resources in the study area and the objectives of the optimization model, a TDS value of 1000 (mg. L^{-1}) was set as the standard for the optimization of groundwater.

Total dissolved solids (TDS) optimization

Equations (8) through (11) were used to describe the second target function and constraints for qualitative optimization of the aquifer. According to Eq. (8), z_2 was the second objective function. In addition, C_{sta} was the groundwater quality standard (TDS). The penalty function represents the penalty amount added to the second target function when the groundwater quality was not equal to or less than the standard value. In the second penalty function, the constant coefficient ω was set equal to 1000. Figure 3 illustrated the optimization structure of the first model.

In this model, the variable of decision was the volume of groundwater consumption (Q) for each month and for the three years 2014 to 2016. There were 36 variables for decision. Furthermore, the chromosome population size in the study was set to 200 and the number of replications was set to 1000. To determine the population size of chromosomes, the algorithm was run with four populations of 100, 200, 300, and 400 and each population with 400 replications. Ultimately, the optimal population was chosen based on the results of each run.

Optimization of the artificial recharge volume

In the second model, the first target function and the corresponding penalty function were presented according to equations (12) and (14). R_{rech} as the optimal recharge volume by the artificial recharge system (both artificial recharge system and river), including V_{sa} flood storage volume, allocation of surface water resources according to the volume of reservoirs and available water (V_{rbi}), discharge volume of V_{output} recharge system, infiltration volume in the river (V_{ri}), the volume of flood infiltration in the reservoirs (V_{inf}). The unit volume of all water resources was one (MCM), both in monthly and water years from 2014 to 2016. The constant coefficients α, β, and γ in the first penalty function were assumed to be 100. The flood storage volume V_{sa} was simulated and analyzed using ANN for algorithm calculations. The total volume of inflow to the river (V_{rit}), the volume of recharge reservoirs V_{bar}, the volume of water entering from Bilghan to Shahriar (Q_{bi}), the volume of agricultural use Q_{agr}. The reason for the V_{shb} penalty is that the surface water of Bilghan and the flood water stored in the recharge system does not exceed the volume of artificial recharge reservoirs in the system. Furthermore, based on the amount of surface water in Bilghan and downstream agricultural use, the water volume should be allocated to the recharge system and the algorithm should not exceed this limit.

In the above relationships, the decision variable was the volume of water flowing from Bilghan to Shahriar (Q_{bi}). In shr relations, if the volume of the reservoirs was less than the volume of the flood storage simulated by the neural network, and the response to the equation was also greater than zero, the amount of storage or lack of water in the reservoirs is equal to the difference between the volume of the flood storage and the volume of the reservoirs. However, if the volume of the reservoirs were equal to the flood storage volume and the answer to the equation was zero, there would be no shortage of water in the reservoirs during the flooded months. In other words, its volume is calculated to be zero. During the non-flooded months, there will be a shortage of water in the reservoirs as much as their volume. Thus, the shortage of water for artificial recharge depends on the amount of water in the flooded and non-flooded months as well the volume of the reservoirs in the recharge system. Because the volume of outflowing floodwaters from the output recharge system enters the large sand holes at the end of the alluvial fan after leaving the artificial recharge system and entering the aquifer, they were estimated to be recharge from the outlet section of the artificial recharge system in the total recharge volume.

Calculation of optimal level changes by the artificial recharge system

Z_2 represented the second target function, while Eq. (25) represented the penalty for non-observance of the maximum groundwater level changes. To calculate the changes of groundwater level changes, the value of wrchb was calculated as Eq. (24), where input and output are the groundwater inlet and outlet volumes at the boundaries of the domain, R_{ra} was infiltration volume from precipitation, R_{con} was the infiltration volume from domestic water, industry, and agriculture, R_{ri} was the infiltration volume by the river, W was the consumption volume by withdrawal wells, A was the area of the aquifer (km^2), and S_y was the special discharge (dimensionless). The constant-coefficient in the second penalty function (λ) was 1000. wrchb was calculated in (m). In the model, the maximum allowable changes of groundwater

level ΔL_{MAX} according to the artificial recharge system, range, and aquifer conditions was 0.04 m per month.

The level changes resulting from the optimal recharge volume and then calculating the associated limitation were minimized to optimize the recharge volume is optimized in accordance with the available water resources and the level changes during the month. This results in a relatively small increase in level changes. Therefore, some places in the Shahriar plain will not be ponded water, and there will always be space for artificial recharge in the soil layers. Therefore, permanent recharge is possible. In addition, in this case, the planning of groundwater and different uses, especially agricultural use, are more suitable and the behavior of the aquifer is predictable at an acceptable level. Therefore, groundwater level changes are calculated and optimized based on this issue.

During the artificial recharge period, the decision variable for each month was the volume of inflow water from Bilghan to Shahriar, resulting in 36 decision variables for 3 years. Chromosome population sizes were calculated in this model as in the first one. The calculations estimated the number of chromosomes to be 400 and the number of replicates to be 1000. Figure 4 showed the optimization structure of the second model.

Results And Discussion

Allocation of optimal exploitation volume of groundwater resources

In this research, according to the intended objectives, the Pareto-optimal front was discovered and the best optimal responses were determined. In addition, the optimal extraction volume was determined based on the problem's objectives and the limits of changes of groundwater level and groundwater quality and was proportional to the changes of groundwater level and quality. Therefore, changes in the water table play an important role in determining the optimal exploitation volume. Figure 5 depicted the changes between the current groundwater consumption and the optimal groundwater consumption in the study area and over time. Based on the results, the optimal consumption volume of the domestic, industrial, and agricultural sectors totaled 1602 (MCM) in water years 2014, 2015, and 2016, which was 658 (MCM) less than the current exploitation volume. In addition, the optimal volume of the aquifer was 534 (MCM) per year, which was 29% less than the average volume of the current harvesting.

The priority in this study was to first allocated to domestic and industrial sectors and then the agricultural sector. Thus, based on the conditions of resources and consumption in the study area, reduced consumption can be applied to the agricultural sector. The allocation of the optimal volume of groundwater resources in the study period was shown in Table 3. From the table, it can be seen that the domestic and industrial sectors were fully covered, but the agricultural sector was supplied with only 38% of the surface and groundwater resources on average. This figure has decreased by 26% compared to the current situation. According to Ye et al., (2018), groundwater consumption is reduced by 24%, indicating

that the area under crops in the region should be reduced to increase the proportion of supply needed by the agricultural sector.

Table 3
Optimal allocation of groundwater resources in the study period

water year	Optimal allocation to consumption (mcm)			Total
	Agriculture	Domestic	Industry	
2014	237	230	60	527
2015	242	226	58	526
2016	265	227	57	549

The results of the present study show that, the changes in the optimal groundwater level compared to the changes in the level of the artificial recharge system increased significantly during the period of these studies. This increase can be attributed to a decreased groundwater extraction in various sectors. Similarly, Farhadi et al., (2016) studied the management of groundwater in the Daryan aquifer in Fars Province using the modeling framework (Nash), which includes the MODFLOW simulation model, ANN, and a multi-objective genetic algorithm optimization model (NSGA-II). They found that the extraction of groundwater resources was 58% lower than the current condition and the groundwater level increased by 3 m. Consequently, the optimal exploitation volume significantly affected groundwater level changes that were related to each other.

From the results, the changes of the optimal groundwater level in 2014, 2015, and 2016 were − 0.5 m, 4 m, and 5 m, respectively, while the changes due to artificial recharge systems increased by 9, 9, and 10 m, respectively. The maximum and minimum optimal monthly volumes during the study period were 69 and 21 (MCM) in the water year 2014 and 2015, respectively. In addition, the optimal water table increased by 1 and 0.4 m compared to the neural network estimate, and the range of increase of this variable was the same. Since the harvesting volume changes proportionally to the changes in groundwater level. Therefore, the ranges of variation of the variables in question are also related. This factor causes the optimal level to increase compared to the values determined by the neural network. When the optimal exploitation policy is implemented, the average groundwater level increases by 9 meters per year, thus increasing the stability of the groundwater system.

In addition, Rezaei and Safavi (2020) found that the cumulative decline in groundwater level is significantly reduced throughout the planning period, resulting in the long-term stability of the groundwater while maintaining water efficiency at the surface. Figure 6 illustrated the effect of the optimal consumption volume on changes in the optimal groundwater level in the study area and during the desired period.

The quality value of groundwater (TDS) was within the normal range during the study period, except in April and May of the water year 2014, when it was 1099 and 1020 $mg.L^{-1}$, respectively. In contrast, the

TDS concentration calculated with the neural network was in the standard range for this period. In addition, all the optimal values of the variables studied were calculated and improved below the standard and proportional to the amount consumed.

Table 4 displayed the TDS in the desired period using an artificial and optimal neural network. As a result of the neural network, the qualitative variable was found to be 346 and 467 $mg.L^{-1}$ below the average and standard values for the entire study period. In addition, the average values obtained by the neural network were estimated to be 84 $mg.L^{-1}$ less in 2014, while this parameter was 19 and 64 $mg.L^{-1}$ higher in 2015 and 2016, respectively.

Compared to the estimates of the artificial neural network, the optimal groundwater concentration of the study area decreased by 119, 119 and 125 $mg.L^{-1}$ in 2014, 2015, and 2016, respectively. Since the maximum and minimum volumes of optimal monthly consumption occurred in 2014 and 2015, the maximum and minimum TDS concentrations were 695 and 383 $mg.L^{-1}$, respectively, a decrease of 22 and 12% compared to the current situation. Again Here, the reduction interval of this variable was the same due to its relationship to the volume extracted from the aquifer. This shows that the algorithm was trying to further reduce the months with a higher volume of consumption in the desired period. This results in a lower volume withdrawn from the aquifer, which can be controlled as an important factor influencing the behavior of the aquifer along with changes in the water table and water quality. Figure 7 demonstrated the effects of the optimal consumption rate on the optimal TDS concentration of the groundwater in the study area and during the study period.

Table 4. Total dissolved solids observational of ground water, resulting

Water year	Total dissolved solids (ml/l)		
	Observations	Artificial neural network	Optimal
2014	732	648	529
2015	628	648	529
2016	601	666	541

The volume of surface water in Bilghan (Shahriar plain) was calculated as a decision variable in the study. As this volume of water was allocated downstream in agriculture and the artificial recharge system for the aquifer, the rest was out of reach and flows into the Fashafoyeh dam and its downstream areas. Consequently, the amount of volume allocated downstream of Bilghan should be planned and optimized to be used for artificial recharge and agricultural use, and the rest should be transferred out of range.

Figure 8 illustrated Bilghan's optimal surface water volumes, the optimal allocation of Bilghan surface water volumes to the artificial recharge system, and the optimal volumes of Bilghan surface water monthly. According to this figure, were 0.8 and optimal recharge volumes to the artificial recharge system during the study period. According to this figure, the minimum and maximum optimal volumes of Bilghan

surface water were 0.8 and 14 (MCM) per month Furthermore, the minimum optimal volume allocations of Bilghan surface water were 0 and 3 (MCM) per month. Accordingly, the optimal volume of Bilghan surface water and the allocation of optimal volume averaged 4 and 1 (MCM) per month, respectively.

In calculating the optimal allocation of Bilghan surface water, in addition to the objective functions, other parameters were also calculated, such as the constraints on the optimal volume of Bilghan surface water, the optimal allocation of volume, and the maximum allowable changes in groundwater level, which has an important influence on the determination of this important parameter. Also, the optimal recharge volume plays a key role in determining the optimal level changes, the constraint related to the maximum allowable groundwater level changes, and the optimal recharge and its estimation. Therefore, the optimal level change and recharge volume are closely related. According to this study, the minimum and maximum optimal recharge volumes were zero and 15, respectively, corresponding to an average of 3 (MCM) per month. This parameter also increased by 53 (MCM) compared to the flood recharge. Hao et al., (2018) used an optimization method for the groundwater artificial recharge systems in an alluvial fan in Beijing, China. In terms of recharge rates, they formulated a nonlinear program to maximize the amount of surface water injected into the aquifers under certain constraints and proved that the amount of water fed into the aquifers increased and that the optimal performance of this artificial recharge system resulted in greater recovery of groundwater storage capacity. Therefore, it can be argued that when the artificial recharge systems are used optimally, both recharge and groundwater storage increase.

In this study, the changes in the optimal level resulting from the estimation of the first model were estimated by applying the optimal use of groundwater resources, and the changes in the optimal level resulting from the estimation of the second model were estimated by applying the optimal recharge volume through the river and artificial recharge system. According to Table 5 the optimal level changes resulting from the estimation of the second model were larger than those of the current (manual) level. The consumption of different parts of groundwater resources has a significant impact on reducing the volume of groundwater resources, while the optimal use of surface water resources and artificial recharge systems had reduced the impact of consumption on the aquifer. Due to these conditions, the second model reduced the changes of groundwater level by 14% during the study period. Karamouz et al., (2021) developed a method for assessing artificial groundwater recharge (AGR) that includes non-stationary kriging, numerical modeling, and long-term sustainability of supply and demand. By using this system in the region, they found that groundwater level drawdown was reduced by about 30%. Thus, by implementing measures that promote the optimal operation of artificial recharge systems, not only was groundwater recharge increased but the resilience of the aquifer was also improved.

Table 5
Manual and optimal level changes resulting from the second optimization model

year	Annual Manual level changes	Annual optimal level changes	difference between the optimal and manual annual level changes
2014	-10	-9	1
2015	-5	-4	0.9
2016	-4	-4	0.7

Since the amount of consumption of the different sectors of the groundwater resources did not significantly affect the amount of groundwater and the groundwater table, the exploitation of the aquifer was optimized. Therefore, the first optimization model was considered as a backup for the second optimization model. This is because the first model optimizes groundwater extraction, while the second model optimizes artificial recharge. Accordingly, the first model neutralizes the impact of groundwater resources on the performance of the artificial recharge system and significantly increases the total groundwater level. Table 6 showed the difference between the optimal level changes compared to the current situation in the first and second models and the multi-objective modeling platform as a whole difference in the changes in the optimal level changes. According to this table, the changes in the optimal groundwater level caused by the two models and the optimal operating pattern have increased compared to the current situation.

Table 6. Difference between manual and optimal level changes resulting from the first and second optimization models (m)

year	difference between the optimal and manual annual level changes in the first model	difference between the optimal and manual annual level changes in the second model	Total difference between the optimal and manual annual level changes
2014	9	1	10
2015	9	0.9	10
2016	9	0.7	10

Conclusion

In this study, the first and second models within the multi-objective modeling platform optimized the use of groundwater and artificial recharge systems, respectively. Considering the constraints on the change in groundwater level and groundwater quality, as well as the constraints on the changes due to the artificial

recharge system, the multi-objective modeling platform estimated the best solution set from the two optimization models. It also calculated the best optimal values based on these solutions. The results were used to develop a policy for optimal use of the aquifer. The estimated total optimal volume of consumption of all sections during the study period was less than the current volume.

Since domestic and industrial water requirements were prioritized in this study, they were met first. Then, the water required for the agricultural sector, which was less than the current ones, was supplied from surface and groundwater sources. Therefore, the cultivated area had to be reduced to increase the water supply of the agricultural sector. Because of the proportional calculation of consumption concerning changes in groundwater levels and groundwater TDS content, the range of changes was the same for all variables. Therefore, the optimal use policy of the first model created a balance between the amount of use, changes in groundwater level, and groundwater quality. In addition, the withdrawal from the aquifer decreased by 29% compared to the current period. In addition, the TDS concentration in groundwater decreased by 18%, while the changes of groundwater level increased by 28 m compared to the neural network estimate.

In the second model, the artificial recharge system was fed by the river and the decision variable was the amount of water entering the downstream area (Shahriar Plain) from the Bilghan Diversion Dam. As for the optimal amount of surface water in Bilghan, part of it was used in the agricultural sector of the study area, and another part was used for artificial recharge. The rest of the water flows into Fashafoyeh Dam and downstream. In the model, the storage volume in the reservoirs of the artificial recharge system of ANN was simulated, entered into the algorithm along with other data, and calculated to develop the optimal use policy for the artificial recharge system. To calculate the optimal quantity allocation of Bilghan surface water, target functions, parameters such as constraints on the optimal quantity of Bilghan surface water, the optimal quantity allocation, and the maximum allowable groundwater level changes were considered. We calculated the maximum allowable groundwater level changes because they significantly affected the determination of the desired parameters. In the second model, the optimal recharging volume for the artificial recharge system increased by 119%, indicating that the optimal use policy for the artificial recharge system increased the water table by 14% during the study period. Combined with the performance level between the recharge volume and the changes in the optimal groundwater level, this will improve the conditions of the aquifer.

To significantly reduce the effects of groundwater withdrawal volume in the different sectors on the volume of groundwater resources and changes in the groundwater table, the use of the aquifer was optimized in the first model, which neutralized the effects of groundwater resource use on the performance of the artificial recharge system. Ultimately, the multi-objective modeling platform resulted in a significant increase in groundwater level changes. In other words, based on the results of the modeling platform, the optimal groundwater level increased by 30 m and an average of 10 m per year during the study period. In addition, the results confirmed that by combining the multi-objective modeling platform with optimal management policy, several important factors are supported simultaneously. In addition, the optimal management model adoption reduced the quantitative and qualitative problems of the aquifer,

increased the stability of groundwater resources, and prevented more complex problems. Overall, we presented the multi-purpose modeling platform as a practical, convenient, accurate, and cost-effective tool with the desired speed.

Declarations

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Conflict of Interest: Authors certify that there is no conflict of interest in this research.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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Figures

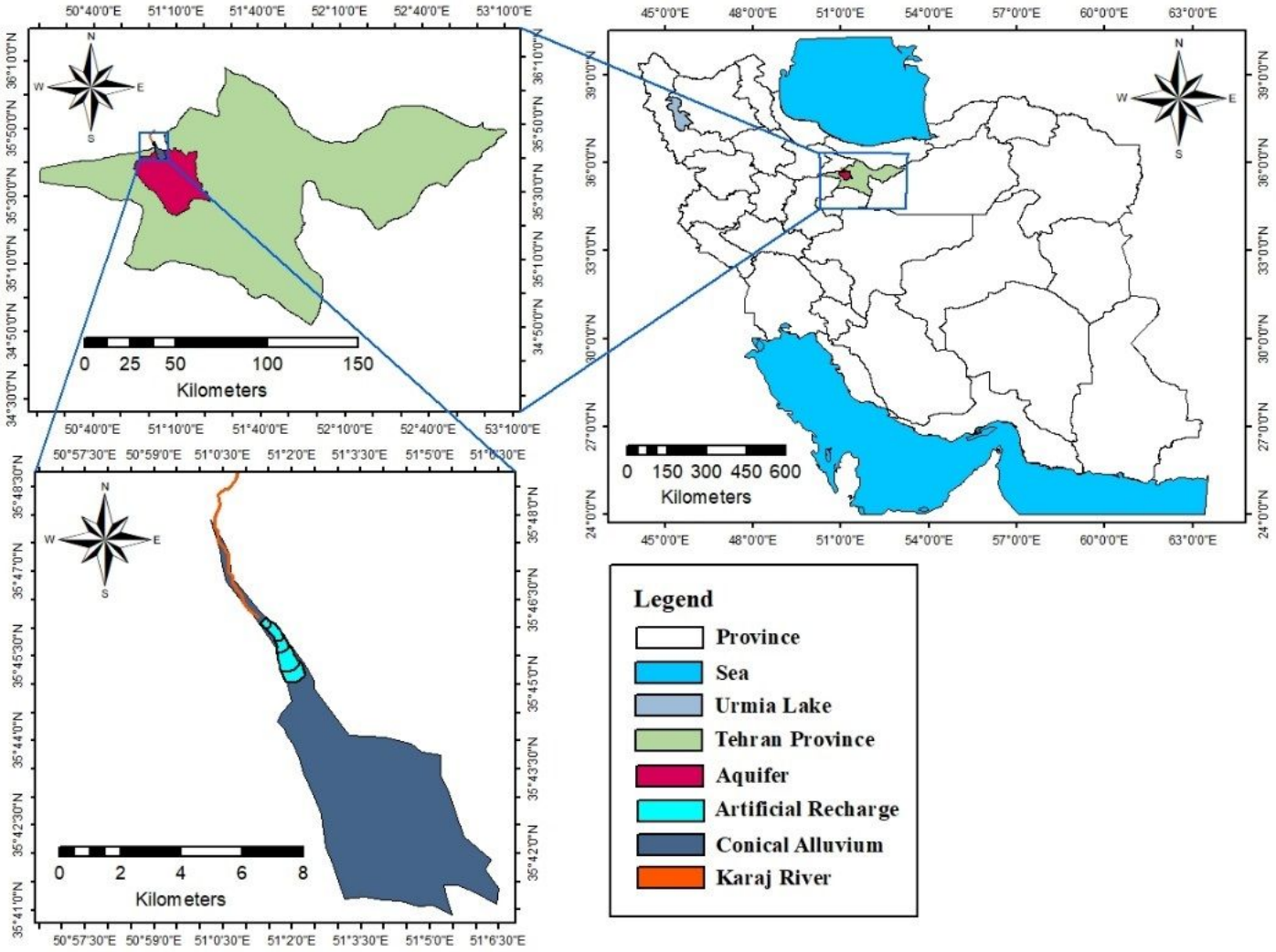

Figure 1

Location of artificial recharge system in Shahriar plain

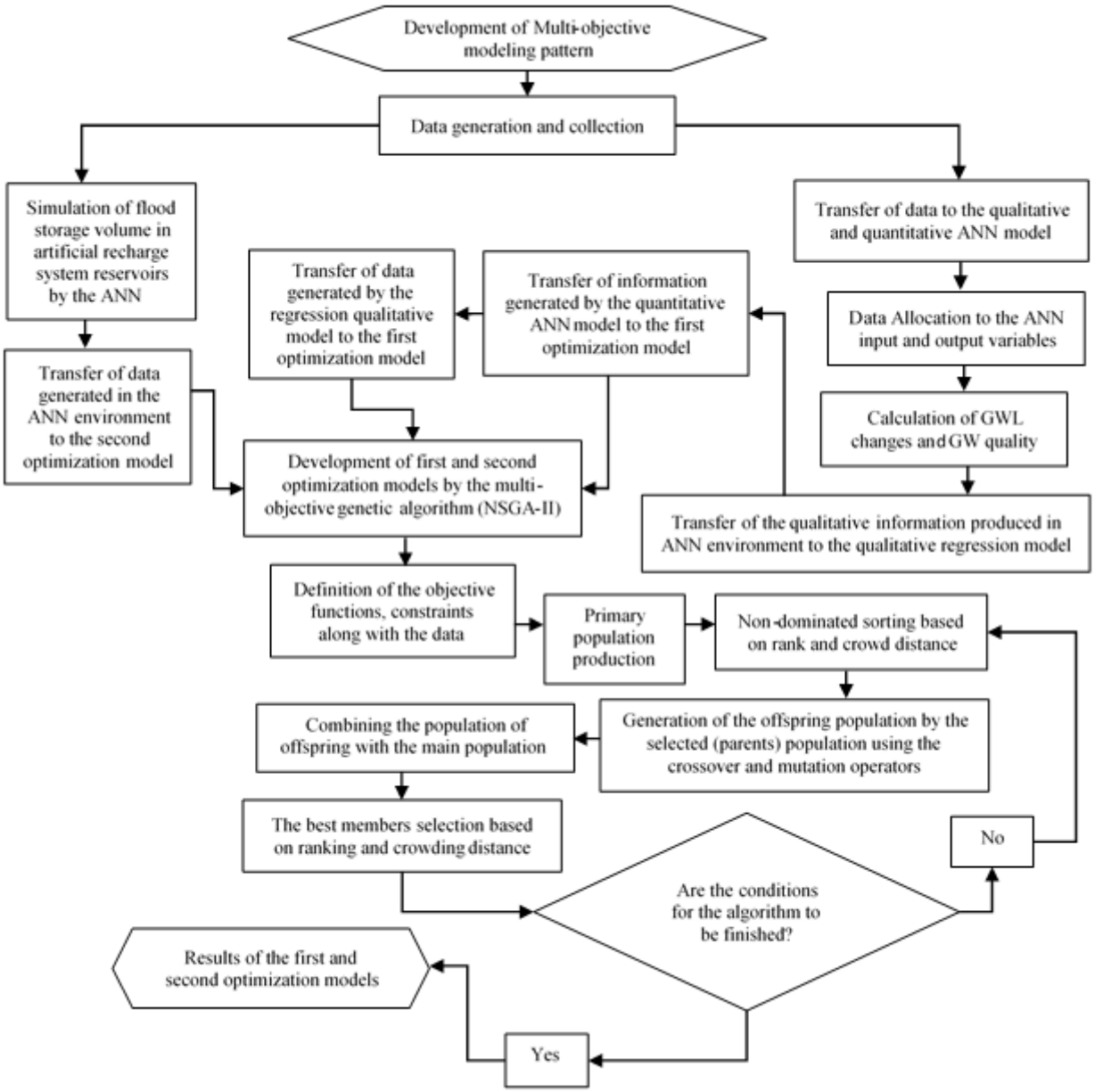

Figure 2

Overview of the multi-objective modeling platform computing process

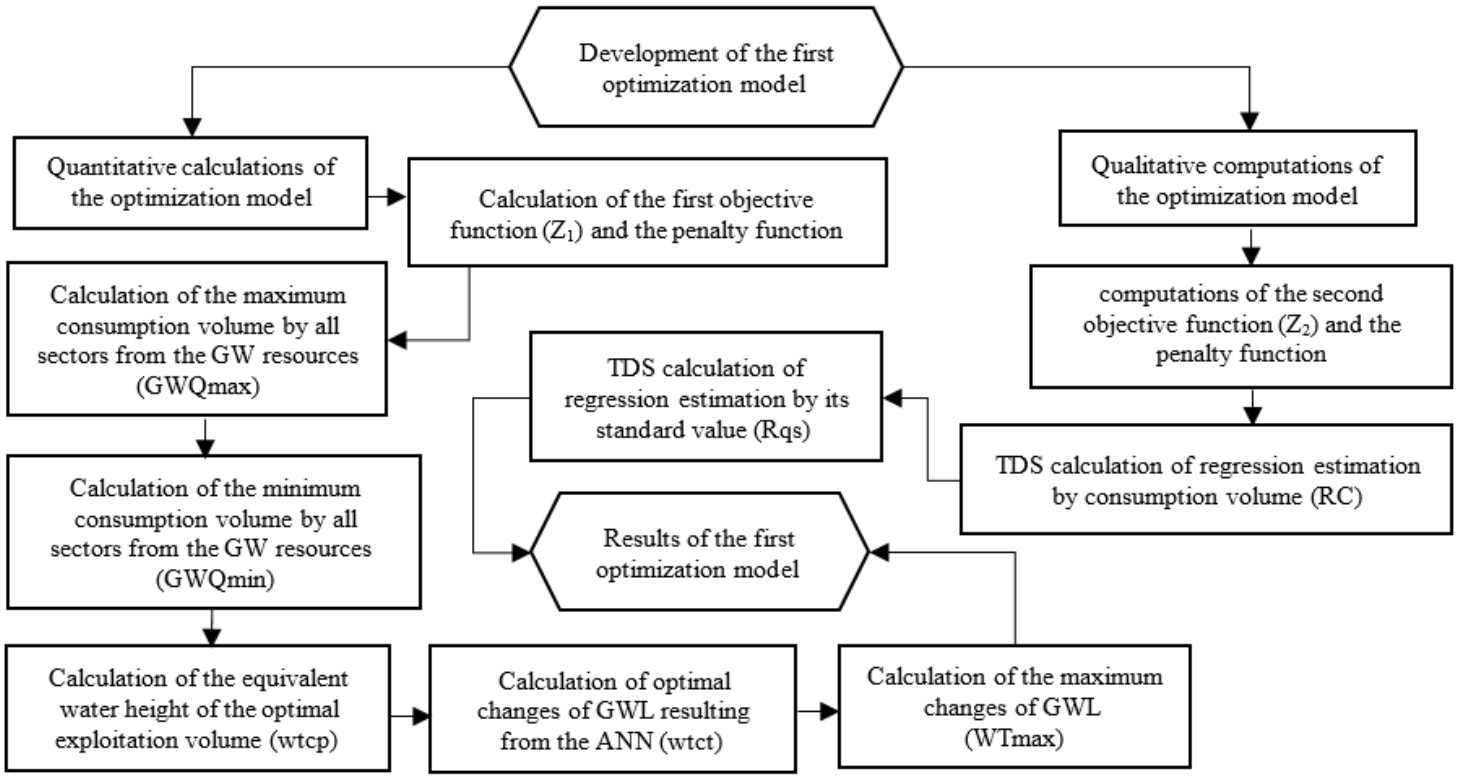

Figure 3

Quantitative and qualitative optimization overview of aquifer

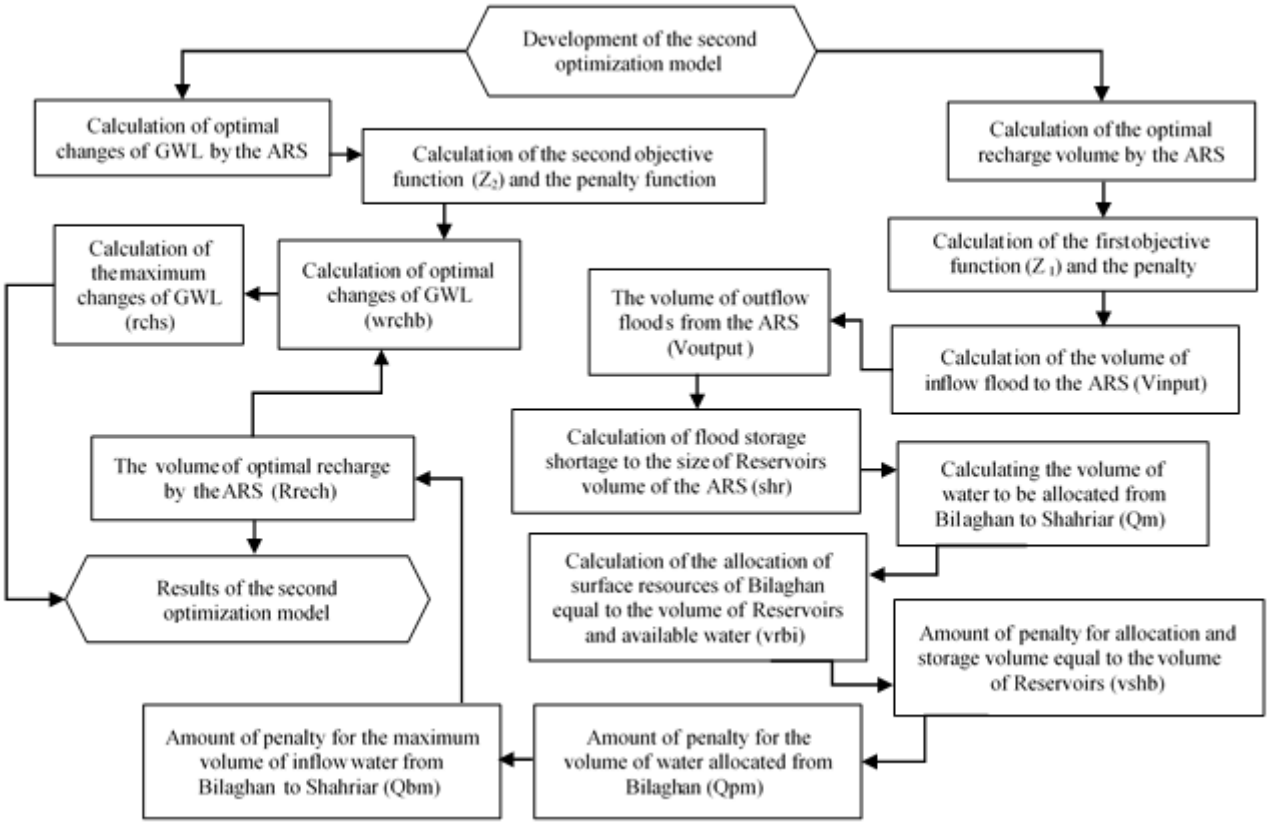

Figure 4

Groundwater level optimization model overview using artificial recharge system

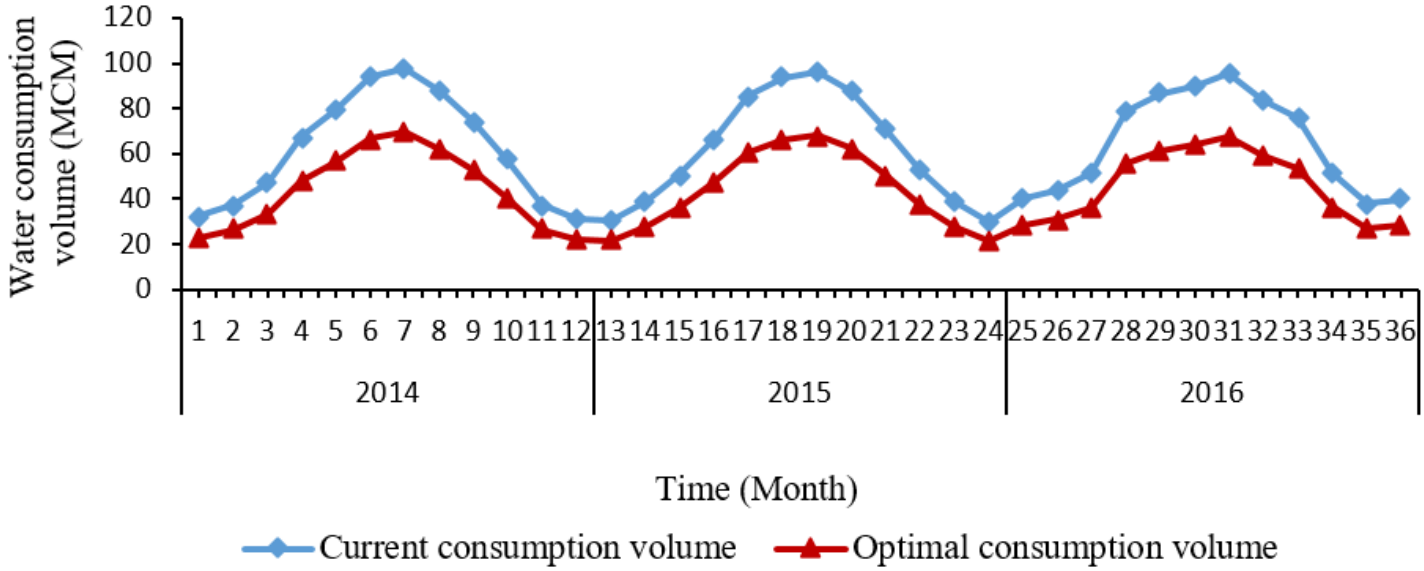

Figure 5

The volume of current and optimal groundwater consumption in the study area

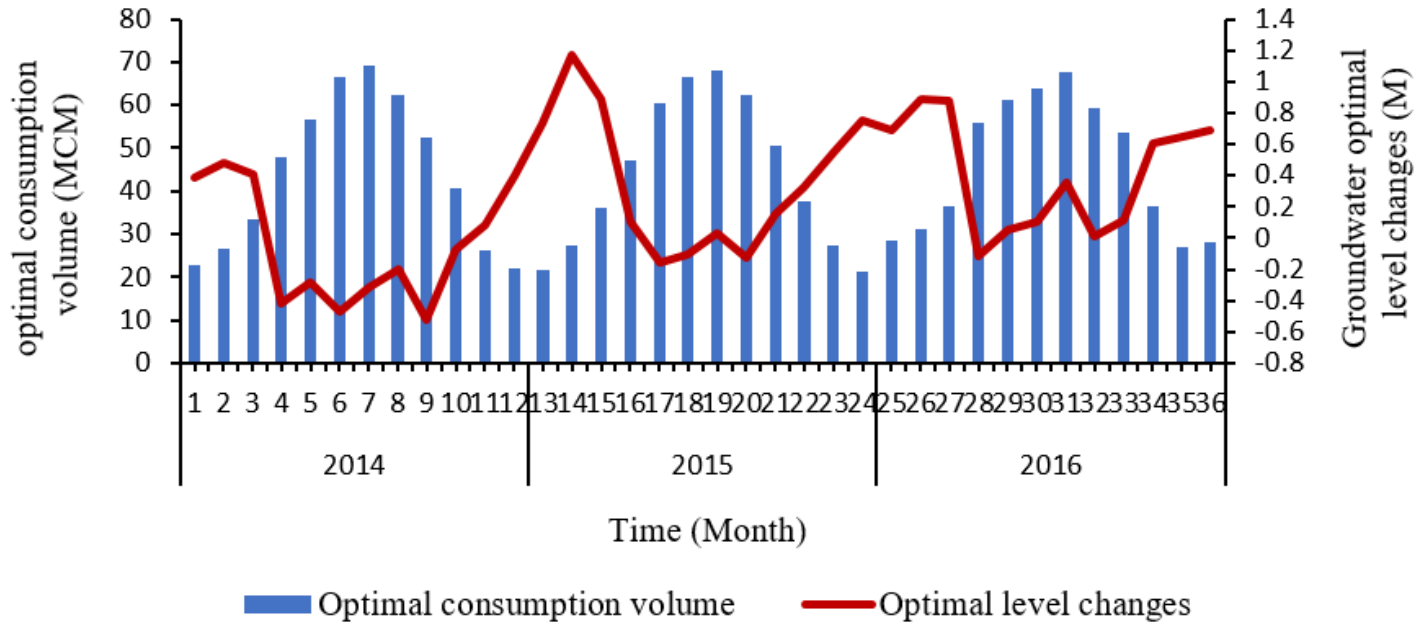

Figure 6

Consumption volume and changes in the optimal groundwater level in the study area

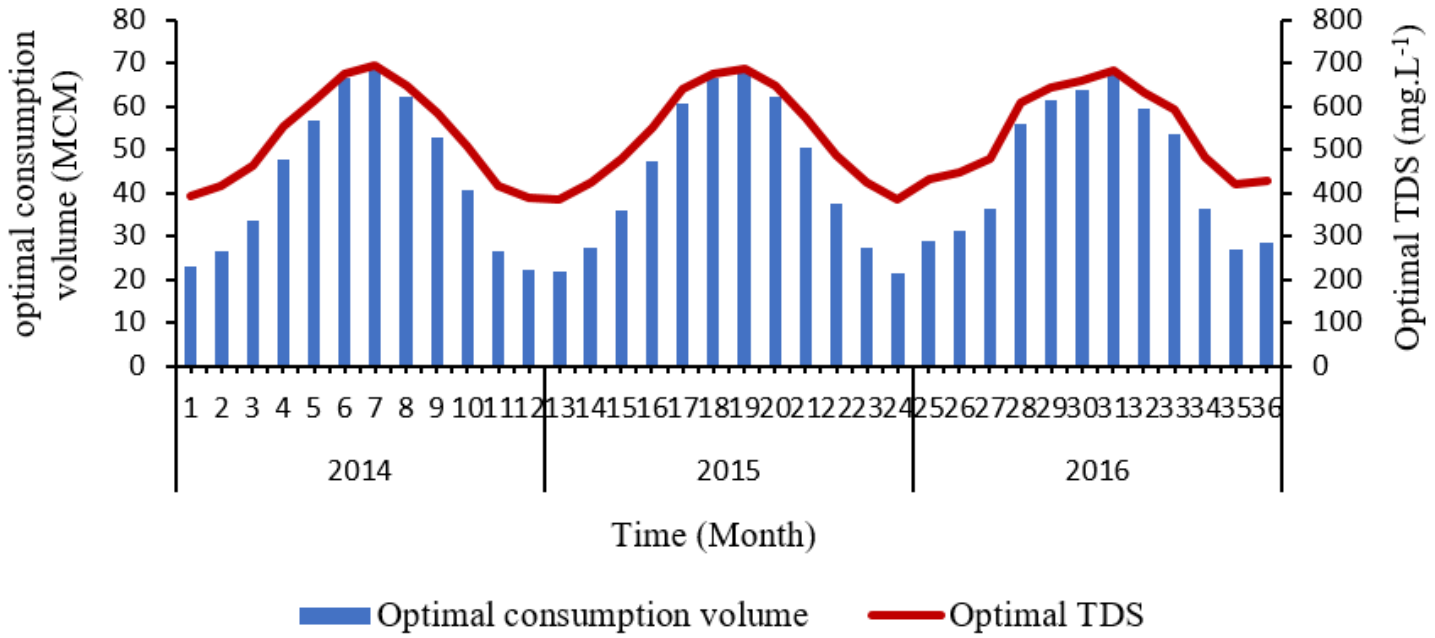

Figure 7

Consumption volume and Total dissolved solids of optimal groundwater in the study area

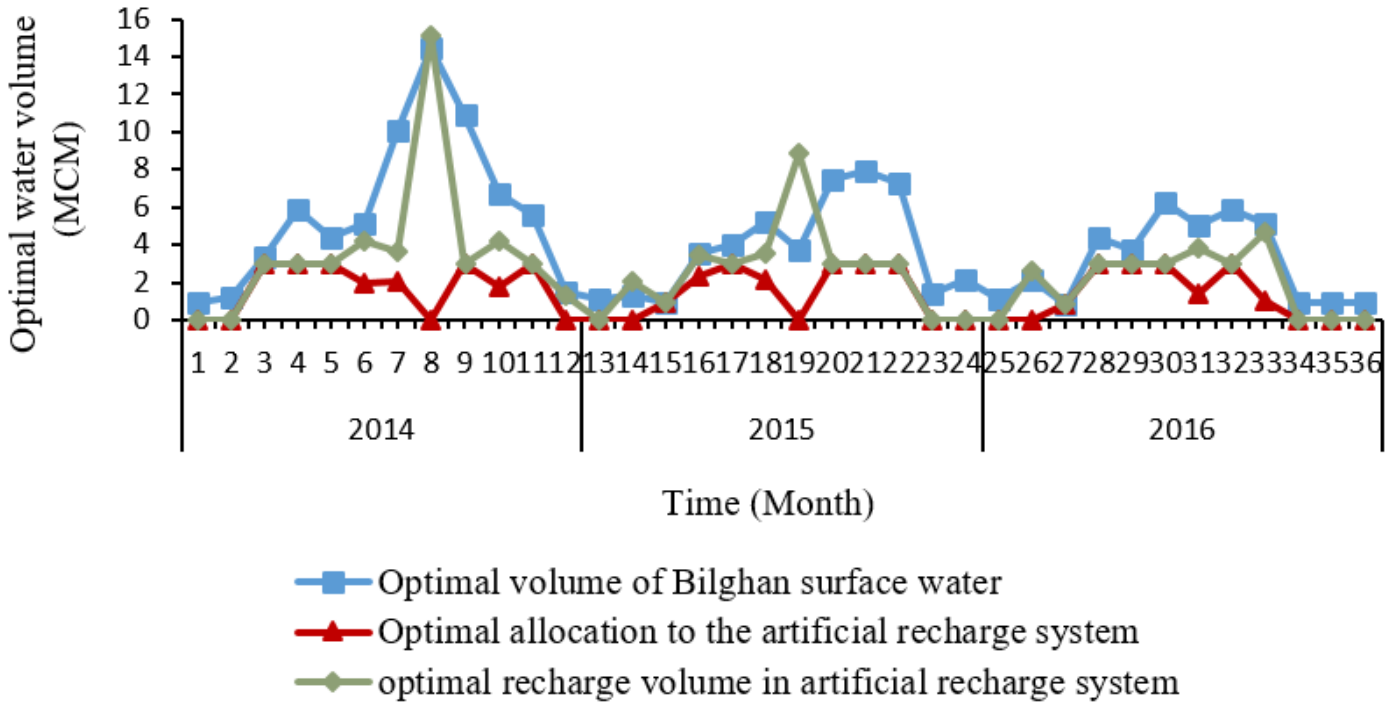

Figure 8

Optimal volume of Bilghan surface water and optimal allocation volume of Bilghan surface water to the artificial recharge system, and optimal recharge volume in this system