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A Hybrid Meta-Heuristic for a Bi-Objective Stochastic Optimization of Urban Water Supply System

AZADEH DOGANI[1], ARASH DOURANDISH[1], MOHAMMAD GHORBANI[1], AND MOHAMMAD REZA SHAHBAZBEGIAN[2,3]

[1]Department of Agricultural Economics, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad 9177948974, Iran
[2]Department of Geography and Planning, Faculty of Humanities, Tarbiat Modares University, Tehran 14115-111, Iran
[3]Department of Interdisciplinary Water Technology, Faculty of Interdisciplinary Science and Technology, Tarbiat Modares University, Tehran 14115-111, Iran

Corresponding author: Arash Dourandish (dourandish@um.ac.ir)

ABSTRACT The restoration and remodeling of the urban water supply system are traditional challenges for water companies due to either aged existing water supply networks or lodging expansion. These challenges involve the uncertainties induced by their lengthy-planned prospects and the impossible exact prediction of forthcoming events. In this regard, correlations exacerbate unpredictable data and parameters and probably undermine taking effective decisions in this context. Therefore, the remodel and restoration decision of water supply systems must be made using approaches that can effectively deal with correlation uncertainties. The present study develops a bi-objective stochastic optimization model that can handle interrelated uncertain parameters in the water supply system remodeling and restoration issue. The proposed mathematical model is validated using the data of the Mashhad Plain water supply system as a real case study, followed by performing and comparing different levels of conservatism and reliability. As a complex optimization problem, an efficient algorithm is needed to solve the problem. To this end, a hybrid meta-heuristic algorithm, which is a combination of the Red Deer Algorithm (as a newly introduced nature-inspired heuristic) and Simulated Annealing (as a traditional local search algorithm), is proposed. Considering the advantages of these algorithms, it is possible to alleviate the disadvantages of current methods when solving large-scale networks. Finally, an extensive comparison and discussion are made and then the main findings with practical solutions are presented to significantly evaluate the proposed model and algorithm.

INDEX TERMS Optimization, water supply, hybrid metaheuristic, red deer algorithm (RDA), simulated annealing (SA).

I. INTRODUCTION

A Municipal Water Supply System (MWSS) provides the designs of physical infrastructures for water purification from different high-grade water supplies (such as dams and aquifers) and water delivery to several demand sites in the urban areas [1], [2]. Since MWSS components are deteriorated during the use and consumption, such systems need periodical rehabilitation and occasional expansion depending on housing expansion and rising population [3], [4]. Moreover, water resource shortage has forced authorities to constantly monitor factors reducing the effectiveness of the MWSS [5]. In this sense, water companies should occasionally present a strategy for the remodel and restoration of MWSS. Although several studies have proposed optimization models and algorithms for the design of MWSSs, most of them only consider the total cost. Thus, there is no study on the seepage minimization in addition to the total cost using a stochastic optimization model for the case of Mashhad Plain water system.

Regarding the limitation of available financial sources in water companies, MWSS Remodel and Restoration Problem (MWSSRRP) has been comprehensively studied by focusing on the traditional cost minimization goal. However, because of the role of other performance indicators involved in this process, only a few articles have been published in

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recent years addressing other performance indicators [6], [7]. For instance, Chandapillai *et al.* [8] presented the water distribution equity among user zones in addition to the cost-efficiency as two performance benchmarks for optimizing the water supply network. Also, energy usage and greenhouse gas emissions have been introduced as two other measures by Tsakiris [9].

According to Lansey [10], leakage reduction has received negligible attention in previous investigations. Water seepage may range from 15% to 65% in the finest and the poorest events, respectively. Hence, water loss through leakage accounts for the main drawback in the efficacious functioning of MWSSs representing declined income for facilities and countermined service quality [11], [12], as well as energy resource waste [13]. As stated by Engelhardt *et al.* [14], guaranteeing no seepage of the components of an MWSS is not economically justified. Accordingly, it is necessary to establish a proper equilibrium between the expenses of the activities necessary for leakage reduction and the number of water losses. The reliability of the system is another essential performance indicator possibly conflicting with the cost objective that may be considered as a continuous supply of high-grade water for demand zones in a variety of forthcoming setups. The (re)designing decision models of MWSS seek to design a strategy for an upcoming long-run prospect. Using such a design, the decision-makers can consult predicted data because of lacking data concerning the achievement of decision parameters. Particularly, impreciseness is the indispensable component of predicted data. Impreciseness in future forecasted water demand and precipitation are two common issues confronted when using such systems. Uncertainty, therefore, has circumvented MWSSs, ignoring which will bring about poor decisions. In these systems, the consequences of making decisions under determinate presumptions are double-sided: (1) less net profit (more expensive supply of the desirable water than anticipated) and (2) elevated system's possibility (failure is described as unfulfilled demand or violation of other system restrictions such as excessive harvest of water) [15], [16].

Unfulfilled demands would result in various unpleasant influences on socioeconomic improvement [17], [18]. Moreover, the harvest of water from resources higher than allowable levels may give rise to environmental damages. Social discontentment and environmental harms jeopardize sustainable development. It is, therefore, advisable to apply a conservative approach to immunize the MWSS versus uncertainty. Despite some research efforts on handling uncertainty in MWSS R & R problems, such studies sometimes overlook the consequences of uncertainty in model parameters [19].

Among the procedures employed to address uncertainty, stochastic programming (SP) is widely used in research works [20], [21]. For instance, chance-constrained programming was used by Xu and Goulter [22] and Kapelan *et al.* [3], to address demand uncertainty. Two-stage and multi-stage stochastic programming methods were utilized by Watkins *et al.* [23] and Kracman *et al.* [24] to develop and plan a multi-reservoir water supply system. Similarly, fuzzy mathematical programming has shown the potential of the expressing uncertain parameters by possibilistic distributions [25]–[28]. A formulation of a fuzzy mathematical programming model was introduced for a multi-reservoir system consisting of a downstream reservoir and several upstream parallel reservoirs [29]. To take the benefits of stochastic and fuzzy programming, Shibu and Reddy [30] proposed an MWSS design problem by applying a fuzzy stochastic programming method where a triangular fuzzy number was assigned to the water demand [31].

All of the reported models assign possibilistic and/or probabilistic functions to uncertain elements. In most cases, however, either of the two is not attributable. When historical data are not sufficient or reliable, or in cases where it is not possible to establish that similar historical pattern continues to recur in the future, it might be not possible to reasonably explain uncertain parameters with probabilistic distributions. In a few instances, uncertain factors cannot be presented as fuzzy numbers. In these situations, based on uncertainty programming studies, it is appropriate to denote the uncertain factors with closed convex sets with no mention of the equivalent probability or possibility distribution. Within the MWSS project area, Chung *et al.* [1] and Hendalianpour *et al.* [32] utilized closed convex sets for modeling several demand-side uncertain parameters. Nevertheless, the authors ignored the whole supply-side uncertain parameters, although neglecting the supply-side uncertainty may result in resource inadequacy. Additionally, in realistic water supply problems, uncertain factors are typically correlated strongly with one another. For instance, some associations exist among inflows to and outflows from a dam in a given timeframe. In a dry timespan, the dam surface evaporation rises with the river discharge into the dam along with decreased precipitations on its surface. This major issue has been completely ignored in available investigations.

Zhang *et al.* [33] used a multi-level multi-objective stochastic model to examine the sustainable management of water resources in an arid zone for agriculture in the northwest of China. They proposed a new optimization modeling approach consisting of a Multi-Level Multi-Objective Stochastic Programming (MLMOSP) and used the weight quantification method to formulate the sustainable water allocation of that area. These authors investigated four objectives including the number of key factors affecting water allocation systems, describing the main conflicting goals at each decision-making level, considering exchanges between conflicting goals, and reflecting the leader relationships following different scenarios of surface water accessibility. A comparison of several models showed that the MLMSOP approach could not only ensure more practical results to achieve decision-making goals at different levels but also help reduce groundwater extraction under different runoff flow scenarios.

Sustainable management of agricultural water resources is essential for regional development promotion and environmental revitalization. Zhang *et al.* [34], presented a new method of mathematical programming called the multi-objective chance-constrained programming with uncertain weights (MCUW). This model can have uncertain weights of goals without a certain distribution. It can also deal with unknown parameters by a known probability distribution, and create solutions with different risks of limitation. To demonstrate the application of the proposed MCUW approach, it was implemented in a case study caused by the problem of agricultural water management in northwestern China.

Rain Water Harvesting (RWH) has been used as an alternative to supply water to places undergoing overexploitation of water resources. Pérez-Uresti *et al.* [35] developed a multi-objective optimization model to assess the potential of RWH as an alternative water resource and then design an optimal water distribution network where natural and alternative resources serve as an integrated system. This model was developed for three different goals of maximum profit, minimum groundwater consumption, and minimum investment cost. A case study was conducted for Queretaro City in Mexico to demonstrate the application of the proposed method. They found that 27% of domestic demand was supplied by RWH in Queretaro City, leading to a significant improvement in destruction-prone deep wells.

In recent years, cases of drinking polluted water have occurred increasingly, leading to considerable economic losses and social issues. Hu *et al.* [36] utilized a multi-objective optimization model for two goals of minimizing the volume of polluted water exposed to public view and minimized the operating costs of water supply and gates. Finally, they proposed a non-dominated sorted genetic algorithm-II (NSGA-II) with an EPANET simulation to validate the model and the proposed method. They also examined the effects of different parameters on the performance of their proposed algorithm.

According to Sepahvand *et al.* [37], climate change increases water demand sharply in arid and semiarid areas, thereby reducing the volume of water resources. Hence, the current research was performed using an optimization simulation model for continual management of groundwater usage to achieve two main objectives: (1) minimizing deficiencies in meeting irrigation needs and 2) maximizing total net agricultural profit for the main crops of an agricultural sector. To achieve these main goals, the Genetic Programming (GP) method was first used to simulate the interactions of water and groundwater levels. Then, the simulation model with a Multi-Objective Genetic Algorithm (MOGA) was presented as the optimization simulation model. The results of this research indicate that the maximum profit increased by 38.9%, 59.37%, and 45% in wet, normal, and dry years, respectively, compared with those of real performance obtained for a case study.

To cover this research gap, the present article puts forward a bi-objective mathematical model for balancing the minimization of the overall remodel expense and water leakage. A stochastic pattern was employed to address uncertainty using a conservative method. As far as the authors are aware, this study is the first to extensively consider the uncertainty outlined as closed convex sets in both the demand-side (indeed, demand and precipitation in demand zones) as well as supply-side (indeed, outflows and inflows from and to resources). Besides, our investigation considers correlations among uncertain parameters aiming at approaching the realistic context in MWSS R & R problem. To handle interrelated uncertain factors, our designed Stochastic Optimization (SO) model can handle constraints where their Right-Hand Side (RHS) values are equivalent to the sum of several interrelated uncertain factors. To propose the solving for the contrast between the cost and reliability, mathematical models have been formulated with a wide range of demand constraint violation probabilities. Thus, the authorities can interact to attain the desired tradeoff within the cost and the demand fulfillment reliability. The main contributions of this paper are as follows:

1. A bi-objective mathematical model for balancing the minimization of the overall remodel expense and water leakage
2. Consider the uncertainty outlined as closed convex sets in both the demand-side (indeed, demand and precipitation in demand zones) as well as supply-side (indeed, outflows and inflows from and to resources)
3. Proposed hybrid meta-heuristic algorithm with the combination of Red Deer Algorithm (RDA) as a newly-introduced nature-inspired heuristic and Simulated Annealing (SA)

The current article continues in the following order: The related MWSSR & R problem, stimulated by the Tehran water network, is detailed and developed in Section 2. In Section 3, the projected and executed models are run for some examples encouraged by the Mashhad Plain water supply system. In the end, concluding remarks and some recommendations for future studies are presented in Section 4.

II. PROBLEM DESCRIPTION AND FORMULATION

The fundamental construction of the relevant MWSS (Figure 1) indicates the presence of several influxes and effluxes to and from a dam. Although the volume of dam water is reinforced by the precipitation and river flow, it is reduced by vaporization, leakage, water transfer to treatment centers, and the release of water to the basin for ecosystem requirements. Notably, the precipitation in a timeframe, which specifies the extent of aridity throughout the involved duration, may influence the quantity of vaporized water, the surface streams release to the dam, and the quantity of water required by the ecosystem. The precipitation impacts on the other influxes and effluxes from and to the dam are characterized by ordinary dotted lines in Figure 1.

In the examined MWSS, water transfer occurs through installations (indeed, dams to treatment centers) via the

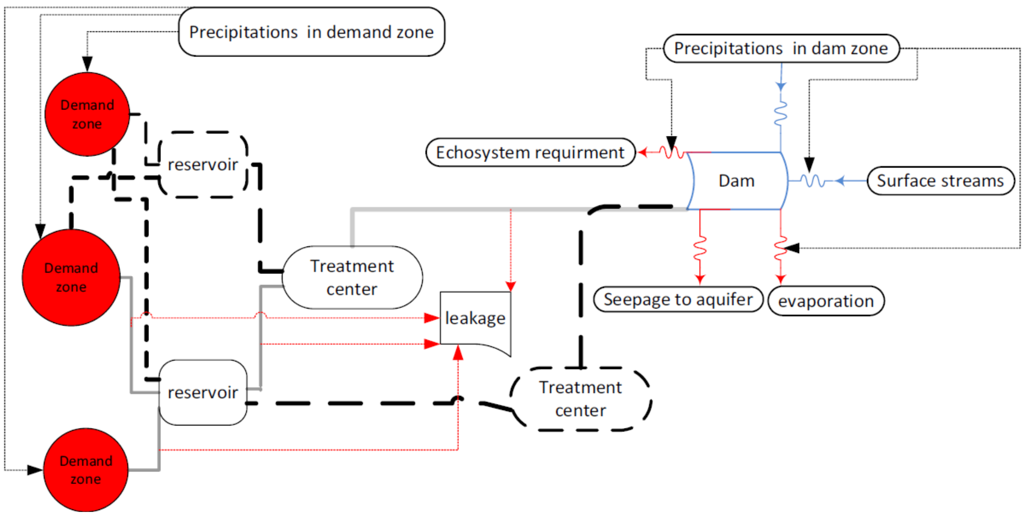

FIGURE 1. Demonstration of the related macroscopic urban water supply system.

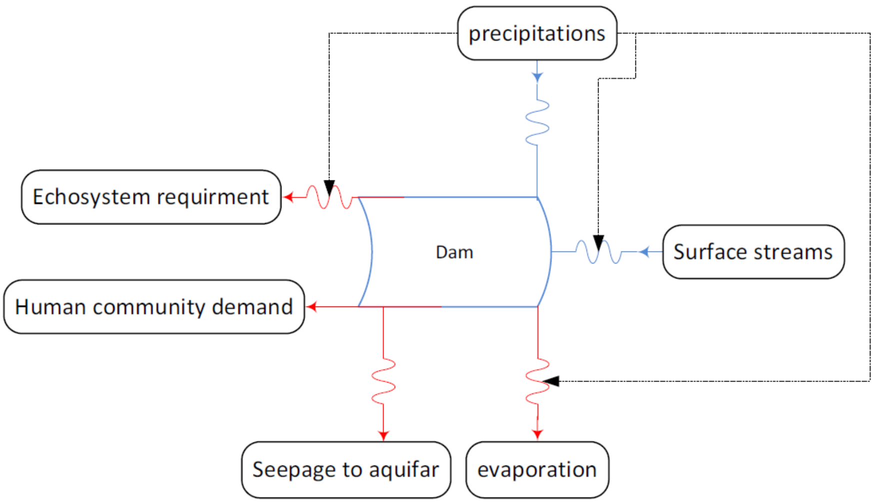

FIGURE 2. Factors affecting the dam inflow and outflow.

pipelines that can be old (continual lines denote existing pipelines). Hence, considerable water losses may affect the MWSS. The water company not only must decrease water loss between various paths but also must decide regarding pipeline restoration or new pipe fitting in the network depending on pertinent costs. The feasible and installable facilities and pipeline pathways are presented by bold dotted lines in Figure 2. The lines with fluctuations denote the uncertain flow rates. Water transfer is done from the dam to the treatment center for purification. Afterward, water is directed to reservoirs to adjust water pressure and velocity and add chlorine for water protection from contamination. The aridity of weather is a parameter influencing the level of demand in various demand zones. The demand level rises during a timeframe with a lesser amount of precipitation. Additionally, precipitation partly fulfills the demand, which concerns irrigating planted spaces of houses. As described above, the key decisions adopted in the introduced model could be classified as below:

Strategic decisions:

– Establishing novel treatment centers and reservoirs;
– Installing novel pipelines; and
– Restoration of old pipelines.

Tactical decisions:

– Allotment of water within various pathways from dams to treatment centers;
– Allotment of water within various pathways from treatment centers to reservoirs; and
– Allotment of water within various pathways from reservoirs to the demand zone.

A. MODEL FORMULATION

The following provides the description of symbols applied to formulate the pertinent MWSSR&R problem. Remarkably, the tilde sign ($\sim$) distinguishes uncertain input parameters from other ones.

Indices:

i: Index of dams

j: Index of service (treatment) centers

r: Index of reservoirs

k: Index of demand areas (household and industrial)

l: Index of water pipelines

t: Index of Time periods

Parameters:

dia_l: Diameter of water pipelines l

c_l^{line}: Cost per transfer unit of pipeline l

LR: Leakage rate and water loss

$LR_{ij}^{da-to-tr}$: Water loss rate from the dam i to service centers j

$LR_{jr}^{tr-to-res}$: Water loss rate from service centers j to reservoir r

$LR_{rk}^{res-to-dem}$: Water loss rate from the reservoir r to demand center k

$Mo_{i,t}$: Critical level of water in the dam i at the end of time-period t based on environmental issues

BJ_{jt}: Critical level of water in the treatment center j at the end of time-period t

BR_{rt}: Critical level of water in the reservoir r at the end of time-period t

$Cpipe_{ij}^{da-to-tr}$: Maximum flow capacity for a pipeline connecting dam i to the service center j

$Cpipe_{jr}^{tr-to-res}$: Maximum flow capacity for a pipeline connecting treatment center j to the reservoir r

$Cpipe_{rk}^{res-to-dem}$: Maximum flow capacity for a pipeline connecting the reservoir r to demand center k

$Ctran_{ij}^{da-to-tr}$: Unit distribution cost from the dam i to the treatment center j

$Ctran_{jr}^{tr-to-res}$: Unit distribution cost from treatment center j to reservoir r

$Ctran_{rk}^{res-to-dem}$: Unit distribution cost from the reservoir r to demand area k

Io_i^{dam}: Baseline volume of water in the dam i at the start of planning time

Io_j^{treat}: Baseline volume of water in the treatment center j at the start of planning time

$Io_r^{resrvoir}$: Baseline volume of water in the reservoir r at the start of planning time

$Cstab_j^{treatment}$: Cost of the treatment center j

$Cstab_r^{reservoir}$: Cost of the reservoir r

$Copr_j^{treatment}$: Cost of unit operation at the treatment center j

$Copr_r^{reservoir}$: Cost of the unit operation in the reservoir r

$Chold_j^{treatment}$: Cost of unit holding at the treatment center j

$Chold_r^{reservoir}$: Operating capacity of the treatment center j

$oprcap_j^{reservoir}$: Operating capacity of the reservoir r

e'_{jrl}: Equals to 1 if a pipeline with diameter l exists between treatment center j and r at the onset of planning time; otherwise, it is 0

$L_{jr}^{tr-to-res}$: Distance of treatment center j with the reservoir r

$L_{rk}^{res-to-dem}$: Distance of reservoir r to demand area k

$L_{ij}^{da-to-tr}$: Distance of dam i to the treatment center j

Vel: Maximum permissible water velocity in pipelines

$\tilde{d}_{kt}$: Amount of demand center k at time-period t

$frdz_{kt}$: Precipitation in the region k at time-period t

$AAGR_k$: Area of the region k

$ADAM_i$: Area of the dam i

$f\tilde{r}_{it}$: Precipitation per unit area of the dam i

$r\tilde{r}_{it}$: Runoff release to the dam i at time-period t

$e\tilde{r}_{it}$: Evaporation rate of the dam i at time-period t

$s\tilde{r}_{it}$: Watershed subsidence of dam i at time-period t

$o\tilde{r}_{it}$: Outflow rate from the dam i for ecosystem conditions at time-period t

ρ: Correlation coefficient

p'_{ijl}: Equals 1 if a pipeline with diameter l exists between dam i and treatment center j at the onset of planning, otherwise $= 0$

n'_{rkl}: Equals 1 if a pipeline with diameter l exists between dam i and reservoir r at the onset of planning, otherwise $= 0$

y'_j: Equals 1 if the treatment center j is accessible.

z'_r: Equals 1 if the reservoir r is available, otherwise $= 0$.

Decision Variables:

X_{ijt}: Quantity of water transported from dam i to treatment center j at time-period t

B_{jrt}: Quantity of water transported from the treatment center j reservoir r at time-period t

W_{rkt}: Quantity of water transported from the reservoir r to demand area k at time-period t

$Q_{ijt}^{da-to-tr}$: Water flow from dam i to treatment center j at time-period t

$Q_{jrt}^{tr-to-res}$: Water flow from the treatment center j to the reservoir r at time-period t

$Q_{rkt}^{res-to-dem}$: Water flow from the reservoir r to demand area k at time-period t

$Q_{rkt}^{res-to-dem}$: Quantity of water in the dam i after time-period t

I_{jt}^{treat}: Quantity of water in the treatment center j after time-period t

$I_{rt}^{reservoir}$: Quantity of water in the reservoir r after time-period t

y_j: Equals 1 when treatment center j requires installation, otherwise $= 0$

z_r: Equals 1 when reservoir r requires installation, otherwise $= 0$

p_{ijl}: Equals 1 when a novel pipeline with a diameter of l needs to be mounted between dam i and treatment center j, otherwise $= 0$

Objective Functions: The MWSSRRP was considered as the cost minimization problem; thus, the first objective function is devoted to minimizing the cost. Besides, the minimization of seepage, which has received little attention, is another objective function in the offered model. *Cost minimization:* In the problem of MWSSRRP, overall cost includes (1) installation cost and established costs of reservoirs and treatment centers, (2) cost of water distribution at the facility, (3) installation of new pipeline, (4) cost of water reposition at reservoirs and treatment centers, and (5) treatment at the facility. Accordingly, the first objective function is written as follows:

$$\begin{aligned}
Min\, Z_1 = &\sum\nolimits_j Cstab_j^{treatment} y_j + \sum\nolimits_r Cstab_r^{resrtvoir} Z_r \\
&+\sum\nolimits_j \sum\nolimits_r \sum\nolimits_t B_{jrt} Copr_j^{treatment} \\
&+\sum\nolimits_j \sum\nolimits_r \sum\nolimits_t W_{rkt} Copr_r^{reservoir} \\
&+\sum\nolimits_j \sum\nolimits_r \sum\nolimits_t B_{jrt} Ctran_{ij}^{da-to-tr} \\
&+\sum\nolimits_j \sum\nolimits_r \sum\nolimits_t W_{rkt} Ctran_{rk}^{res-to-dem} \\
&+\sum\nolimits_j \sum\nolimits_r \sum\nolimits_t X_{ijt} Ctran_{ij}^{da-to-tr} \\
&+\sum\nolimits_j \sum\nolimits_t \frac{1}{2} Cold_j^{treatment} \\
&\times \left(\sum\nolimits_i X_{ijt} \left(1 - \frac{\sum_r B_{jrt}}{\sum_i X_{ijt}}\right) + BJ_{jt}\right) \\
&+\sum\nolimits_r \sum\nolimits_t \frac{1}{2} Cold_r^{reservoir} \\
&\times \left(\sum\nolimits_k W_{rkt} \left(1 - \frac{\sum_j B_{jrt}}{\sum_k W_{rkt}}\right) + BR_{rt}\right) \\
&+\sum\nolimits_i \sum\nolimits_j \sum\nolimits_l C_l^{line} . L_{rk}^{res-to-dem} . n_{rkl} \qquad (1)
\end{aligned}$$

Minimization of Seepage: p_{ijl} is a binary parameter equal to 1, when a pipeline with diameter l exists between facility i and facility j at the onset of planning. If a pipeline exists between facility i and facility j, the leakage rate of this pipeline is indicated by $LR_{ij}^{da-to-tr} - to - tr$. The leakage rate for each recently installed pipeline is represented by LR. The seepage rate in the pipeline path is calculated through the multiplication of the seepage rate by the amount of water transported by the pipeline. To calculate the seepage rate on a route, three considerations are taken into consideration: 1) Seepage rate for a new pipeline fitting route with no previously installed pipeline equals LR; e.g., when $\sum_l p_{ijl} = 0$ and $\sum_l p_{ijl} = 1$, then seepage rate equals to LR; 2) seepage rate for a new pipeline installing route with a previously installed pipeline equals LR; e.g., when $\sum_l p_{ijl} = 0$ and $\sum_l p_{ijl} = 1$, then seepage rate equals LR); 3) seepage rate for a route without a new pipeline equals to previous leakage rate; e.g., when $\sum_l p_{ijl} = 0$ and $\sum_l p_{ijl} = 1$, then seepage rate equals $LR_{ij}^{da-to-tr}$. Eq. (2) estimates the overall seepage rate for each relevant MWSS route over the entire time period. For the above three cases, it has been observed that the actual amount of leakage is obtained by Eq. (2). For instance, take into account the pathway between dam i and treatment center j. In the first case, if $\sum_l p_{ijl} = 0$ and $\sum_l p_{ijl} = 1$ are included in Eq. (2), the leakage rate will be equal to LR. Likewise, in the second case, if $\sum_l p_{ijl} = 0$ and $\sum_l p_{ijl} = 1$ are incorporated in Eq. (2), the seepage rate will equal LR. Finally, in the third case, if $\sum_l p_{ijl} = 0$ and $\sum_l p_{ijl} = 1$, water transfer is available through the pipeline and leak rate will equal $LR_{ij}^{da-to-tr}$. It is noteworthy that LR is much lower than $LR_{ij}^{da-to-tr}$.

$$\begin{aligned}
Min\, Z_2 = &\sum\nolimits_t \Big[\sum\nolimits_i \sum\nolimits_j \left(\sum\nolimits_i P_{ijt}\right) . X_{ijt} . LR \\
&+\sum\nolimits_j \sum\nolimits_r \left(\sum\nolimits_i e_{jrl}\right) . B_{jrt} . LR\Big] \\
&+\sum\nolimits_r \sum\nolimits_k \left(\sum\nolimits_l n_{rkl}\right) . W_{rkt} . LR \\
&+\sum\nolimits_i \sum\nolimits_j \left(\sum\nolimits_L P'_{ijl}\right) . X_{ijt} . LR_{ij}^{da-to-tr} \\
&+\sum\nolimits_j \sum\nolimits_r \left(\sum\nolimits_l e'_{jrl}\right) . B_{jrt} . LR_{jr}^{tr-to-res} \\
&+\sum\nolimits_r \sum\nolimits_k \left(\sum\nolimits_l n'_{irkl}\right) . W_{rkt} . LR_{rk}^{res-to-dem} \\
&-\sum\nolimits_i \sum\nolimits_j \left(\sum\nolimits_l P_{ijl}\right) . \left(\sum\nolimits_l P'_{ijl}\right) . X_{ijt} . LR_{ij}^{da-to-tr} \\
&-\sum\nolimits_j \sum\nolimits_r \left(\sum\nolimits_l e_{jrl}\right) . \left(\sum\nolimits_l e'_{jrl}\right) . B_{jrt} . LR_{jr}^{tr-to-res} \\
&-\sum\nolimits_r \sum\nolimits_k \left(\sum\nolimits_l n_{rkl}\right) . W_{jrt} . LR_{rk}^{res-to-dem} \qquad (2)
\end{aligned}$$

Constraints: The decisions mentioned in the previous sections should be made regarding several limitations, including dam limitations (the balance of water flow and harvesting limitation equilibrium) and logical limitations (i.e., network topology, capacity, and demand limitations) that guarantee demand satisfaction in consumer areas. Mathematical formulas for the above limitations are expressed below [38].

Dam Constraints: Due to environmental concerns, a crucial and predetermined quantity of water (i.e., $Mo_{i,t}$) must be supplied in the dam at any timeframe. Fatahi and Fayyaz [39] addressed the dam inflow and outflow. Precipitation ($fr_{i,t}$) and river flow ($rr_{i,t}$) increase the water volume in the dam. On the other hand, evaporation ($er_{i,t}$), settlement ($sr_{i,t}$), water transfer to treatment centers, and river water discharge ($or_{i,t}$) reduce the amount of dam water. As mentioned above, precipitation, river flow, evaporation, settlement, and river water discharge are variable parameters. Besides, there is a correlation between input and output flows. Precipitation directly affects river flow and evaporation, and water discharge into the ecosystem basin occurs indirectly because the volume of ecosystem demand decreases during a rainy timeframe. In the current article, it is assumed that input and output flow rates fluctuate at some intervals due to probable distribution and only the upper and lower bounds are attributed to the flows.

Accordingly, the uncertainty parameter can be shown in a time-period with specified upper and lower limits. To this end, dam-related uncertainty parameters are shown in Eqs. (3-7), where random parameters $\xi_{i,t}, \eta_{i,t}, \gamma_{i,t}, \delta_{i,t}$ vary in the interval of -1 to 1 with unknown distribution functions. Moreover, parameters marked with $(-)$ correspond to nominal values (center of distance) and those marked with $\wedge$ denoting a constant deviation from nominal values. Furthermore, correlations between the parameters are shown in these equations using correlation coefficients. For instance, $rr_{i,t}$ is a finite unknown parameter representing river flow to dam i at time-period t. A correlation also exists between $rr_{i,t}$ and precipitation at any timeframe. In Eq. (3), $rr_{i,t}$ is the nominal flow of the river in the time frame, $rr_{i,t}$ is half the uncertain time frame, and $f\hat{r}_{it}.\rho_1$ is its association with precipitation in the dam area. Eq. (9a) estimates the net flow rate to dams at each time frame. Eq. (9) guarantees flow balance in the dam and calculates the amount of dam water at the end of every timeframe. Eq. (9b) assures that the quantity of water remaining in the dam at the termination of every time frame is higher than the crucial level for the environment.

$$rr_{it} = r\bar{r}_{it} + \xi_{it}.r\bar{r}_{it} + \eta_{it}.f\hat{r}_{it}.\rho_1 \quad \forall i, t \tag{3}$$

$$f\tilde{r}_{it} = f\bar{r}_{it} + \eta_{it}.f\hat{r}_{it}. \quad \forall i, t \tag{4}$$

$$er_{it} = e\bar{r}_{it} + \gamma_{it}.r\bar{r}_{it} + \eta_{it}.fr_{it}.\rho_2 \quad \forall i, t \tag{5}$$

$$sr_{it} = s\bar{r}_{it} + \theta_{it} + s\hat{r}_{it} \quad \forall i, t \tag{6}$$

$$Or_{it} = O\bar{r}_{it} + \delta_{it}.r\bar{r}_{it} + \eta_{it}.f\hat{r}_{it}.\rho_2 \quad \forall i, t$$

$$\xi_{it}, \eta_{it}, \gamma_{it}, \theta_{it}, \delta_{it} \in [-1 \quad 1] \quad \forall i, t \tag{7}$$

$$br_{it} = r\bar{r}_{it} + f\hat{r}_{it}.ADAM_I - er_{it} - sr_{it} - or_{it} \quad \forall i, t \tag{8}$$

$$I_{it}^{dam} = Io_i^{dam} + \sum\nolimits_{l=1}^{t}\left(-\sum\nolimits_j X_{i,j,l} + b\tilde{r}_{il}\right) \quad \forall i, t \tag{9a}$$

$$I_{it}^{dam} \geq MO_{it} \quad \forall i, t \tag{9b}$$

Logical constraints. In case no treatment centers exist in position j, pipeline routes cannot be terminated and initiated from site j, as denoted in Eqs. (10a) and (10b). Similarly, Eqs. (11a) and (11b) impose the above restrictions on the reservoirs. Eqs. 12 and 13 ensure that no other facility can be established at any locality if the installation is accessible at the onset of planning. Finally, Eq. (13) prevents installing over one type of pipeline (with a certain diameter) in every route.

$$y_j + \acute{y}_i \geq \left(\sum\nolimits_i p_{ijl}\right) \quad \forall i, t \tag{10a}$$

$$y_j + \acute{y}_j \geq \left(\sum\nolimits_l e_{jrl}\right) \quad \forall j, r \tag{10b}$$

$$z_r + \acute{z}_r \geq \left(\sum\nolimits_l e_{jrl}\right) \quad \forall j, r \tag{11a}$$

$$z_r + \acute{z}_r \geq \left(\sum\nolimits_l n_{jrl}\right) \quad \forall r, j \tag{11b}$$

$$y_j + \acute{y}_j \leq 1 \quad \forall j \tag{12}$$

$$z_r + \acute{z}_r \leq 1 \quad \forall r$$

$$\sum\nolimits_l p_{ijl} \leq 1 \quad \forall i, j, \quad \sum\nolimits_l e_{jrl} \leq 1 \quad \forall j, r, \tag{13}$$

$$\sum\nolimits_l n_{rkl} \leq 1 \quad \forall r, k \tag{14}$$

Capacity Constraints: Depending on the capacity (volume) of the facility, the amount of water transported to the facilities should not exceed the quantified amount. Eqs. (15a) and (16a) estimate the quantity of water available at the termination of every time frame at reservoirs and treatment centers. Eqs. (15b) and (16b) guarantee that the quantity of water in a treatment center or reservoirs does not surpass the maximum capacity of the respective volume. Additionally, reservoirs and treatment centers have a particular treatment capacity for water treatment and transfer at every timeframe. Treatment capacity restrictions are calculated using Eqs. 17 and 18. Eqs. (19a), (20a), and (21a) estimate the maximum permissible flow of pipelines between installations because of the diameter of the pipeline and maximal potential velocity. Eqs. (19-b), (20-b), and (21-b) guarantee that flow rate via the pipeline route is lesser than maximal permissible flow. The flow rates of $Q_{ijt}^{da-to-tr}$, $Q_{jrt}^{tr-to-res}$, and $Q_{rkt}^{res-to-dem}$ are obtained by dividing the quantity of transported water by the time frame duration.

Demand Restrictions: The demand for an area is met by the water transferred from the supply network and the level of precipitation in that area. The amount of regional precipitation and demands are variable. Furthermore, precipitation over a timeframe specifies the intensity of drought during that timeframe. An increase in drought frequency and intensity lead to a consequent increase in demand. Therefore, the demand and precipitation levels are correlated over a time period. $frdz_{kt}$ represents the quantity of regional precipitation in each area k, which varies randomly with an unidentified distribution $\left[\overline{frdz_{kt}} - frd\hat{z}_{kt}, \overline{frdz_{kt}} + frd\hat{z}_{kt}\right]$. Eq. (22) is a mathematical symbol of $frdz_{kt}$. ϕ_{kt} is a random symmetric parameter with unidentified distribution in $[-1\ 1]$. The unknown demand for area k, $frdz_{kt}$, is affected by the amount of precipitation in area k. Eq. (23) is a mathematical symbol of $\hat{d}_{kt}$, where $fr\hat{d}z_{kt}.\rho_4$ denotes the maximal potential impact of precipitation in area k based on the demand of area k. Eq. (24) shows that demand is satisfied in every consumer region.

$$\begin{aligned} I_{jt}^{treat} = I_{j,t-1}^{treat} &+ \sum\left(\sum P_{ijl}\right) X_{ijt}\,(1-LR) \\ &+ \sum\sum \acute{P}_{ijl} X_{ijt}\left(1 - LR_{ij}^{da-to-tr}\right) \\ &- \sum\sum\left(\sum P_{ijl}\right)\acute{P}_{ijl}\left(1 - LR_{ij}^{da-to-tr}\right).X_{ijt} \\ &- \sum\nolimits_r B_{jrt} \quad \forall j, t \end{aligned} \tag{15a}$$

$$I_{jt}^{treat} \leq Vol_j^{treatment}.\left(y_j + y_j'\right) \quad \forall j, t \tag{15b}$$

$$\begin{aligned} I_{rt}^{resevoir} = I_{r,t-1}^{reservoir} &+ \sum\nolimits_j\left(\sum\nolimits_l jrl\right) B_{jrt}\,(1-LR) \\ &+ \sum\nolimits_l\sum\nolimits_i \acute{e}_{jrl} B_{jr}\left(1 - L_{jr}^{tr-to-res}\right) \\ &- \sum\nolimits_j\sum\nolimits_l\left(\sum\nolimits_l e_{jrl}\right)\acute{e}_{jrl}\left(1 - LR_{jr}^{tr-to-res}\right).B_{j,r,t} \\ &- \sum\nolimits_k W_{r,k,t} \quad \forall r, t \end{aligned} \tag{16a}$$

$$I_{rt}^{reservoir} \leq Vol_r^{reservoir}.\left(z_r + y_r'\right) \quad \forall r, t \tag{16b}$$

$$\begin{aligned} &\sum\nolimits_i\left(\sum\nolimits_l P_{ijl}\right) X_{ijt}\,(1-LR) \\ &\quad + \sum\nolimits_l\sum\nolimits_i \acute{P}_{ijl} X_{ijt}\left(1 - LR_{ij}^{da-to-tr}\right) \\ &\quad - \sum\nolimits_i\sum\nolimits_l\left(\sum\nolimits_l P_{ijl}\right)\acute{P}_{ijl}\left(1 - LR_{ij}^{da-to-tr}\right).X_{ijt} \\ &\quad \leq oprcap_j^{tratment} y_j \quad \forall j \end{aligned} \tag{17}$$

$$\begin{aligned} &\sum\nolimits_j\left(\sum\nolimits_l e_{jrl}\right) B_{jrl}\,(1-LR) \\ &\quad + \sum\nolimits_l\sum\nolimits_j \acute{e}_{jrl} B_{jrt}\left(1 - LR_{jr}^{tr-to-resr}\right) \\ &\quad - \sum\nolimits_j\sum\nolimits_l\left(\sum\nolimits_l e_{jrl}\right) e_{jrl}\left(1 - LR_{ij}^{tr-to-res}\right).B_{jrt} \\ &\quad \leq oprcap_r^{reservoir} Z_r \quad \forall r \end{aligned} \tag{18}$$

$$Cpipe_{ij}^{da-to-tr} = \frac{\pi}{4}.vel.\left(\sum_{l}\left(P_{ijl}.dia_l^2 + \acute{P}_{ijl}.\left(1-P_{ijl}\right)dia_l^2\right)\right) \quad \forall i,j \tag{19a}$$

$$Q_{ij}^{da-to-tr} \le Cpipe_{ij}^{da-to-tr} \quad \forall i,j,t \tag{19b}$$

$$Cpipe_{jr}^{tr-to-res} = \frac{\pi}{4}.vel.\left(\sum_{l}\left(e_{jrl}.dia_l^2 + \acute{e}_{jrl}.\left(1-e_{ijl}\right)dia_l^2\right)\right) \quad \forall i,j \tag{20a}$$

$$Q_{jr}^{tr-to-res} \le Cpipe_{jr}^{tr-to-res} \quad \forall j,r,t \tag{20b}$$

$$Cpipe_{rk}^{res-to-dem} = \frac{\pi}{4}.vel.\left(\sum_{l}\left(n_{rkl}.dia_l^2 + \acute{n}_{rkl}.\left(1-n_{rkl}\right)dia_l^2\right)\right) \tag{21a}$$

$$Q_{rk}^{res-to-dem} \le Cpipe_{rk}^{res-to-dem} \quad \forall r,k,t \tag{21b}$$

$$frd\tilde{z}_{kt} = \overline{frdz_{kt}} + \varphi_{kt}.frd\hat{z} \quad \forall k,t \tag{22}$$

$$\tilde{d}_{kt} = \bar{d}_{kt} + \varepsilon_{kt}.\hat{d}_{kt} + \varphi_{kt}.frd\hat{z}.\rho_4 \quad \forall k,t$$
$$\varepsilon_{kt},\varphi_{kt} \in [-1 \quad 1] \quad \forall k,t \tag{23}$$

$$\sum_{r}\left(\sum_{r} n_{rkl}W_{rkt}\right)(1-LR) + \sum_{l}\sum_{r}\acute{n}_{rkl}W_{rkt}\left(1-LR_{rk}^{res-to-dem}\right) - \sum_{l}\sum_{r}\left(\sum_{l} n_{rkl}\right)\acute{n}_{rkl}\left(1-LR_{rk}^{res-to-dem}\right).W_{rkt} + AAGR_k.frdz_{kt} \ge d_{kt} \quad \forall k,t \tag{24}$$

B. LINEARIZATION

Eqs. (15a), (16a), (17), (18), and (24) represent nonlinear conditions owing to binary output and continual non-linear variables. To avoid the complication of such a nonlinear model, nonlinear terms are changed to linear ones, for which it is necessary to define an auxiliary variable, X_{ijt}, as follows:

$$\left(\sum_{l} p_{ijl}\right).x_{ijt} = x'_{ijt} \tag{25}$$

Eq. (15a) is linearized by substituting $\left(\sum_l p_{ijl}\right).x_{ijt}$ and x'_{ijt} and addition of constraints (26)-(28) to the set of constraints. It guarantees that when $\sum_l p_{ijl} = 0$, the auxiliary variable equals zero and when $\sum_l p_{ijl} = 1$, the auxiliary variable is equal to 0. At the same time, M is a large predetermined number.

$$x'_{ijt} \le M\left(\sum_{l} p_{ijl}\right).x_{ijt} \tag{26}$$

$$x'_{ijt} \le x_{ijt} \tag{27}$$

$$x'_{ijt} \ge M\left(\left(\sum_{l} p_{ijl}\right)-1\right).x_{ijt} \tag{28}$$

Other nonlinear conditions in Eqs. (16a), (17), (18), and (24) are converted to equivalent linear conditions.

III. SOLUTION ALGORITHM

Over the past 30 years, the significance of the optimization problems has raised due to the huge growth in the complexity and size of industrial organizations [40]. Thus, several efforts have been made by managers to discover optimal solutions and control the entire organization. Meta-heuristic algorithms are important, cost-efficient, and easy instruments in this regard [41]. For the first time, John Holland presented the Genetic Algorithm (GA) in 1975 for solving complex and huge problems. Since then, several meta-heuristics have been developed inspired by artificial processes or nature; for example, Ant Colony Optimization (ACO) inspired by the ant colonies' pheromone trail performance; SA based on metals annealing procedure [42]; Harmony Search (HS) motivated by the improvising procedure of music composing; Particle Swarm Optimization (PSO) inspired by the social performance of fish schooling or bird flocking; Imperialist Competitive Algorithm (ICA) based on imperialistic competition; Keshtel Algorithm (KA) inspired by Keshtels' feeding performance; and Glow-worm Swarm Optimization (GSO) based on the glow-worms' flashing performance. Other algorithms developed for this purpose are Whale Optimization Algorithm (WOA) motivated by bubble-net hunting strategy of humpback whales' social performance [43], the Salp Swarm Algorithm (SSA) inspired by swarm performance of slap' chain, and more recently Social Engineering Optimizer (SEO) as an intelligent and single-solution algorithm [44]. In summary, each meta-heuristic algorithm includes distinct characteristics and advantages including the design motivated by natural laws or phenomena theoretically [45], requiring fewer mathematical conditions, and reduced computational complexity [46].

In recent years, some papers have been published on the applications and characteristics of recent meta-heuristics [47], [48], as well as on its exploitation or intensification. These papers focus on probable good areas in solution space [49] to discover new ranges and improve the algorithm. Examples of operators in diversification and intensification phases include mutation and crossover operators in Gas, different empires carrying diversification in ICA, Keshtels searching potential places in KA, and a bubble-net hunting strategy in the WOA.

A new metaheuristic was developed based on the No-Free-Lunch (NFL) theory, where no meta-heuristic optimization algorithm exists for solving all optimization problems and the possibility for a better performance of a novel meta-heuristic algorithm. Therefore, the focus of the present study is on a new meta-heuristic algorithm known as the RDA inspired by red deer mating to solve various problems successfully. The Scottish Red Deer (Cervus Elaphus Scoticus) is a sub-species of red deer living in the British Isles. Over a breeding season, male Red Deer (RD) roars repeatedly and loudly to inspire hinds since females favor a high roaring over a low one [50]. Normally, the red deer mating outlines include a dozen or more mating attempts before the first successful one. A harem is a group of females mating with the head of the harem or male commander who occupies the territory and protects the other hinds in his harem. It mates with numerous females to make a new generation.

The mathematical model presented in Section 2 reveals that the proposed model is an NP-hard model; therefore, it is solved using meta-heuristic algorithms. The integrated method of SA and the RDA is applied in this study. The solution method will be briefly explained in the following.

A. RDA

This algorithm was introduced by Fathollahi-Fard [51]. RDA starts with an initial population divided into two female and male deer groups. Male deer compete on attracting female deer through struggling, and their mating behavior is the basis of the proposed evolutionary algorithm. During the reproduction season, the brocket loudly makes noise frequently. The roaring rate has a direct relationship with doe attraction, reproductive success, and struggling ability.

The maximum roaring rate of a brocket is about eight roars per minute before struggling, and the brocket continues to roar in the absence of a rival. In the struggling stage, the deer stand up and roar against each other, and then move toward one another in the second stage. Brockets are divided into two groups of "commanders" and "ordinary deer". Also, a group of does (harem) is formed by the commanders. The population size of each harem is based on the commanders' roaring and fighting ability. After the formation of a harem, the commanders and brockets of each harem fight to seize it. Ultimately, commanders' mate with both their harem does and those of other harems. Brockets also mate with the nearest female doe without considering harem restriction.

In brief, the roar of a brocket is the local search in a solution space. Competition between commanders and brockets is also considered as a local search, but only the better solution is accepted in this process. Harems are formed after roaring and fighting and allocated to the commanders according to their power. The commander of a harem mates with 1% of does in his harem and also with one percent of does in other harems. Mating processes lead to the production of offspring, which is taken as the creation of new solutions in the solution space. As shown in Figure 2, the blue parts represent the focus phase, the red parts denote the diverse phase, and the green parts indicate escaping the local optimum. The stopping conditions of this algorithm include the number of iterations, the quality of the best response, and the running time.

B. THE HYBRID RDA

Hybrid algorithms are frequently used in real-world optimization. In this case, an algorithm is used for the general approach, but in the return operation, it is converted to another algorithm with more efficiency on small data. In this research, a combination of SA and RDA simulation is applied as a new hybrid algorithm, and its parameters are adjusted for one of the intended dimensions. In this algorithm, RDA and SA serve as the main ring and as a tool for local search, respectively.

The two phases of roaring and fighting, which are related to the focus phase, are eliminated from the RDA. To this end, the SA algorithm is used as the search tool instead of these two steps. This algorithm generally uses the SA as the focus phase and the RDA as the diverse phase. In each generation, every male brocket is a basic answer to SA. A hybrid optimization algorithm will be used for the problem of this study, which combines the SA and RDA, abbreviated as H-RS. The

Algorithm 1 The Combined RDA-SA Algorithm

Initialize the Red Dee's population.
Calculate the fitness, sort them, and form the hinds (*Nhind*) and male RDs (*Nmale*).
Set the Pareto optimal fronts.
while (t < maximum number of iteration)
for each male RD
sub = 1;
while (sub < maximum number of sub-iteration)
Create a neighbor of this solution by a procedure, which is depicted in Fig. S.3.2 from Supplementary
Material S.3.
if the new solution is better than prior
Replace the old solution with a new solution.
Else
Compute $\delta, \delta = |f_{old} - f_{new}|$.
If rand < exp$(-\delta/T)$
Replace the new solution.
End if
End if
sub = sub + 1;
end while
end for
Update T.
Sort the males and form the stags and the commanders.
Form harems:($V_n = v_n - max_i\{v_i\}; p_n = \left|\frac{v_n}{\sum_{i=1}^{N_{com}} v_i}\right|; N.harem_n = round\{p_n.N_{hind}\}$).
for each male commander
Mate male commander with the selected hinds of his harem randomly.
New = $\frac{com+hind}{2}$;
Select a harem randomly and name it k.
Mate male commander with some of the selected hinds of the harem.
end for
for each stag
Calculate the distance between the stag and all hinds and select the nearest hind.
$New = \frac{stag+hind}{2}$;
Mate stag with the selected hind.
end for
Select the next generation with roulette wheel selection.
Update the Pareto optimal solutions.
$t = t + 1$
end while
Consider the best front and evaluate the solutions by assessment metrics.

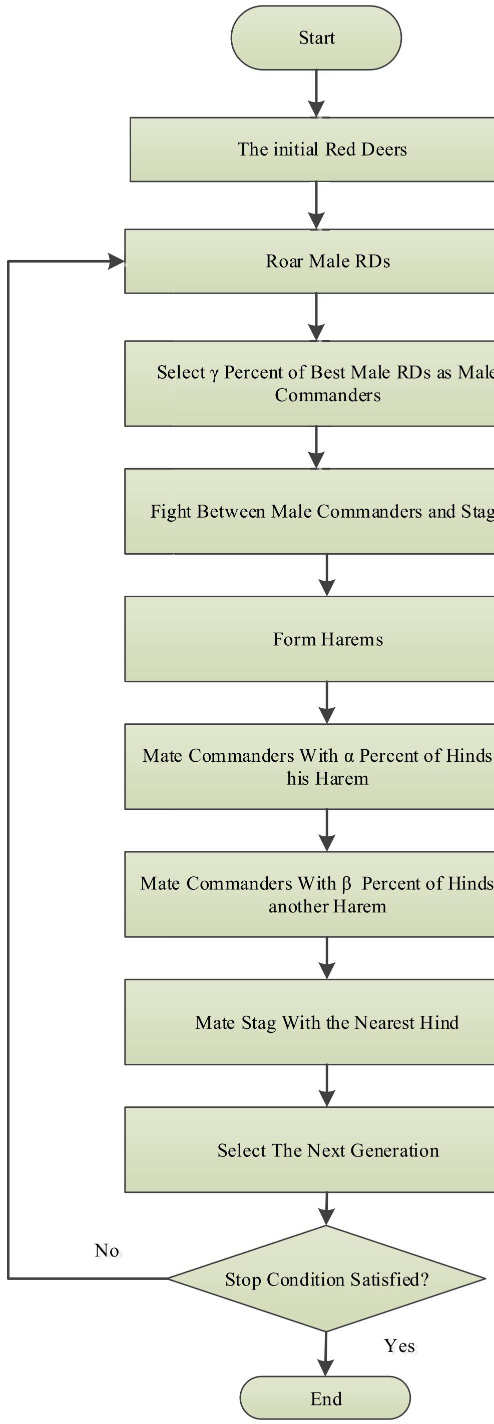

FIGURE 3. Flowchart of the RDA [53].

RDA is a population-based algorithm consisting of multiple stages. This combination was designed to decline computation time and exclude some stages by substituting SA rules. The steps of this algorithm are implemented by the following pseudo-code [52]:

C. PARAMETER SETTING

The results of meta-heuristic algorithms depend on the values of input parameters. In the following, the adjustment of the values for the parameters of the proposed algorithms is explained. For this purpose, a stopping condition of reaching 200 iterations is considered. To do the tuning of the algorithms, the design of experiments is widely used in many systems as an important tool to evaluate the performance of the processes and modifications. Parameter setting methods include:

- Reference to the literature
- Trial and error method
- Complete experimental procedures
- Taguchi method
- Response level method
- Adaptive neural network and fuzzy neural network
- The use of meta-heuristic algorithms (before or during the implementation)

In this paper, the Taguchi method is utilized to set the parameters. To further study this tuning approach, the readers are referred to [51], [52], [54].

TABLE 1. Groundwater resources of Mashhad Plain (2016-17 water year).

Type of water source	well	stepwell	spring	total
Number	6704	1084	656	8444
Harvest per year (million square meters)	797.9	104.3	65.1	967.4

Source: Khorasan Razavi Regional Water Company

TABLE 2. Mashhad Plain renewable water resources and volume of surface and underground harvests.

subject	Underground water	surface	total
The volume of renewable water (Million cubic meters per year)	748.8	97.7	882.6
Uses	Underground water	surface	total
Agriculture	641.7	60.3	702
Drinking and Health	177	97.3	274.2
Industry	58.8	0	58.8
Services	89.9	0.7	90.7
total	967.4	158.4	1125.7

Source: Khorasan Razavi Regional Water Company

TABLE 3. Candidate factors and levels in the RDA and SA hybrid algorithm.

Parameter	Level values		
	L 1	L 2	L 3
Maximum iteration (MaxIt)	200	100	150
Population size (nPop)	100	100	300
Number of males (nMale)	20	35	50
Percentage of commanders (gamma)	0.5	0.6	0.8
Percentage of inside the harems (alpha)	0.4	0.6	0.7
Percentage of outside the harems (betta)	0.3	0.5	0.5

TABLE 4. Experimental design with L9 orthogonal array for our hybrid algorithm RDA-SA.

Running order	Algorithm parameters						Response values
	Betta	**Alpha**	**gamma**	**nMale**	**nPop**	**MaxIt**	**MID**
1	L1	L1	L1	L1	L1	L1	6.9517
2	L1	L2	L2	L1	L2	L2	37.162
3	L1	L3	L3	L1	L3	L3	3.0812
4	L2	L1	L2	L2	L1	L2	9.465
5	L2	L2	L3	L2	L2	L3	5.6565
6	L2	L3	L1	L2	L3	L1	9.5747
7	L1	L1	L1	L3	L1	L3	16.3752
8	L1	L2	L2	L3	L2	L1	14.2128
9	L1	L3	L3	L3	L3	L2	7.9231

TABLE 5. Values obtained from solving objective functions individually for the real case study.

Real Problem		Objective Functions					
		First			Second		
		Upper Bound	Optimum	Lower Bound	Upper Bound	Optimum	Lower Bound
1	5#35#22#30#12	2848983	2478414	413098	2015582	1878983	819227

TABLE 6. Values obtained from solving objective functions individually.

Problem No		Objective Functions					
		First			Second		
		Upper Bound	Optimum	Lower Bound	Upper Bound	Optimum	Lower Bound
1	5#2#2#2#2	513098	478414	448983	515582	478983	419227
2	5#2#4#2#2	514998	459498	419227	617134	459227	465045
3	10#2#4#2#2	612758	513582	465045	511383	485045	328718
4	15#3#6#3#3	627052	572653	528718	179323	558718	614612
5	20#3#6#3#3	684757	668797	614612	91830	64612	557581
6	20#4#8#4#4	960872	934814	957581	971230	917581	419227
7	25#3#6#3#3	7619334	734047	711284	773348	741284	657581
8	25#4#8#4#4	1105375	1000450	911234	1080687	1021234	711284
9	30#4#6#3#3	7139437	673021	647067	761890	657067	551134
10	30#4#8#4#4	9140264	890816	828335	874060	868335	647067
11	35#5#10#5#5	1264842	1183635	1114468	1195016	1174468	828335
12	40#5#10#5#5	1333464	1304632	1251081	1744923	1251081	1014468
13	45#5#10#5#5	1164437	1082616	1050060	1068808	1050060	1011081
14	50#5#10#5#5	1183096	1160548	1138023	1662736	1138023	1050060
15	55#5#10#5#5	1342214	1305200	1089772	7576414	1279772	1138023
16	60#5#10#5#5	1285473	1228238	1150361	1686542	1200361	957581
17	65#5#10#5#5	1194309	1162677	1051263	1644138	1151263	711284
18	70#5#10#5#5	1418665	1324376	1028701	1765623	1128701	1011234
19	75#5#10#5#5	1100367	1071419	1003668	1576966	1063668	647067
20	80#5#10#5#5	1194366	1160817	1015069	1615454	1145069	828335

Before tuning, we need to define the details of our case study to solve it. This information and data are given in Table 1-2. Then, regarding the tuning, we considered three levels of L1, L2, and L3 for each parameter. These values are adopted from the main idea of this algorithm [54]. Table 3 presents the levels for six parameters of the RDA. To do all cases for the experiments, i.e., a full factorial method, a large number of tests (3^6) must be performed, which is very time-consuming. In this regard, the Taguchi method proposes some orthogonal arrays. To set our parameters, L9 is selected as a suitable experimental design for setting the proposed parameters. The L9 array is an experimental design with nine experiments instead of all 3^6 tests. The experimental designs for the algorithm are presented in Table 4. Also, Table 4 shows the mean ratio obtained for each level of factors related to the algorithm and optimal levels of input parameters of this algorithm.

IV. SOLVING THE MATHEMATICAL MODEL AND COMPARISON

Mashhad plain, a sub-basin area of Qaraghum basin (with a total area of 44491 m^2 covering Mashhad, Chenaran, Quchan, Binalood, Neyshabur, Kalat, and Dargaz cities) is located in the north of Khorasan province. The plain covers an area of over 10,000 m^2, including 6,000 m^2 of highlands and 4000 m^2 of a vast alluvial plain. Mashhad plain is one of the most important plains of Khorasan Razavi and one of the potential areas for agricultural production, with a negative

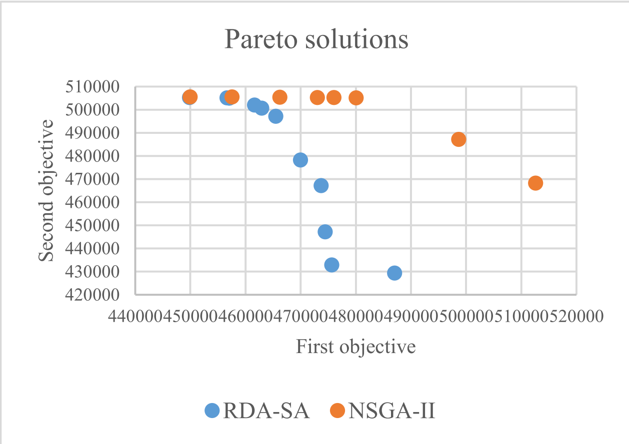

FIGURE 4. Non-dominated solutions in the first test problem.

groundwater balance as in many plains of the country. The average depth of groundwater is 48 m with a constant reserve of 5.5 billion m^3 in Mashhad plain. Over 136 million m^3 of water is overexploited annually from the groundwater sources of the plain. There is a total of 935 million m^3 renewable water, with a total aquifer discharge factor of 1071 million m^3 in the study area. Due to the limitation and seasonality of surface water resources, the bulk of irrigation water is extracted from groundwater resources, and the share of groundwater outflows reaches over 75% for agricultural uses. In the current situation, this water overharvest has caused an annual decline of 1.47 m (even 3-7 m in some places) in water tables and land subsidence up to 25 cm/y in the area. After solving this case study, the results are given in Table 5.

As shown in Table 1, the total collection of groundwater resources in Mashhad plain in 2016 to 2017 is equal to 967.4 million cubic meters, which was collected from a total of 8444 items (wells, stepwell, and springs). The table also shows the amount of harvest from each source.

Table 2 shows the volume of renewable water resources from groundwater and surface water resources, which are equal to 74.88 and 97.7 million cubic meters from 2016 to 2017, respectively. However, the amount of extraction from these resources is 96.47 and 158.4 million cubic meters, which is about 183 and 61 million cubic meters of overdraft from these sources for various uses. These values are shown in detail in the table 2.

The performance assessment of multi-objective algorithms is much more complicated than assessing single-objective algorithms [55]–[58]. As there are many criteria, only one assessment metric may not be efficient to evaluate the answers of proposed algorithms [55]–[58]. In general, for a good performance, a response provided by multi-objective algorithms should have at least three following metrics:

- **The number of Pareto Solution (NPS):** This metric is the number of Pareto solutions. An algorithm with more Pareto solutions will be a better algorithm [54].
- **Mean Ideal Distance (MID):** This value is equal to the distance of Pareto points of the algorithm from the ideal point. A lower value of this metric brings the better capability of the algorithm. For mathematics of this metric, see [51], [52].
- **Maximum Spread (MS):** This metric shows the uniform distribution of Pareto solutions in the solution space. A higher value of this metric is preferable. For mathematics of this metric, see [54].

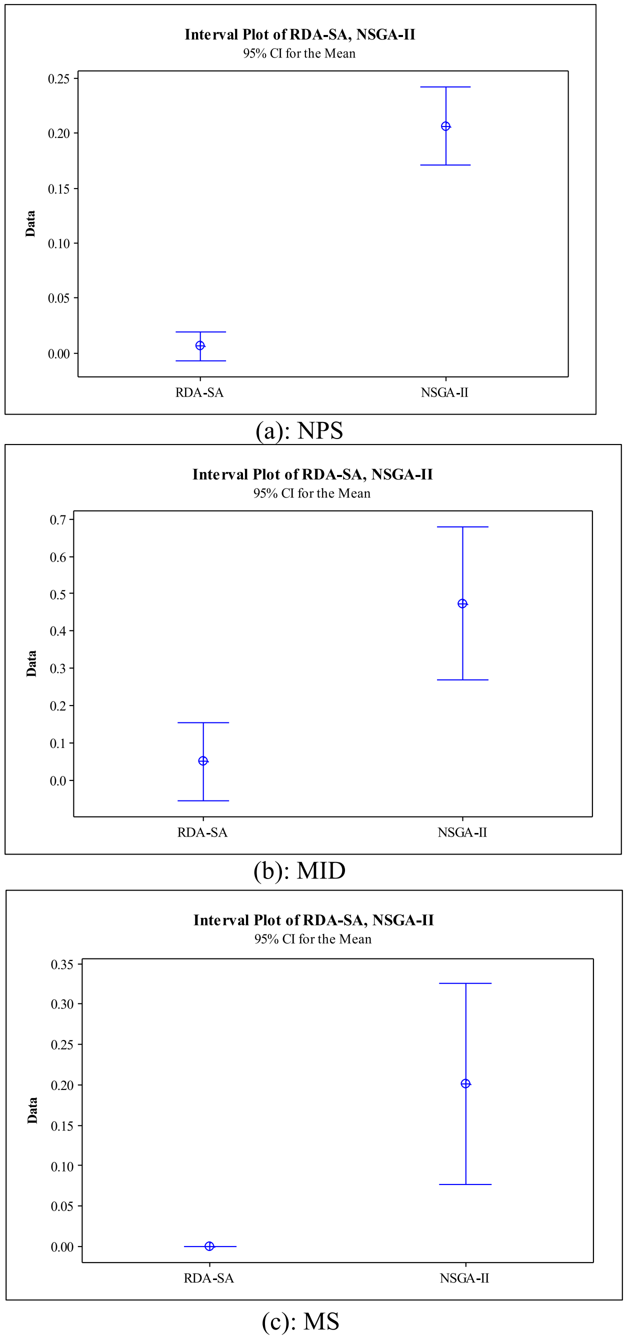

FIGURE 5. Interval plots for the robustness of RDA-SA and NSGA-II.

To analyze the algorithms, we defined different tests with small and large complexities. A total of 20 tests are generated with regards to benchmarks in the literature [20]–[30]. For each test problem, we considered the upper and lower bound

TABLE 7. Pareto metrics for the tests problems of different sizes in RDA-SA and NSGA-II.

		RDA-SA			NSGA-II		
	Problem No.	**NPS**	**MID**	**MS**	**NPS**	**MID**	**MS**
1	5#2#2#2#2	11	0.1233	5656	8	0.3616	4326
2	5#2#4#2#2	13	0.7741	12276	9	0.8845	10126
3	10#2#4#2#2	8	0.5463	7232	6	0.639	6535
4	15#3#6#3#3	6	0.2154	5747	4	0.42	5243
5	20#3#6#3#3	9	0.5512	7636	7	0.6863	7624
6	20#4#8#4#4	6	0.2342	4507	5	0.3645	3033
7	25#3#6#3#3	11	0.4354	6732	9	0.5742	6029
8	25#4#8#4#4	7	0.4522	6459	8	0.6125	6459
9	30#4#6#3#3	9	0.7461	10661	7	0.8963	0455
10	30#4#8#4#4	9	0.3423	4917	7	0.4523	3613
11	35#5#10#5#5	5	0.3428	4625	4	0.4328	4227
12	40#5#10#5#5	4	0.008	2802	3	0	2412
13	45#5#10#5#5	5	0.1286	8535	4	0.2286	7734
14	50#5#10#5#5	6	0.2257	4245	5	0.3897	3849
15	55#5#10#5#5	5	0.2859	45894	4	0.3549	3574
16	60#5#10#5#5	6	0.7871	9825	5	0.8631	8329
17	65#5#10#5#5	8	0.5233	8215	7	0.6617	7917
18	70#5#10#5#5	8	0.5359	7448	6	0.6569	7144
19	75#5#10#5#5	10	0.4332	6911	9	0.6562	5815
20	80#5#10#5#5	7	0.6325	7389	5	0.7305	6956

of the solutions based on the Pareto solutions of the meta-heuristics. Also, we considered the optimal solution, which is the average of the Pareto fronts (Table 6).

The results of the three assessment metrics are given in Table 7. To confirm the performance of our hybrid RDA-SA, we used the non-dominated sorting genetic algorithm (NSGA-II) as a well-known algorithm in the literature. Based on the results of Table 7, the performance of our hybrid algorithm is generally much better than NSGA-II. As an example of Pareto solutions, the first test problem (5#2#2#2#2) was solved. The non-dominated solutions of both algorithms are depicted in Figure 4. In this example, the solutions of RDA-SA overcome the solutions of NSGA-II.

To further analyze the performance of the algorithms statistically, the interval plots for each assessment metric are provided. In this regard, we first normalize the data and then depict the data to show the robustness of the algorithms. In these plots, as shown in Figure 5, the lower value brings the better accuracy and robustness of the algorithms. Figures 5(a), (b), and (c) are respectively related to NPS, MID, and MS metrics. Once again, as it is evident from all plots, our RDA-SA is highly efficient in comparison with NSGA-II in all criteria.

V. CONCLUSIONS

The present article addressed the remodel and renovation of a macroscopic model, the so-called, MWSSRRP. The whole cost of remodeling and the quantity of water wastage via seepage were taken as performance parameters for optimization of the relevant network designing. Also, uncertainty was considered in some essential input factors and a risk-averse stochastic method was employed to handle this problem. The introduced stochastic model can consider correlations among uncertain factors as a key feature of realistic water systems. The computations of solving for our proposed model revealed the superiority of our proposed hybrid RDA-SA algorithm in comparison with NSGA-II through different criteria and analyses. Our findings can be extended in upcoming investigations concerning the following issues: 1) incorporating catastrophic events (i.e., disruptions) including earthquakes and floods, 2) incorporating other essential performance measures relating to social concerns aiming at responding the necessity of sustainability, and 3) incorporating some essential technically relevant facets in water supply systems like pressure heads and pipes' raggedness.

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AZADEH DOGANI is currently pursuing the Ph.D. degree in agricultural economics with the Ferdowsi University of Mashhad, Iran. Her main research interests include resilience and change climate and its effect on the agricultural sector.

ARASH DOURANDISH is currently an Associate Professor with the Department of Agricultural Economics, Faculty of Agriculture, Ferdowsi University of Mashhad. His research interests include mathematical programming, production economics, agricultural insurance, and farm management.

MOHAMMAD GHORBANI is currently a Professor with the Department of Agricultural Economics, Faculty of Agriculture, Ferdowsi University of Mashhad. His research interests include urban economics, advanced econometrics, agricultural marketing, water market, environmental valuation and economics, and management of agricultural irrigation.

MOHAMMAD REZA SHAHBAZBEGIAN is currently an Assistant Professor of hydropolitics and systems analysis with Tarbiat Modares University, Tehran, Iran.