Water Resources Management (2022) 36:3129–3152
https://doi.org/10.1007/s11269-022-03193-2

Selecting the Best Approach to Modeling the Performance of Water Supply System Using the Combination of Rough Set Theory with Multi-Criteria Decision Making

Sadaf-Sadat Mortezaeipooya[1] · Parisa-Sadat Ashofteh[1] · Parvin Golfam[1]

Received: 18 February 2022 / Accepted: 13 May 2022 / Published online: 18 June 2022

Abstract
The purpose of this study is to select the best modeling approach (simulation or optimization) for operation the water supply system using multi-criteria decision-making method. For this purpose, the Geophysical Fluid Dynamics Laboratory-Earth System Models (GFDL-ESM2M) and the Model for Interdisciplinary Research on Climate-ESM (MIROC-ESM) models were selected to predict the changing trend of the climatic variables of rainfall and temperature, respectively. Then Artificial Neural Network (ANN) model and a decision support system tool named Cropwat were used to simulate water resources and consumption; and to model the behavior of the water supply system, the MODified SYMyld (MODSIM) (as simulator) and the modeling language and optimizer LINGO 18 (as optimizer) were used in the future time period (2026–2039) and the results were compared with the baseline period (1987–2000) for the Idoghmush reservoir (Iran). The results of MODSIM simulation model show that the indexes of reliability, vulnerability, reseiliency and flexibility in the future time period under the RCP2.6 emission scenario compared to the baseline time period decreased by 9%, decreased by 22%, increased by 4%, and decreased by 2%, respectively. The results of the LINGO 18 optimization model show that the reliability, vulnerability, resiliency and flexibility indexes in the future time period under the RCP2.6 emission scenario compared to the baseline time period decreased by 13%, decreased by 17%, increased by 14% and increased by 3%, respectively. Due to the different results obtained from optimization and simulation approaches for the study area, the Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) multi-criteria decision-making method was used to select a more appropriate approach. The results show that for water resources management planning, the simulation approach is given priority over the optimization approach due to its characteristics.

Keywords LINGO 18 optimization model · MODSIM simulation model · Reservoir performance indexes · Multi-atributive ideal-real comparative analysis multi-criteria decision-making method · MAIRCA · Rough-AHP weighting method · Climate change

✉ Parisa-Sadat Ashofteh
PS.Ashofteh@qom.ac.ir

Extended author information available on the last page of the article

1 Introduction

The climate change phenomenon affects on the climatic parameters, especially temperature and precipitation directly and indirectly, which have been studied in different regions. For example, Marengo et al. (2012), using the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) and the application of the HadCM3 climate model, stated that temperature will rise between 4 and 6 °C due to extreme heat in the southern American continent. Zarghami et al. (2016) studied the temperature, precipitation, and runoff changes of Yamchi Dam in the time period (2011–2030) using the HadCM3 climate model under the RCP2.6, RCP4.5 and RCP8.5 scenarios. The results showed that the temperature will increase by 0.77 °C and precipitation will decrease by 11 mm. Rani and Sreekesh (2019) evaluated the flow responses under the climate change scenarios in the western Himalayan watershed using the Soil and Water Assessment Tool (SWAT) and cartosat Digital Evaluation Model (DEM). The results showed with the slow disappearance of snow cover as a result of rising temperature, the water availability will be reduced in the second half of this century. Nabeel and Athar (2020) estimated rainfall in wet and dry days for Pakistan using 25 climate models under the fifth IPCC report with RCP4.5 and RCP8.5 scenarios. Generaly, the results showed that under both emission scenarios, the average annual rainfall and the number of wet days in future time periods will decrease compared to the baseline time period, but rainfall volume per a wet day will increase. Daba and You (2020) investigated the climate change effects on the Awash River with using the CSIRO-MK3-6-0 and MIROC-ESM-CHEM climate models under RCP4.5 and RCP8.5 scenarios. The results showed that temperature, precipitation amount and river discharge volume will decrease in the future years due to climate change. Mandal et al. (2021) investigated the effects of climate change on the hydrology and biomass yield of the tropical river basin under the HadGEM2-ES, MIROC-ESM, NCAR-CCSM4, CSIRO-MK3-6-0 and CESMI-CAM5 climate models. Dau et al. (2021) assessed the water availability in the Huong river basin in Vietnam under the climate change effects and population growth. The results showed that the future time, temperature and annual rainfall will be increased by 0.2 to 3.5 °C and 1 to 8% respectively and water shortages wouldn't exist without considering population projections in 2080s.

The trend of changing temperature and precipitation parameters in the coming years will change the supply and demand of water resources, which requires the use of management tools based on optimization or simulation approaches with the aim of optimal efficiency of available water resources. For instance: Shenava and Shourian (2018) presented a model for reservoir optimal operation with the aim of enhancing downstream demands supply and flood damage mitigation by coupling MODSIM and Competitive Optimization Algorithm (ICA) for Gotvand dam in Iran. Sherafatpour et al. (2019) presented an integrated hydro-economic model for allocating agricultural water by coupling the Positive Mathematical Programming (PMP) economic model and MODSIM water allocation planning model for Zayandeh Rood dam in Iran.

Fadaeizadeh and Shourian (2019) investigated the optimum water resources allocation through quantification of the agricultural demands by combining the MODSIM and the Particle Swarm Optimization (PSO) algorithm in the Atrak River Basin in Iran. Jamshidpey and Shoorian (2021) used the Gray Wolf Optimization (GWO) algorithm and the MODSIM to investigate the climate change effects on the Zayandehrud river and agricultural water demand in the Borkhar plain in Iran. The results showed that the cultivation area will decrease due to lack of water resources and agricultural water demand will increase due to rising the temperatures. Behboudian and Kerachian (2021) evaluated the resiliency of water supply system in Zarrinehrud river basin using MODSIM. The results showed that 40% reduction in agricultural water demand by 2023 will maximize the the water supply system resiliency index. Ashrafi et al. (2022) evaluated the water and soil stability of Zarrinehrud basin using the SWAT and the MODSIM models under climate change. The results showed that the best management scenario was to allocate water to Lake Urmia from new sources, rehabilitate irrigation and drainage networks, and modify the cultivation pattern. Pourmoghim et al. (2022) used the SWAT-MODSIM coupled model to evaluate the resiliency and improve the condition of Lake Urmia against droughts resulting from human activity.

Quantifying the results of different management models is necessary to better understand the current status of the water supply system and efficiency of the long-term policies for the future time interval. Reservoir performance indexes are one of the most valid methods for measuring the efficiency of the water supply system. Ashofteh et al. (2017) used reservoir performance indexes to evaluate the performance of the Gharnaghu multipurpose dam with the aim of irrigating agricultural lands under climate change conditions. The results showed that the time reliability, vulnerability, resiliency and flexibility indexes in the future period will be decreased by 18%, increased by 150%, decreased by 33% and decreased by 47%, respectively compared to the baseline time period. Ashofteh et al. (2019) evaluated the best adaptation scenario with climate change effects on the water resources and consumptions in Gharnaghu water supply system with eight reservoir performance indexes including time reliability, volumetric reliability, availability, supply to demand, and sum of squared deficits. Golfam et al. (2019b) used Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) MCDM methods to determine the best adaptation scenario with climate change in the agricultural sector in Gharnaghu basin during the period (2040–2069). The results showed that the best alternative using the AHP model was reducing agricultural water by 25% with weight equal to 0.335, while the TOPSIS model showed that the best alternative was reducing demand by 15% with a distance of 0.20805 from the ideal alternative. As well as, Golfam et al. (2019a) evaluated the agricultural water supply under five climate change adaptation scenarios for the period (2040–2069) using two methods of multi-criteria decision making: the VIKOR (VIse Kriterijumsk Optimizacija Kompromisno Resenje) and Fuzzy Order Weighted Average (FOWA). The results showed that using both VIKOR and FOWA methods, the fifth altenative (reducing water consumption in the agricultural sector by 25%), was the best scenario for adaptation to climate change. Ashofteh et al. (2020) presented a methodology in order to select the best alternative for river-water transferring based on the Interactive Multi-Criteria Decision-Making (TODIM) method in the Khodaafarin irrigation network, Iran. The results of AHP weighting method showed the investment costs was the most effective criterion and results of the TODIM method revealed that water transferring through earthen canal to a pumping lift station was the best option. Theochari et al. (2021) developed a methodology in Geographic Information System (GIS) using a MCDM approach with several spatial criteria to propose suitable locations for hydrometeorological and hydrometric station network in the Sarantapotamos river basin in the western part of the Attica Region, Greece.

Abdi-Dehkordi et al. (2021), evaluated the water resources systems in the Karun basin using seven indexes of quantitative water stress, water quality, environmental water stress, agricultural revenue, agricultural/industrial water productivity, irrigation system cost, and water transfer revenue.

According to the multi-dimensional nature of water resources management due to the presence of decision-makers and policy-makers and their multiple considerations on one hand and presence of stakeholders with different goals on the other hand, selection a common strategy in which all groups are satisfied with maximum benefit is very difficult. One of the most widely used tools to overcome this challenge is multi-criteria decision-making methods. These methods have evolved to adapt to different types of programs and issues, so that small changes in these methods have created a variety of branches. A combination of different concepts along with methods that are in their original form, can be used more effectively (Velasquez and Hester 2013). Various MCDM methods have been used in water resources management, including evaluating and prioritizing water conservation strategies using the Preference Ranking Organization Method for Enrichment Evaluation (PROMITHEE II) method to assess alternatives based on gray numbers for Ontario, Canada (Kuang et al. 2014); Identification of optimal groundwater remediation strategies for a naphthalene-contaminated site by using the developed PROMETHEE-TOPSIS method (He et al. 2020); Investigation of flood susceptibility in temperate Mediterranean climate using MAIRCA method (Hadian et al. 2022).

The purpose of present study is to select the best approach between simulation and optimization approaches for water resources management in the future time interval using MAIRCA decision-making method. Given that the decision-making to choose the appropriate approach is for the future time period, first climatic processing of climatic parameters of temperature and precipitation must be done.

In this study, the proper climatic models for temperature and precipitation were GFDL-ESM2M and MIROC-ESM based on the results of their evaluation. In Sect. 2, the method and results of evaluating climate models will be described in detail.

2 Materials and Methods

Climate models were first evaluated from the Fifth Assessment Report (AR5) of the IPCC, and after selecting the best model, temperature and precipitation scenarios were created under the emission scenarios of RCP2.6 and RCP8.5. Then the discharge of the dam reservoir in the future years was estimated using the ANN conceptual model and the amount of irrigation water demand in the agricultural sector was estimated with the Cropwat model.

In the next step, the water supply system and demand status will be simulated using the MODSIM model, and optimized with LINGO 18 model. Reservoir performance indexes will be calculated using the results of both models. In the last step, the MAIRCA decision-making method will be used to determine the most appropriate approach for policy-making of reservoir operation based on the performance indexes of each of them. Also the AHP method developed with Rough Set Theory (RST) called Rough-AHP will be used to weight the criteria. The flowchart of the present study is shown in Fig. 1.

2.1 Step 1: Selection the Climate Models, Climatic Scenario Generation for Temperature and Rainfall

2.1.1 Evaluation of Climate Models

Suitable climatic model was selected for the study area among the 28 models in the fifth IPCC report under two scenarios RCP2.6 and RCP8.5 using statistical criteria including correlation coefficients (r), Root Mean Square Error ($RMSE$), Mean Absolute Error (MAE),

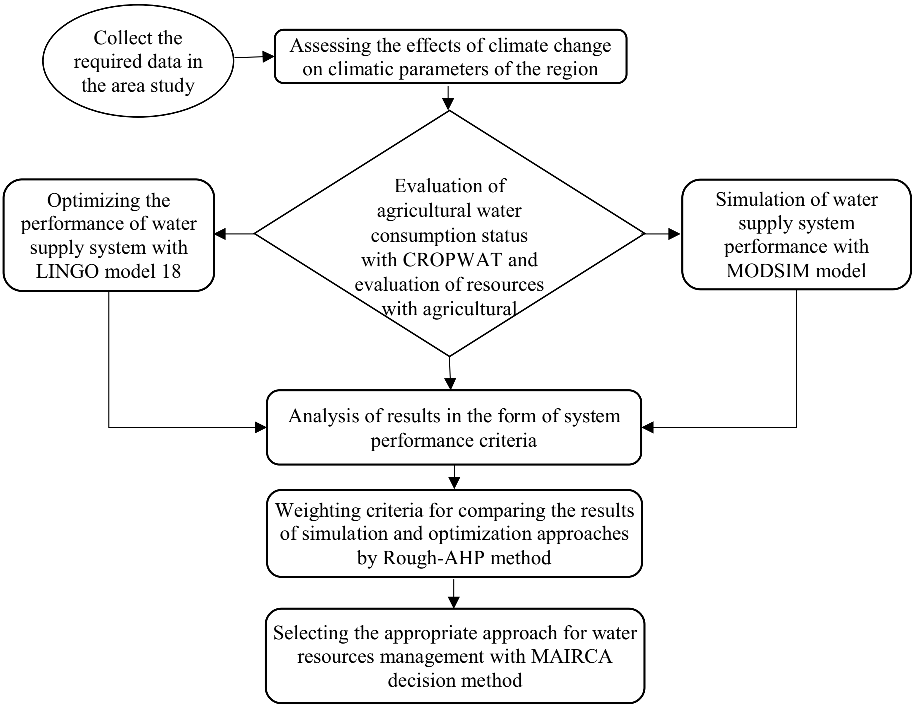

Fig. 1 Flowchart of this methodology

and Nash–Sutcliffe Efficiency (*NSE*) coefficient. The results of coefficients are presented in Table 1.

As shown in Table 1, the GFDL-ESM2M climate model with *r*, *RMSE*, *MAE*, and *NSE* equal to 91%, 8.1 mm, 6.0 mm, and 0.8, respectively have the best performance among other climate models for rainfall model. Also, MIROC-ESM climate model with *r*, *RMSE*, *MAE*, and *NSE* equal to 98%, 2.9 °C, 2.1 °C, and 0.9 has the best performance among other climate models for temperature.

2.1.2 Generating Climatic Scenarios of Temperature and Rainfall

After selecting the appropriate climatic model, rainfall and temperature values are extracted for historical data under two RCP2.6 and RCP8.5 climatic scenarios and climatic data are extracted and downscaled using Geographic Information System (ARC

Table 1 Criteria for selecting a suitable climatic model for rainfall and temperature

Parameter	Climate model name	*r* (%)	*MAE* (mm/°C)	*RMSE* (mm/°C)	*NSE* (dimensionless)
Rainfall	GFDL-ESM2M	91.2	6.0 (mm)	8.1 (mm)	0.8
Temperature	MIROC-ESM	98.4	2.1 (°C)	2.9 (°C)	0.9

GIS) software. The results are shown in Fig. 2. According to Fig. 2a, the amount of rainfall in the future (2026–2039) will increase by 17 and 25% compared to the base (1987–2000) under the RCP2.6 and RCP8.5 scenarios, respectively. This increase is especially in spring and autumn and in April and October, when the rainfall is usually higher than other months. As shown in Fig. 3b, the temperature will increase by 1.5 and 1.3 °C relative to the base in the future under the RCP2.6 and RCP8.5 scenarios. The results of climate change scenarios are used to calculate reservoir discharge and water consumption for the agricultural sector in the next step.

2.2 Step 2: Calculation of Reservoir Discharge by ANN and Agricultural Water Consumption by Cropwat

2.2.1 Calculate the Resevoir Discharge

In this research, the ANN conceptual model was used to estimate the inflow to the reservoir in the future time. For this purpose, long-term time series of temperature and precipitation

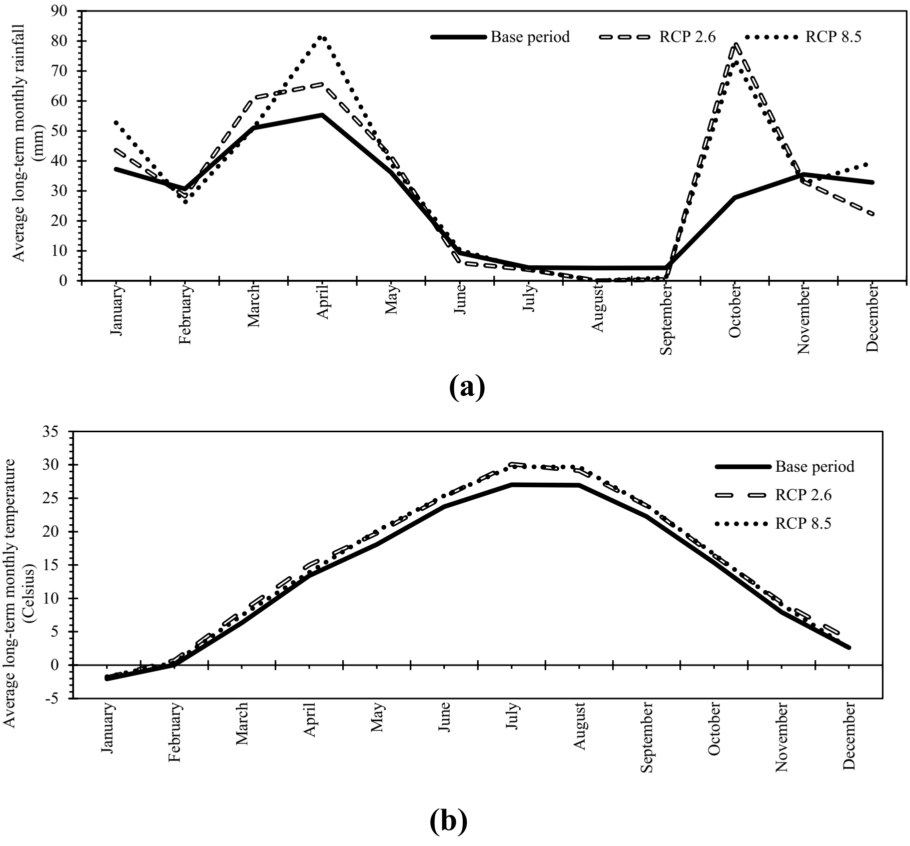

Fig. 2 Comparison of average long-term monthly of (**a**) precipitation and (**b**) temperature, in the base and future periods

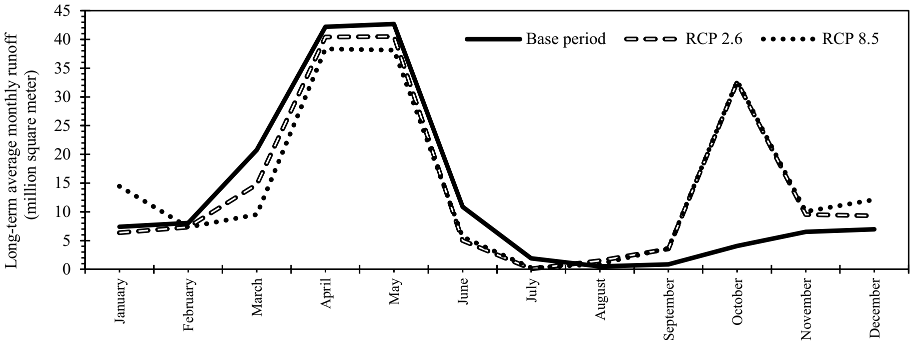

Fig. 3 Comparison of average long-term monthly of inflow to reservoir in the base and future periods

were included in the ANN model. First, two middle layers and one output layer with five hidden neurons were considered. The function type for the middle and output layers are both hyperbolic nonlinear. In this study, MATLAB (2022) was used to build the ANN model. The features of the ANN model are described below. The 75% of the observed data was used to train the model. Number of layers is equal to 4 and number of neurons in the middle layer is 5–20. The middle and output layer transfer function arr Sigmoid Function-Hyperbolic Functions. Number of Repetitions per Run is 1000.

ANN performance in calibration and validation with *RMSE* and *MAE* equal to 7.9 and 5.2 m^3/s and *NSE* equal to 0.8 and *r* equal to 90%, respectively, showed that this model can be reliable for simulating reservoir discharge in the future. Because RMSE is 7.9 m3 / s and MAE is 5.2 m3 / s, which shows that the data simulated by the model are slightly different from the amount of each input data, and also the NASH coefficient of 0.8 indicates the good performance of the model in the simulation. Next, the future runoff time series for the RCP2.6 and RCP8.5 scenarios are obtained, as shown in Fig. 3. According to Fig. 3, the inflow to the reservoir will increase by 12 and 13% in the future compared to the base under the RCP2.6 and RCP8.5, respectively. The reason for this increase in runoff can be considered a significant increase in precipitation obtained from the GFDL-ESM2M model in the future period under both emission scenarios in October compared to the base period, so that the average precipitation under both emission scenarios is about 2.7 times the precipitation in October of the base time period.

2.2.2 Estimate the Amount of Water Consumption in the Agricultural Sector

The Cropwat model (developed by FAO (2009)) was used to calculate the water consumption of the agricultural sector in the future. Temperature and rainfall time series were used as input to the Cropwat model for the future time period. The rate of evapotranspiration of the reference crop (ET_0) was calculated by the Monteith-Penman-FAO equation based on climatic data including minimum and maximum temperature, relative humidity, radiation duration, and wind speed.

Changes in water demand in the future period under emission scenarios compared to the base period are presented in Fig. 4. According to Fig. 4, irrigation water demand in the agricultural sector will increase by about 15% in the future over the base period under both RCP2.6 and RCP8.5 scenarios.

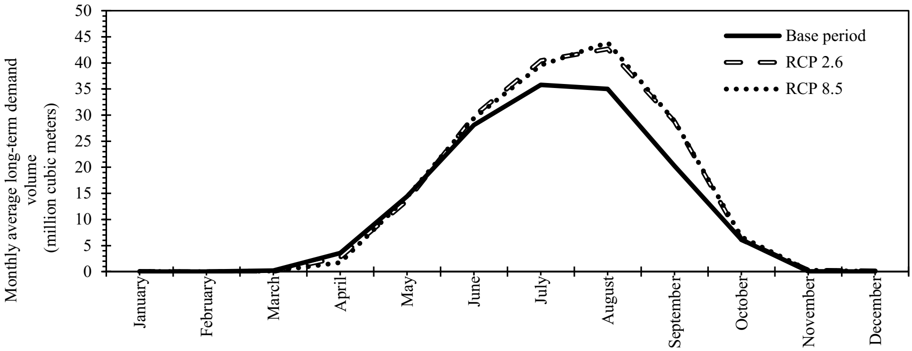

Fig. 4 Comparison of average long-term monthly of water required by the agricultural sector in the base and future periods

The results of ANN and Cropwat models are used to simulate and optimize the water supplying system.

2.3 Step 3: Simulation and Optimization of Water Supplying System Using MODSIM and LINGO 18 Respectively, and Calculation the Water Supply System Performance Indexes

2.3.1 MODSIM Simulation Model

The MODSIM model is a decision support system for operation planning and water resource management developed by Colorado State University. This model is designed in such a way that managers and decision-makers are able to fully understand the complex and coordinated actions required in river management, assess the effects of hydrology, economics, environment, etc. In addition, they will be able to take the necessary steps for long-term executive planning, drought planning, agricultural and environment water rights analysis (Labadie 2006). The newer versions of MODSIM, developed with the NET Framework, also allow the user to customize MODSIM for each component, including input and output reports, and also it provides access another models that run concurrently with MODSIM without need to change the original source.

The Network Flow Programming (NFP) method is used to determine the amount of water allocation between the demand nodes and water resources in MODSIM, and the water allocation between the consumption nodes is solved repeatedly at each time step to minimize the cost of the network flow. For this purpose, the problem is solved by Lagrangian relaxation algorithm (Bertsekas and Tseng 1994) and the optimization parameters of U_{lt}, L_{lt}, b_{it}, and network flow are repeated until convergence is achieved. The general equation in the NFP method is obtained at each time step by sequentially solving the network flow optimization from Eqs. (1) to (3) (Labadie 2006):

$$\begin{aligned}&\mathit{Minimize}\ \textstyle\sum_{l\in A} c_l q_l\\&\mathit{Subject\ to}:\end{aligned}\tag{1}$$

$$\sum_{l\in O_i} q_l - \sum_{k\in I_i} q_k = b_{it}(q);\ \ i\in N \tag{2}$$

$$L_{lt} \le q_l \le U_{lt};\ l\in A \tag{3}$$

where, A = total network links; N = set of network nodes; O_i = set of output links from node i; I_i = all input flow links to node i; q_l = flow at link l; C_l = flow cost coefficient in link l; L_{lt} = low flow limit at junction l; U_{lt} = high flow limit at junction l, and b_{it} = profit (positive) and loss (negative) of node i at time t.

2.3.2 LINGO 18 Optimization Model

The LINGO 18 optimization model is a powerful tool for solving linear and nonlinear models. This model has various capabilities, including very advanced solvers with high model speed, simple expression of the mathematical model in the software environment, high power of model analysis, having various mathematical, statistical and probabilistic functions. In the present study, the objective function in the LINGO 18 optimization model is to minimize deficiencies. The objective function is to minimize the relative deficit in water allocation to the agricultural sector per month. The objective function and the corresponding constraints are considered according to Eqs. (4) to (8):

$$Minimize\ Def = \sum_{t=1}^{n} \left(\frac{D_t - \mathrm{Re}_t}{Dave_t}\right)^4 \tag{4}$$

$$S_{t+1} = S_t + Q_t - \mathrm{Re}_t - \frac{EV_t \times (aS_t + b)}{1000} \tag{5}$$

$$S_{\min} \le S_t \le S_{\max} \tag{6}$$

$$0 \le R_t \le D_t \tag{7}$$

$$\begin{cases} SP_t = S_t + Q_t - \frac{EV_t \times (aS_t + b)}{1000} - S_{\max} \\ SP_t = 0 \end{cases} \tag{8}$$

which, D_{ef} = objective function; D_t = water demand per month; $Dave_t$ = average water demand per month; Re_t = monthly release rate; S_t = the amount of reservoir storage at the beginning and end of period t; S_{t+1} = the amount of reservoir storage at the beginning and end of period $t+1$; Q_t = volume of inflow to the dam reservoir per month; EV_t = evaporation rate from dam lake; S_{max} = total reservoir capacity; S_{min} = dead volume of the dam; SP_t = amount of spill volume from the dam; n = length of operation period; a and b = constants obtained from the surface-volume curve of the reservoir, such that $A = a\ S_t + b$ (A is the reservoir lake surface) (a and b are 0.0568 and 0.7855, respectively).

2.3.3 Water Supply Performance Indexes

In order to evaluate the efficiency of water supply system, it is necessary to measure it by reservoir performance indexes. By monitoring the performance of the reservoir through the performance index, the efficiency of the reservoir in the face of climate change can be investigated. In this study, four indexes of reliability, resiliency, vulnerability and flexibility will be used, the first three of them were first proposed by Hashimoto et al. (1982) to evaluate the performance of reservoirs. Due to the lack of a similar trend in the changes of the first three indexes, Loucks (1997) presented the flexibility index, which is a combination of the above three indexes. The characteristics of the four indexes are given in Table 2. In this Table, lack of water supply means failure system, and water supply indicates the success of the system. As can be seen from the concept of Table 2, high reliability, high resiliency, low vulnerability, and consequently high flexibility is considered desirability for any water supply system project.

2.4 Step 4: Selection the Best Modeling Approach Using MAIRCA MCDM Method

2.4.1 Multi-Criteria Decision-Making Method

In order to adopt a proper operation policy and allocation of water resources in accordance with the status of the water supply system in the future, the most effective approach should be selected from simulation and optimization models according to different criteria.

(a) **Weighing the criteria set using Rough-AHP method**

The first step in multi-criteria decision-making methods is to determine the appropriate criteria to the problem being decided and to choose the weighting method. In the present study, the Rough-AHP method is used to weight the criteria.

AHP weighting and ranking method is one of the most well-known multi-criteria decision-making methods that has been used by experts in various fields (Saaty 1980). The steps of the AHP method include the following steps:

Step 1: The first step is to identify the problem accurately and model the goal, criteria, and alternatives levels.

Step 2: In this step, pairwise comparison matrixes are provided for water resources management experts to determine the preference of the two criterias. Pairwise comparison is done according to the preference of each criterion over the other criterion by assigning a number from 1 (indicates equal importance) to 9 (indicating absolute importance). The expression of the preference of the criteria is given in the form of numbers in Table 2.

When the problem has m alternatives and n criterias, a $n \times n$ pairwise comparison matrix must be created and n matrixes of $m \times m$ pairwise comparison must be formed. The pairwise comparison matrix is constructed according to Eq. (9):

$$a_{ij} = \frac{1}{a_{ji}} \tag{9}$$

where a_{ij} = the preference of element i over element j. The main diameter of the pairwise comparison matrix is 1, because the preference of each criterion over itself is equal to 1. Upper-triangular elements of the pairwise comparison matrix are scored

Table 2 Characteristics of four performance evaluation indexes of water supply system

Index name	Index definition	Mathematical expression
Reliability	Indicates the ratio of "number of successes" to "total time period"	$\begin{cases} REL = \frac{N}{T} \times 100 \\ N = \sum_{t=1}^{T} C_t(\mathrm{Re}_t \geq D_t) \end{cases}$
Resiliency	Indicates the ratio of "system failure after success" to "total number of failures"	$\begin{cases} RES = \frac{N''}{N'} \times 100 \\ N'' = [\sum_{t=1}^{T} C_t'(\mathrm{Re}_t < D_t \ni \mathrm{Re}_{t+1} > D_{t+1})] \\ N' = 1 - N \\ deficit_t = \sum_{t=1}^{T} \lvert \mathrm{Re}_t - D_t \rvert \end{cases}$
Vulnerability	Indicates the ratio of "sum of deficits" to "product of the total time period in average demand"	$\begin{cases} VUL = \frac{\sum_{t=1}^{T} deficit_t}{T \times Dave_t} \\ deficit_t = \sum_{t=1}^{T} \lvert \mathrm{Re}_t - D_t \rvert \end{cases}$
Flexibility	It is the product of reliability, resiliency, and non-vulnerability, and indicates the system's response to change	$FLE = REL \cdot RES(1 - VUL) = \frac{N \cdot N''}{T.N'} \times \left(1 - \frac{\sum_{t=1}^{T} deficit_t}{T \times Dave_t} \right)$

where, REL = temporal reliability (%); RES = resiliency index (%); VUL = vulnerability index (%); FEL = flexibility index; N = the number of months in which the release from the reservoir is equal to or greater than the demand at the downstream of the reservoir; N' = number of months in which release from reservoir is less than demand at the downstream of the reservoir; T = operation interval; D_t And D_{t+1} = the volume of demand at the downstream of the reservoir at time t and $t+1$, respectively; $Dave_t$ = average amount of demand in the whole operation period; Re_t and Re_{t+1} = release volume from the reservoir at time t and $t+1$, respectively; C_t = counting function (such that it considers releases equal to or greater than demand over the entire operating period); C_t' = counting function (in such a way that it considers the release of less than demand in the whole period of operation); N'' = number of failures after successes; $deficit_t$ = amount of water shortage

by the experts, and lower-triangular elements are obtained using the reciprocal principle. The numberical expression for preferences presented in Table 3.

Step 3: In this step, the relative weight of each alternative regarding to each criterion is calculated using various methods such as geometric mean, arithmetic mean, linear mean. To calculate the weight vector in AHP method, the geometric mean method is used in which, first the geometric mean of the elements of each row is calculated and then the obtained vector is normalized and the weight vector is obtained.

Step 4: In this step, the Decision Cosistency Rate (DCR) is calculated, which indicates the confidence of experts in judging the preference of the criteria. The decision cosistency rate is the result of dividing the Decision Consistency Index (DCI) by Decision Random Incomatibility Index (DRI) and is obtained according to Eqs. (10) and (11).

Table 3 Numerical expression of preferences

Preference of criteria	1	3	5	7	9	2,4,6,8
Description	Equal preference	Medium preference	Strong preference	Very strong preference	Infinite preference	Intermediate values

$$DCR = \frac{DCI}{DRI} \tag{10}$$

$$DCI = \frac{\gamma_{max} - n}{n - 1} \tag{11}$$

where, λ_{max} = the eigenvector of the matrix, and n = the dimension of the matrix. Saaty (1977) suggested that the *DRI* be equal to or less than 0.1, otherwise the pairwise comparison of the criteria should be repeated.

(b) **Rough set theory**

Rough set theory, proposed by Pawlak (1982), is a mathematical tool that is able to deal with subjective and imprecise concepts. The most important feature of RST is to check the mental information of experts without the need for any additional hypotheses and information. In other words, in this theory the ambiguity in the data is not expressed through the membership function, but is expressed using a boundary region of the set. The boundary region is the difference between the upper approximation and the lower approximation, which can neither be rejected as a member of the goal nor can it be rejected. Figure 5 shows the concept of RST.

Another important feature of RST is the calculation of the degree of satisfaction from the judgment of the experts, which also indicates the need for change in judgments. The following are the steps of the Rough-AHP weighting method:

- Creating a hierarchical analysis model
- Performing pairwise comparisons between criteria according to the goal level
- Controling the *DRI*
- Aggrigation the expert's opinions and converting them to the rough set at the group level through calculating upper and lower approximations

In this step, to calculate the upper and lower approximations, first the geometric mean of the same elements is calculated from the pairwise comparison matrices and then the upper and lower approximation sets are determined based on Eqs. (12) and (13) respectively.

$$Upper\ approximation : \overline{PX}\left(GM_{ij}\right) = \bigcup_{d=1}^{D} \left\{ Y \in U_{ij} | R(Y) \geq GM_{ij} \right\} \tag{12}$$

$$Lower\ approximation : \underline{PX}\left(GM_{ij}\right) = \bigcup_{d=1}^{D} \left\{ Y \in U_{ij} | R(Y) \leq GM_{ij} \right\} \tag{13}$$

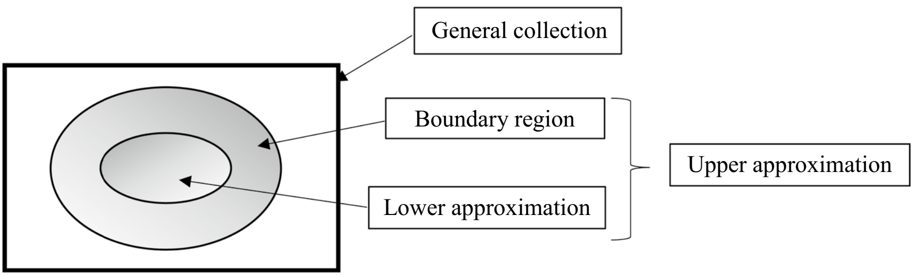

Fig. 5 Demonstration of the concept of Rough Set Theory

where $\underline{PX}(GM_{ij})$ = Lower approximation set; $PX(GM_{ij})$ = Upper approximation set; D = number of experts; GM_{ij} = geometric mean, and U = are the general set.

The most important reason for using geometric mean to aggregate expert opinions is that it preserves the reciprocal property of the pairwise comparison matrix without violating the Pareto principle (Forman and Peniwati 1998).

- Calculate the upper and lower limits and the rough number of each element

  The upper limit, the lower limit, and the rough number of each element are calculated based on Eqs. (14) to (16), respectively:

$$\text{Upper Limit} = \text{Lim}(\text{GM}_{\text{ij}}) = \left(\prod_{\text{m}=1}^{\text{N}} \text{y}_{\text{ij}}\right)^{1/\text{N}_{\text{ij}}} \tag{14}$$

$$\text{Lower Limit} = \underline{Lim}(GM_{ij}) = \left(\prod_{m=1}^{N} x_{ij}\right)^{1/M_{ij}} \tag{15}$$

$$RN(GM_{ij}) = (\underline{Lim}(GM_{ij}), Lim(GM_{ij})) \tag{16}$$

  where, $Lim(GM_{ij})$ = upper limit; $\underline{Lim}(GM_{ij})$ = low limit; N = number of members of the upper approximation set; M = number of members of the upper approximation set; GM_{ij} = geometric mean, and RN = the rough numbers of each element.

- Create an aggrigated pairwise comparison matrix based on rough numbers
- Calculate the degree of satisfaction from judgments

  In this step, the degree of satisfaction with the judgments is calculated using the convex linear composition (Ayağ and Özdemir 2009) according to Eq. (17):

$$P = \vartheta Lim(GM_{ij}) + (1 - \vartheta)\underline{Lim}(GM_{ij}) \quad 0 \leq \vartheta \leq 1 \tag{17}$$

  where, P = degree of satisfaction with the judgment and ϑ is a number between zero and 1, the value of which is determined by experts. In the present study, the value of ϑ is considered equal to 0.5.

  Criteria for the present study include: (1) model preparation cost, (2) operation policy approach, (3) the quality of the solutions of each model and (4) the time of construction and execution of models. The criterion of model preparation cost is negative and other criteria are positive. A negative criterion is a criterion that is better to be the minimum, while a positive criterion is better to be the maximum.

(c) **MAIRCA MCDM Method**

In the present study, the MAIRCA ranking method is used to determine the priority of the appropriate approach to water resources management. The MAIRCA method was first developed by Pamacur et al. (2014). The main idea of this method is to determine the gap between the ideal and empirical weights, and finally the sum of the gaps for each criterion determines the final gap for each alternative. In this method, the alternative with the best rating will be the one that has the minimum distance from the final gap. In other words, the alternative with the lowest value for the final gap has the value closest to the criterion ideal weight. The following are the steps of the MAIRCA method:

(I) **Forming the initial decision matrix**

In this step, the initial decision matrix is formed based on the aggregation of expert opinions to evaluate the performance of each alternative based on each criteria assuming the existence of *m* alternatives and *n* criterias ccording to Eq. (18).

$$\mathrm{A}=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{18}$$

where, X = initial decision matrix; A_m = alternatives; and C_n = problem criteria.

(II) **Determine the preference according to the choice of alternatives**

The basic assumption of the MAIRCA method is that at the beginning of the decision-making process, the experts are neutral in choosing the alternatives and therefore the probability of choosing the alternatives is equal. The preference of selecting an alternative from the *m* alternative is calculated based on Eq. (19):

$$P_{A_i}=\frac{1}{m};\sum_{i=1}^{m}P_{A_i}=1,\quad i=1,2,\ldots,m \tag{19}$$

where, P_{Ai} = the preference of each alternative.

(III) **Calculation of theoretical evaluation matrix**

In this step, the theoretical evaluation matrix is obtained by multiplying the preference of the alternatives by the weight of the criteria and in accordance with Eq. (20):

$$T_P=\begin{bmatrix} t_{P11} & \cdots & t_{P1n} \\ \vdots & \ddots & \vdots \\ t_{Pm1} & \cdots & t_{Pmn} \end{bmatrix}=\begin{bmatrix} P_{A1}w_1 & \cdots & P_{A1}w_n \\ \vdots & \ddots & \vdots \\ P_{Am}w_1 & \cdots & P_{Am}w_n \end{bmatrix} \tag{20}$$

where, T_P = theoretical evaluation matrix; t_{Pij} = theoretical evaluation matrix elements; and w_i = weight of criteria.

Given that the preference of all alternatives is equal, the T_P matrix can be represented as Eq. (21):

$$T_p=P_A\begin{array}{c} \begin{matrix} \quad w_1 & \qquad\qquad w_n \end{matrix} \\ \left[P_{A_i}*w_1 \;\ldots\; P_{A_i}*w_n\right] \end{array} \tag{21}$$

(IV) **Formation of a real assessment matrix**

In this step, the real assessment matrix is calculated based on the product of the initial decision matrix elements in the theoretical evaluation matrix elements. The values of the real assessment matrix are calculated based on the profit or cost of the criterion, respectively, based on Eq. (22).

$$\begin{gathered} T_r=\begin{bmatrix} t_{r11} & \cdots & t_{rln} \\ \vdots & \ddots & \vdots \\ t_{rm1} & \cdots & t_{rmn} \end{bmatrix} \\ t_{rij}=t_{Pij}\left(\frac{x_{ij}-x_i^-}{x_i^+-x_i^-}\right),\ \textit{for benefit criteria} \\ t_{rij}=t_{Pij}\left(\frac{x_{ij}-x_i^+}{x_i^--x_i^+}\right),\ \textit{for cost criteria} \end{gathered} \tag{22}$$

where, T_r = real evaluation matrix; t_{rij} = the elements of the real evaluation matrix; x_{ij} = the element of initial decision matrix; x^{+}_{i} = maximum value of specified criterion; x^{-}_{i} = The minimum value of the specified criterion.

(V) **Calculate the total gap matrix**

In this step, the total gap matrix is calculated based on the difference between the elements of the theoretical evaluation matrix and the real assessment matrix according to Eq. (23).

$$G = T_P - T_r = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ \vdots & & \ddots & \vdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix}$$
$$g_{ij} = \begin{cases} 0, & if \quad t_{Pij} = t_{rij} \\ t_{pij} - t_{pij}, & if \quad t_{pij} > t_{pij} \end{cases} \tag{23}$$

(VI) **Calculate the final values of criteria functions for alternatives**

In this step, the value of the criteria functions is calculated by summing the rows of the gap matrix for each alternative according to Eq. (24):

$$\mathrm{Q_i} = \sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{g_{ij}} \tag{24}$$

where, Q_i = the criteria function. The final ranking of the alternatives is based on the values of the criterion function. The best alternative is the one with the lowest Q_i value.

3 Case Study

Study area in this research is Aidoghmush basin that with an area of 1802 square kilometers located in East Azerbaijan province in Iran. This basin is adjacent to Gharnaghuchai basin in the north and Ajichai basin in the south. The 80-km-long Idoghmush River originates from the Ghur-Ghur heights and flows into the Ghezel Ozan River. The height of this basin varies from 1100 to 2500 m. Also, the annual discharge of this dam is about 170×10^6 m^3 and the average annual rainfall is 378 mm. The most important objective of Idoghmush dam construction is to supply water needed for the agricultural sector of the region (Ashofteh et al. 2013).

4 Results

4.1 Result of MODSIM Simulation Model

The results of system simulation with MODSIM model for base and future periods under RCP 2.6 and RCP 8.5 were obtained and the results are presented as reservoir performance indexes in Table 4. According to Table 4, changes in reservoir performance indexes in the future over the base have decreased in some cases and increased in others. Lack of the same trend in changes in reservoir performance indexes shows that for planning of water supply systems in the future years should not only consider changes in

Table 4 Reservoir performance indexes with simulations in MODSIM model for baseline and climate change periods

Index (%)	Time period of operation of water supply system		
	Baseline	Climate change RCP2.6	Climate change RCP8.5
Reliability	59	54	56
Vulnerability	16	12	11
Resiliency	42	44	46
Flexibility	21	21	23

reservoir inflow volume during operation period, but also examine the reservoir inflow changes in each month is very important in determining the amount of indexes and finally developing a suitable model for releasing the reservoir. According to Table 4, the reliability rate under the RCP2.6 scenario decreased by 9% compared to the base period and the vulnerability index decreased by 17%. The significant reduction in vulnerability indicates that demand shortages occurred in the months when the system was more vulnerable. Also, the resiliency has increased by 4% under the RCP2.6 scenario compared to the base period, which indicates that the ability of the system to return to the desired state will be in a better position than the base period and the flexibility index under the RCP2.6 scenario will not change much compared to the base period. According to Table 4, the reliability index and vulnerability index under the RCP8.5 scenario will decrease by 5 and 30%, respectively, compared to the base period, and the resiliency index will increase by 9% that indicates the ability of the system to return to the desired state, which will lead to a 10% increase in the flexibility index. This indicates that the system will be more flexible in dealing with the adverse effects of climate change in the future period under the RCP8.5 scenario than the base period and also better than the future period under the RCP2.6 scenario.

4.2 Result of LINGO 18 Optimization Model

The results of reservoir performance indexes from the optimization model with LINGO 18 model for the base and future period (under RCP 2.6 and RCP 8.5) are given in Table 5. According to Table 5, the changes in reservoir performance indexes in the future period compared to the base period as in the reservoir simulation indexes have

Table 5 Reservoir performance indexes with optimization in LINGO 18 model for baseline and climate change periods

Index (%)	Time period of operation of water supply system		
	Baseline	Climate change RCP2.6	Climate change RCP8.5
Reliability	58	50	54
Vulnerability	20	17	16
Resiliency	39	45	45
Flexibility	18	19	21

decreased in some cases and increased in others. For example, the reliability and vulnerability indexes in the future period under the RCP2.6 scenario have decreased by 13 and 17% compared to the base period, respectively. But on the other hand, the resiliency index has increased by 15% in the future period under the RCP2.6 compared to the base period. This means that the damage to the system has been such that the system has been able to return to the desired state. Overall, the flexibility index has grown by 4%, which indicates that the system, despite the reduction in reliability, will have more flexibility to the destructive effects of climate change in the future period under the RCP2.6 than the base period. Also, in the future period under RCP8.5 scenario, compared to the base period, the reliability and vulnerability indexes will decrease by 6 and 19%, respectively. On the other hand, the resiliency index will increase by 15% in the future period under the RCP8.5 compared to the base period. Finally, the flexibility index will increase by 13%.

4.3 Results of Rough-AHP Weighting Method

(a) **Hierarchical modeling**

In the first step, after determining the goal level, criteria level, and alternatives level, the hierarchical model was modeled as Fig. 6.

(b) **Criteria pair comparisons and controling the inconsistency rate**

After determining the criteria set and completing the pairwise comparison matrixes by five experts, the inconsistency rate of the experts' judgments was examined using Expert Choice 11 software, which is designed based on the AHP method. Table 6 shows the pairwise comparison matrixes of the first experts and their inconsistency rate. Table 6 is a pairwise comparison matrix of the criteria, the upper half elements of which was completed by the first expert, and the lower half elements were calculated based on the reciprocal principle relative to the original diameter. After entering the above matrix in the Expert Choice model, the inconsistency rate was calculated, the value of which is less than 0.1, which indicates that the expert judgment is consistent.

(c) **Calculate the geometric mean of the same elements in the pairwise comparison matrix**

The same elements in the pairwise comparisons matrix and their geometric mean are shown in Table 7. As shown in Table 7, the lower approximation, the set of numbers

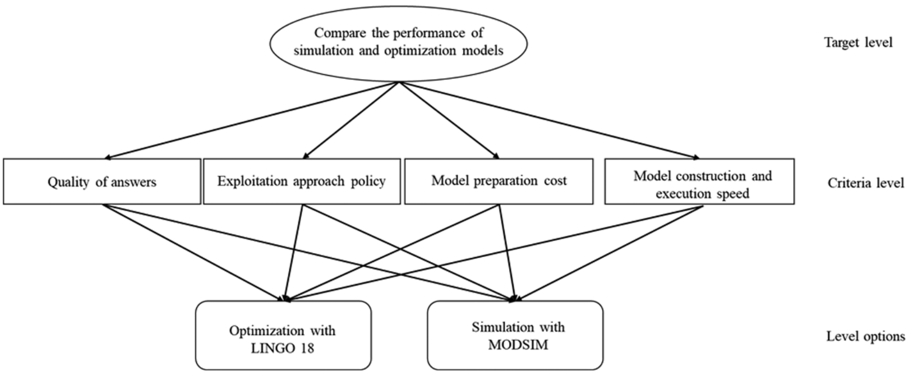

Fig. 6 Scheme of different steps of modeling the weighting of criteria by AHP method

Table 6 Pairwise comparison matrix of criteria according to the goal of the first expert

	C_1	C_2	C_3	C_4
C_1	1	**6**	**3**	**3**
C_2	1.6	1	**0.2**	**2**
C_3	1.3	5	1	**4**
C_4	1.3	1.3	1.4	1
Inconsistency rate	0.09			

C_1=Cost criteria; C_2=Criteria for the reservoir operation policy approach; $C_{3=}$ Quality criterion of solutions of each model; C_4=Criteria for construction and execution of models

smaller than the geometric mean, and the higher approximation, the numbers greater than the geometric mean, are the same elements in the pairwise comparison matrix.

(d) **Calculate the upper limit and the lower limit**

After determining the set of high and low approximations in the previous step, the same elements and their geometric mean were arranged and the upper and lower limits were calculated, the results of which are given in Table 8.

(e) **Formation of cumulative pairwise comparisons based on rough numbers**

The cumulative pairwise comparison matrix was then formed based on rough numbers. To form this matrix, after calculating and placing the upper-half elements, the lower-half elements were calculated based on the reciprocal principle in AHP method. The cumulative pairwise comparison matrix is given in Table 9.

(f) **Calculate the degree of satisfaction from the judgment of experts**

At this stage, the degree of satisfaction with the scoring of experts was calculated. The results are presented in Table 10.

(g) **Calculate the final weight of the criteria**

The criterion final weight of the model preparation cost was 0.437, the criterion of the operating policy approach was 0.273, the criterion of the quality of the solutions was 0.223 and the criterion of construction and execution time of the model was 0.0656. According to the results of the weighting method, the most important criterion in evaluating the alternatives is to consider the model preparation cost, because it can not be used until the model can be prepared.

After that, the criterion of the reservoir operation policy approach is in the second place, because the reservoir operation policy approach has a direct effect on the monthly release from the reservoir and causes significant changes in the process of changing reservoir performance indexes as a basis for future planning.

Table 7 Identical elements in the matrix of pairwise comparisons and geometric mean

	Identical elements in the pairwise comparison matrix					Geometric mean
C_{12}	6	0.11	3	4	0.5	1.316
C_{13}	3	0.2	2	7	0.25	1.159
C_{14}	3	1	2	9	8	3.365
C_{23}	0.2	1	2	5	2	1.319
C_{24}	2	9	3	6	5	4.384
C_{34}	4	8	2	3	3	3.565

Table 8 Calculation of the upper limit and the lower limit

	Arrange the identical matrix elements of pairwise comparisons and their geometric mean						Low limit	Upper limit
C_{12}	0.11	0.5	**1.316**	3	4	6	0.234	4.160
C_{13}	0.2	0.25	**1.159**	2	3	7	0.223	3.476
C_{14}	1	2	3	**3.36**	8	9	1.17	8.485
C_{23}	0.2	1	**1.319**	2	2	5	0.447	2.714
C_{24}	2	3	**4.384**	5	6	9	2.449	6.463
C_{34}	2	3	3	**3.56**	4	8	2.620	5.656

The criterion of construction and execution time of the model is in the last rank, which shows that according to experts, the construction and execution time of the model has no significant effect on the accuracy of the results.

4.4 Result of MAIRCA Decision-Making Method

(a) **Formation of matrices**

In the first step of the MAIRCA decision ranking method, the initial decision matrix was completed by four experts and their opinions were aggregated. Then the theoretical evaluation matrix is formed in the second step. In the third step, the real assessment matrix was calculated. Next, the general gap matrix is formed in the fourth step. The results are presented in Table 11.

(b) **Calculate values of criteria functions**

In the last step, the final values of the criteria functions for each alternative were calculated, which are presented in Table 12. The results of Table 12 show that the simulation approach with MODSIM model with lower criterion function is superior to the optimization approach with LINGO 18 model. The simulation approach with the MODSIM model as a more appropriate approach shows that experts consider the simulation results by simulators widely used in different regions to be more appropriate than the optimization with the LINGO 18 model whose objective function and constraints are determined by policy-makers. Because policymakers may not use the objective function appropriate to the situation of the study area and based on unrealistic results, the status of the water supply system will be more endangered. Also, the provision cost of the LINGO 18 optimization model has led experts to consider free access to the MODSIM simulation model as one of its advantages. The possibility of customization in the MODSIM model has caused it to have a lot of flexibility for modeling a wide range of water systems with different characteristics. Also, the ability of MODSIM

Table 9 Cumulative pairwise comparison matrix based on rough numbers

	C_1	C_2	C_3	C_4
C_1	(1,1)	(0.23, 4.16)	(0.22, 3.47)	(1.81, 8.48)
C_2	(0.24,4.34)	(1,1)	(0.44, 2.71)	(2.44, 6.46)
C_3	(0.288,4.54)	(0.369, 2.27)	(1,1)	(2.62, 5.65)
C_4	(0.117, 0.552)	(0.154, 0.409)	(0.179, 0.381)	(1,1)

Table 10 Matrix of degree of satisfaction with the scoring of experts

	C_1	C_2	C_3	C_4
C_1	1	2.195	1.85	5.145
C_2	0.455	1	1.575	4.45
C_3	0.540	0.634	1	4.135
C_4	0.194	0.224	0.241	1

Table 11 Calculation of decision matrices, theoretical evaluation, real evaluation, general gap

Step 1				
	C_1	C_2	C_3	C_4
A_1	39	70.75	78	50.5
A_2	40.5	74	84	22.5
Step 2				
	C_1	C_2	C_3	C_4
A_1	0.218	0.136	0.111	0.032
A_2	0.218	0.136	0.111	0.032
Step 3				
	C_1	C_2	C_3	C_4
A_1	0	0	0	0.032
A_2	0.218	0.136	0.111	0
Step 4				
	C_1	C_2	C_3	C_4
A_1	0.218	0.136	0.111	0
A_2	0	0	0	0.032

A_1 = optimization approach, A_2 = simulation approach

Table 12 Preferencing and criterion function for each alternative

Alternatives	The total value of the criterion function	Rank
Optimization approach with LINGO 18 model	0.467	2
Simulation approach with MODSIM model	0.032	1

model to provide more quality criteria for solutions based on performance indexes of water supply system, which aims to provide more stakeholder satisfaction, has played an important role in choosing a simulation approach with MODSIM model.

The results of the present study show that choosing the proper approach for managing available water resources is very important and effective. The results of a choice can be cited when it is based on the suitable criteria that reflect the actual decision space. The use of multi-criteria decision-making methods has the ability to consider different criteria to select the best alternative and can include all the opinions of experts and their desired criteria. Also, the general process of this study can be generalized to other case studies.

5 Concluding Remarks

Ensuring the security of water resources, especially in the agricultural sector as one of the infrastructures of sustainable development is of special importance. Preservation of current water resources and planning to deal with factors that could jeopardize the quantity and quality of water resources is essential. The phenomenon of climate change is considered as one of the natural critical factors in the occurrence of water stress and it is necessary to carefully study its effects on climate parameters to minimize its adverse effects.

In addition to identify the effects of any type of threat to water resources, it is necessary that the policy-making approach be considered in accordance with the situation in the study region, because the choice of any approach plays a key role in how decision-makers respond to factors threatening the sustainability of water resources. Choosing the right approach for realistic evaluation of results is influenced by various factors, and one of the best tools for aggregating various opinions of different groups is to use multi-criteria decision-making methods.

On the other hand, in any decision-making process, the inherent uncertainties arising from the human knowledge of the group of experts who are in the first step of each process always challenge the sustainability of the results obtained. So far, various theories have been proposed to reduce the uncertainties. One of the most important is RST theory based on mathematical concepts, which due to its flexibility can be combined with weighting and ranking methods of multi-criteria decisions and reduce uncertainties in the decision-making process.

In the present study, first the effects of climate change were investigated on water supply system in the future period. The results of climatic models showed that in the future time period, the climatic parameter of temperature under RCP2.6 and RCP8.5 scenarios will increase by 1.5 and 1.3%, respectively, compared to the base time period, and the climatic parameter of precipitation will increase by 17 and 25% in the future time period, under RCP2.6 and RCP8.5 emission scenarios respectively, over the base time period.

In the next step, the effects of increasing temperature and rainfall on water required for agricultural irrigation and inflow to reservoir were investigated. The results showed that the water required by the agricultural sector under both scenarios will increase by 15% and the inflow to reservoir under the scenarios RCP2.6 and RCP8.5 will increase by 12 and 13%, respectively. Then the water supply system was modeled with two approaches of simulation with MODSIM model and the optimization with LINGO 18 model and four indexes of reliability, resiliency, vulnerability and flexibility for both approaches were extracted separately. Due to the same amount and trend of performance indexes of water supply system in simulation and optimization approaches, MAIRCA decision-making method was used to select a more appropriate approach.

In this study, Rough-AHP weighting method was used to weight the criteria. In this way, the mental information of the experts is expressed definitively, but with the RST tool they are splited to upper and lower limits and calculated the degree of satisfaction with the judgments. In fact, this method is a response to uncertainties with definite numbers. The results of Rough-AHP method showed that the model provision cost with a weight of 0.475 was the most important criteria and the criterion construction and execution time of the model with a value of 0.065 was the least important criteria for experts. Finally, the criteria of operation policy approach and the criterion of quality of solutions with weights of 0.273 and 0.223, respectively, were ranked second and third. In the last step, with MAIRCA decision-making method, modeling approaches were prioritized and the simulation approach with a criteria function value of 0.467 was selected as the best approach for allocating water resources in the future.

Author Contribution S.-S. Mortezaeipooya developed the theory and performed the computations. P. Golfam verified the analytical methods. P.-S. Ashofteh and P. Golfam encouraged S.-S. Mortezaeipooya to investigate a specific aspect. P.-S. Ashofteh supervised the findings of this work, and P. Golfam helped supervise the project. All authors discussed the results and contributed to the final manuscript. S.-S. Mortezaeipooya wrote the manuscript with support from P.-S. Ashofteh and P. Golfam. P.-S. Ashofteh conceived the original idea.

Availability of Data and Materials Authors have restrictions on sharing data.

Declarations

Ethics Approval The paper is not currently being considered for publication elsewhere. All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Consent to Publish The participant has consented to the submission of the case report to the journal.

Conflict of Interest None.

References

Abdi-Dehkordi M, Bozorg-Haddad O, Chu X (2021) Development of a combined index to evaluate sustainability of water resources systemes. Water Resour Manage 35:2965–2985. https://doi.org/10.1007/s11269-021-02880-w

Ashofteh P-S, Bozorg-Haddad O, Mariño M (2013) Climate change impact of on reservoir performance indexes in agricultural water supply. J Irrig Drain Eng 139(2):85–97. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000496

Ashofteh P-S, Golfam P, Loáiciga HA (2020) Evaluation of river water transfer alternatives with the TODIM multi-criteria decision-making method. Water Resour Manage 34:4847–4863. https://doi.org/10.1007/s11269-020-02694-2

Ashofteh P-S, Rajaei T, Golfam P (2017) Assessment of water resources development projects under conditions of climate change using efficiency indexes (EIs). Water Resour Manage 31(12):3723–3744. https://doi.org/10.1007/s11269-017-1701-y

Ashofteh P-S, Rajaei T, Golfam P, Chu X (2019) Applying climate adaptation strategies for improvement of management indexes a river reservoir irrigation system. Irrig Drain 68(3):420–432. https://doi.org/10.1002/ird.2336

Ashrafi S, Kerachian R, Pourmoghim P, Behboudian M, Motlaghzadeh K (2022) Evaluating and improving sustainability of ecosystem services in river basins under climate change. Sci Total Environ 806:150702. https://doi.org/10.1016/j.scitotenv.2021.150702

Ayağ Z, Özdemir RG (2009) A hybrid approach to concept selection through fuzzy analytic network process. Comput Ind Eng 56(1):368–379

Behboudian M, Kerachian R (2021) Evaluating the resilience of water resources management scenarios using the evidential reasoning approach: the Zarrinehrud river basin experience. J Environ Manage 284:112025. https://doi.org/10.1016/j.jenvman.2021.112025

Bertsekas D, Tseng P (1994) RELAX-IV: A Faster Version of the RELAX Code for Solving Minimum Cost Flow Problems. Report for NSF Grant CCR-9103804, Dept. of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge

Daba MH, You S (2020) Assessment of climate change impacts on river flow regimes in the upstream of Awash Basin Ethiopia: Based on IPCC Fifth Assessment Report (AR5) climate change scenarios. Hydrology 7(4). https://doi.org/10.3390/hydrology7040098

Dau QV, Kuntiyawichai K, Adeloye AJ (2021) Future changes in water availability due to climate change projections for Houng basin, Vietnam. Environ Process 8:77–98. https://doi.org/10.1007/s40710-020-00475-y

Fadaeizadeh K, Shourian M (2019) Determination of the optimal water river basin-wide agricultural water demand quantities meeting satisfactory reliability levels. Water Resour Manage 33:2665–2676. https://doi.org/10.1007/s11269-019-02242-7

FAO (2009) Cropwat 8.0 for windows user guide. Rome. Italy

Forman E, Peniwati K (1998) Aggregating individual judgments and priorities with the analytic hierarchy process. Eur J Oper Res 108(1):165–169. https://doi.org/10.1016/S0377-2217(97)00244-0

Golfam P, Ashofteh PS, Loáiciga HA (2019a) Evaluation of the VIKOR and FOWA multi-criteria decision making methods for climate-change adaptation of agricultural water supply. J Water Resour Manag 33(8):2867–2884. https://doi.org/10.1007/s11269-019-02274-z

Golfam P, Ashofteh PS, Rajaee T, Chu X (2019b) Prioritization of water allocation for adaptation to climate change using multi-criteria decision making (MCDM). J Water Resour Manag 33(10):3401–3416. https://doi.org/10.1007/s11269-019-02307-7

Hadian S, Shahiri Tabarestani E, Pham QB (2022) Multi Attributive Ideal-Real Comparative Analysis (MAIRCA) method for evaluating flood susceptibility in a temperate Mediterranean climate. Hydrol Sci J. https://doi.org/10.1080/02626667.2022.2027949

Hashimoto T, Stedinger JR, Loucks DP (1982) Reliability, resiliency and vulnerability criteria for water resources system performance evaluation. Water Resour Res 18(1):14–20. https://doi.org/10.1029/WR018i001p00014

He L, Shao F, Ren L (2020) Identifying optimal groundwater remediation strategies through a simulation-based PROMETHEE-TOPSIS approach: an application to a naphthalene-contaminated site. J Human Ecol Risk Assess: Int J 26:1550–1568. https://doi.org/10.1080/10807039.2019.1591267

Jamshidpey A, Shoorian M (2021) Crop pattern planning and irrigation water allocation compatiable with climate change using a coupled network flow programming-heuristic optimization model. Hydrol Sci J 66(1). https://doi.org/10.1080/02626667.2020.1844889

Kuang H, Kilgur M, Hipel WK (2014) Grey-based PROMETHEE II with application to evaluation of source water protection strategies. J Inform Sci 294:376–389. https://doi.org/10.1016/j.ins.2014.09.035

Labadie J (2006) MODSIM: Decision Support System for Integrated River Basin Management", International Congress on Environmental Modelling and Software, 3rd International Congress on Environmental Modelling and Software - Burlington, Vermont, USA - July 2006. https://scholarsarchive.byu.edu/iemssconference/2006/all/242

Loucks DP (1997) Quantifying trends in system sustainability. Hydrol Sci J 42(4):513–530

Mandal U, Sena DR, Dhar A, Panda SN, Adhikary PP, Mishra PK (2021) Assessment of climate change and its impact on hydrologycal regimes biomass yield of a tropical river basin. Ecol Ind 126:107646. https://doi.org/10.1016/j.ecolind.2021.107646

Marengo JA, Chou SC, Kay G, Alves LM, Pescuero JF, Soares WR, Santos DC, Lyra AA, Sueiro G, Betts R, Chagas DJ, Gomes JL, Boustamante JF, Tavares P (2012) Development of regional future climate change scenarios in South America using the Eta CPTEC/HadCM3 climate change projections: climatology and regional analyses for the Amazon, Sao Francisco and Parana river basins. Clim Dyn 38:1829–1848. https://doi.org/10.1007/s00832-011-1155-5

MATLAB (2022) "MATLAB software toolbox", version 2022b

Nabeel A, Athar H (2020) Stochastic projection of precipitation and wet and dry spells over Pakistan using IPCC AR5 based AOGCMS. Atmos Res 234:104742. https://doi.org/10.1016/j.atmosres.2019.104742

Pamacur D, Vasin L, Lukovac V (2014) Selection of railway level crossing for investing in security equipment using hybrid Dematel-MAICRA model. XVI International Scientific-Expert Conference on Railways, Serbia, pp 89–92

Pawlak Z (1982) Rough sets. Int J Comput Info Sci 11(5):341–356

Pourmoghim P, Behboudian M, Kerachian R (2022) An uncertainty-based framework for evaluating and improving the long-term resilience of lakes under anthropogenic droughts. J Environ Manage 301:113900. https://doi.org/10.1016/j.jenvman.2021.113900

Rani S, Sreekesh S (2019) Evaluating the responses of streamflow under future climate change scenarios in a Western Indian Himalaya watershed. Environ Process. https://doi.org/10.1007/s40710-019-00361-2

Saaty TL (1977) A scaling method for priorities hierarchical structures. J Math Psychol 15(3):234–281. https://doi.org/10.1016/0022-2496(77)90033-5

Saaty TL (1980) The analytic hierarchy process. McGraw-Hill, New York

Shenava N, Shourian M (2018) Optimal reservoir operation with water supply enrichment and flood mitigation objectives using an optimization and simulation approach. Water Resour Manage 32:4393–4407. https://doi.org/10.1007/s11269-018-2068-4

Sherafatpour Z, Roozbahani A, Hasani Y (2019) Agricultural water allocation by integration of hydro-economic modeling with Bayesian Networks and Random Forest approaches. Water Resour Manage 33:2277–2299. https://doi.org/10.1007/s11269-019-02240-9

Theochari A-P, Feloni E, Bournas A, Batles E (2021) Hydrometeorological - hydrometric station network design using multicriteria decision analysis and GIS techniques. Environ Process 8:1099–1119. https://doi.org/10.1007/s40710-021-00527-x

Velasquez M, Hester PT (2013) An analysis of multi-criteria decision making methods. J Int J Oper Res 10(2):56–66

Zarghami M, Fotookian MR, Safari N, Aslanzadeh A (2016) Reservoir operation using system dynamics under climate change impacts: a case study of Yamchi reservoir, Iran. Arab J Geosci 9:678. https://doi.org/10.1007/s12517-016-2676-3

Authors and Affiliations

Sadaf-Sadat Mortezaeipooya[1] · Parisa-Sadat Ashofteh[1] · Parvin Golfam[1]

Sadaf-Sadat Mortezaeipooya
SS.Mortezaeipooya@stu.qom.ac.ir

Parvin Golfam
P.golfam@stu.qom.ac.ir

[1] Department of Civil Engineering, University of Qom, Qom, Iran