IJE TRANSACTIONS A: Basics Vol. 35, No. 07, (July 2022) 1440-1456

International Journal of Engineering

Journal Homepage: www.ije.ir

Efficient Metaheuristic Algorithms for a Robust and Sustainable Water Supply and Wastewater Collection System

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PAPER INFO

Paper history:
Received 11 April 2022
Received in revised form 29 April 2022
Accepted 07 May 2022

Keywords:
Water Supply and Wastewater Collection
Sustainable Development
Robust Optimization
Red Deer Algorithm
Keshtel Algorithm

ABSTRACT

An efficient design of a water supply and wastewater collection system is significantly important to tackle the natural uncertainty of this system and the sustainable development goals in developing countries like Iran. To address the natural uncertainty in the water supply and the challenge of global warming, this design must be robust and this motivates a robust optimization. To consider the sustainability criteria, this design should cover all economic, environmental and social impacts. Hence, this study develops innovative solutions based on recent and traditional metaheuristic algorithms for a robust and sustainable water supply and wastewater collection system. Red deer algorithm (RDA) and Keshtel algorithm (KA) as the recent algorithms, are employed. These recent algorithms are compared with the state-of-the-art methods like genetic algorithm (GA) and particle swarm optimization (PSO). An application of our model and algorithms, is tested on a case study in North Khorasan province. After performing some analyses on the performance of our algorithms and sensitivities on the model, a discussion is provided to conclude managerial insights and findings for practitioners in the applied system.

***doi**: 10.5829/ije.2022.35.07a.21*

1. INTRODUCTION

The global warming and water threat are two of main concerns which motivate an efficient design for the water supply and wastewater collection system [1]. It goes without saying that the demand of drinking water is highly increased nowadays as the level of community health and population growth, are increased [2]. To integrate the direct flows of water supply from rivers to demand zones with the reverse flows from collecting and recycling of the wastewater, the water resources management is combined by the theory of supply chain management [3, 4]. This paper uses a sustainable supply chain management with the robust optimization to model an efficient design of water supply and wastewater collection system in North Khorasan province in Iran.

Sustainable supply chain management theory is a combination of three legislative requirements in organizations to reduce risks related to environmental pollution (ISO 14000) and to increase the social responsibility corporation (ISO 26000) as well as the economic performance [5, 6]. Given the instability of water resources management from an economic, environmental and social perspectives, the use of sustainable supply chain management for water resources management can be a major challenge from a management perspective for all organizations involved in this field [7, 8]. The use of triple bottom lines of sustainable development with conflicting economic, environmental and social goals, is an issue that is difficult to model and the model of sustainable development for water supply and wastewater network, is rarely contributed in the literature [9].

One of the most important challenges in the logistics management of water supply and wastewater collection is to handle the uncertainty in the supply and demand of water resources and its optimal allocation between facilities to refine, recycle and create the drinking water [9, 10]. Due to the dry and fragile climate of Iran and the variety of recent droughts, the importance of water as a

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vital input is becoming more apparent than ever before. A recent study in water resources management in Iran [1] shows that this country is geographically one of the arid regions of the world. In this regard, the water scarcity is one of the most important concerns for the development of this country. An efficient water network design must be able to control the uncertainty in the water network such as the situation of rainfall, uncontrolled exploitation on the other hand as well as water wasted from the side, increasing consumption, whether urban, industrial and, most importantly, agricultural applications [9]. This is the reason of a poor management of water resources and the water crisis in Iran. This great uncertainty emphasizes the needs to develop a robust optimization technique. Therefore, this study proposes a robust optimization model for the sustainable water network design problem in North Khorasan province in Iran.

One of the most cited and oldest articles in this field can be attributed to Goulter and Morgan [11]. They used a complex integer linear programming to model an inverse water distribution network. In the reverse water distribution network, we collect wastewater and its household uses. They sought to reduce the cost of the water distribution network piping system. Goldman and Saykally [12] in 2003 used a linear programming model to allocate water from the Tigris and Euphrates rivers to the agricultural, urban, and hydroelectric sectors in the Middle East. In this regard, they used a cooperative game theory to identify sustainable allocations that all stakeholders are willing to accept. Ultimately, the output of their model is the allocation of revenue from cooperation between players for different amounts of energy prices as well as economic efficiency.

In 2006, Samani and Mottaghi [13] used a branch-and-bound-based method for solving a linear programming model to analyze the water distribution network design problem. In 2008, Wang et al. [14] considered a collaborative water allocation model in the form of a general mathematical programming approach to model efficient and equitable water allocation among competitive consumers, and addressed it on the issue of large-scale water allocation in the South Saskatchewan River Basin in the province of Alberta in Canada. This optimization model includes two stages. First, the allocation of water rights and second, the reallocation of water and their net benefits, they used methods such as cooperative play to examine how net benefits could be fairly reallocated. In another study, Samani and Zanganeh [15] developed a mixed integer linear programming for a water resource allocation network. Fattahi and Fayyaz [16] developed a multi-objective linear programming for the first time to allocate water resources. The objectives of the proposed problem including economic costs, wastewater reduction and demand level optimization were optimized. In another definitively optimization model in 2011, Verleye and Aghezzaf [17] developed a nonlinear mixed integer programming model to cover all economic dimensions of the problem of allocating water resources in direct and inverse water distribution network.

Due to severe uncertainty in water resources and its consumption and lack of sufficient knowledge in climate forecasting to decide on the allocation of water resources in the long time period, the existing uncertainty at all levels of the water network was modeled by many researchers. In this regard, the use of probabilistic, fuzzy, and robust planning has been widely used in the literature review. For example, in 2012, Eum et al. [18] developed an integrated reservoir management system to change the existing reservoir operation to adapt the climate changes conditions. The reservoir management system included three methods, i.e., the nearest neighbor climate generating model, hydrological model, and the differential evolutionary optimization model. In their research, six probabilistic scenarios were used. Their results have shown that the integrated management system provides optimal control curves for reservoir operation that reflect the hydrological characteristics for future climate scenarios and can be useful for the development of adaptive reservoir operation solutions. In 2013, a model was developed by Kang, and Lansey, [19] based on probabilistic scenarios in the multi-objective optimization platform. The conflicting goals were driven by demand uncertainty and the risk of population growth in the water consumption.

Zhang et al. [20] developed a nonlinear hydraulic model by optimizing system economic costs and demand uncertainty. Steinbrueckh [21] focused on international conflict to find the effects of increasing water scarcity and the use of game theory to model. In 2015, a scenario-based model for measuring water pressure in pipes and its relationship with water consumption demand and its uncertainty was presented by Pérez et al. [22]. In another study, Mortazavi-Naeini, et al. [23] developed a multi-objective scenario-based model with nonlinear programming and pursuit of three goals. Objectives were included minimizing all structural and operational costs of the water distribution system and the expected value of the system and climate change scenarios. Mo et al. [24] analyzed the number of water scenarios in rivers and groundwater resources with distance parameters using a probabilistic programming approach.

In 2016, using this bargaining method, Degefu et al. [25] solved the problem of water sharing in the Nile Basin under critical water conditions and compared the results with the results of using the classical bankruptcy allocation rules. Subsequently, Schwartz et al. [26] developed a robust optimization model to minimize water supply chain costs with hydraulic uncertainty of water fluctuations according to industrial and domestic water demand prediction scenarios. Naderi and Pishvaee [27] developed a bi-objective model for the water network design with the possibility of redesigning and reconstructing after the worst possible scenarios. The objectives of the model were to optimize the expected costs and wastewater network considering the number of uncertain parameters such as demand, water vapor and water loss rate from rivers and groundwater sources. In another similar study, Naderi and Pishvaee [28] proposed an integrated network to consider the water distribution network and the wastewater network using a feasibility planning based on a possible two-stage scenario.

Recently, Ghelichi et al., [29] developed another integrated model to simultaneously consider the forward and backward flows of the water network. A solid planning as a solution for the case study of the city of Mashhad was implemented as their main contribution. Sahebjamnia and Fathollahi-Fard [30] performed a closed-loop supply chain method for the integrated network of water resources allocation using linear mixed integer modeling under fuzzy uncertainty. They used Lagrangian relaxation algorithm as their problem-solving method. In 2020, Fathollahi-Fard et al. [1] implemented an enhanced Lagrangian algorithm using an adaptive strategy for solving the integrated problem of water supply and wastewater collection for a case study in West Azerbaijan province in Iran. Fathollahi-Fard et al. [9] developed a multi-objective optimization model for an integrated water network design based on the goals of sustainability. They used an improved social engineering optimization algorithm as their problem-solving method. Yang et al. [5] introduced an iterative approach to design a water network considering regeneration units. Their method firstly estimates the initial concentrations of regenerated streams and identifies the regenerated streams for reusing and finally allocates the water sources and regenerated streams to industrial, agricultural and urban demands. In 2021, Sakib et al. [10] proposed Bayesian network model to predict and evaluated disasters in the water network based on legal, environmental, safety, political, social, economic, and technical factors. At last but not least, Abdul-Ghani et al., [31] analyzed the environmental impacts of the seawater and wastewater collection in a case study in Malaysia. Their simulation model was run using machine learning algorithms.

One important research gap is to develop an innovative solution for the water supply and wastewater collection models. These models are academically classified as a combinatorial optimization problem and they are naturally NP-hard [9]. The theory of no free lunch [32] confirms that the traditional algorithms may not be efficient for solving the NP-hard optimization problems when they are compared with new algorithms. This motivates our attempts to propose the red deer algorithm (RDA) [33] and Keshtel algorithm (KA) [34] for the first time in the literature in this research area. One goal of our paper is to compare these recent algorithms with two traditional ones including the genetic algorithm (GA) [35] and particle swarm optimization (PSO) [36].

Having a conclusion about our contributions in the proposed problem, although Fathollahi-Fard et al. [9] proposed the concept of sustainable closed-loop supply chain management for the water supply and wastewater collection system, they did not use a robust optimization model and this study for the first time considers environmental emissions, job opportunities and lost working days as the constraints in addition to the logistical constraints for the proposed sustainable water network design problem. It goes without saying that although many real cases were applied to the literature review, this study for the first time evaluates a sustainable water supply and wastewater collection network design in North Khorasan province in Iran as one of water threats in the center of Asia.

Based on aforementioned contributions in comparison with the literature review, the main contributions are twofold. First, a robust optimization is contributed to the address a sustainable water supply chain network with an application a case study in North Khorasan province in Iran. The second contribution is the development of new metaheuristics like RDA and KA for the first time in this research area. Other parts are organized as follows: Section 2 studies the problem description and establishes the proposed robust optimization model. Section 3 is the development of encoding plan for the proposed model and the description of our metaheuristic algorithms. Section 4 is the description of the case study as an application of our study. Section 5 creates a comparison among algorithms and some sensitivity analyses on the proposed model. Finally, Section 6 provides a summary of this research with findings and future works.

2. PROBLEM DESCRIPTION

Here, we illustrate the description of our optimization model and then introduce the concept of robust optimization and finally, the proposed model is developed. A graphical presentation of the proposed water network is given in Figure 1.

In our water system, different water types are existed, i.e., recycled water, wastewater, surface water, sludge water, drinking water, and groundwater. Water resources in the earth are surface water from dams and groundwater from ground water resources. The surface water can be used for agricultural and industrial zones. These groundwater and surface water are collected and transformed into purifying centers and then, drinking water is created. A water distribution network is designed to distribute the drinking water to urban demand zones. Next, the returned water from urban zones is collected by wastewater centers. In these centers, the returned water is

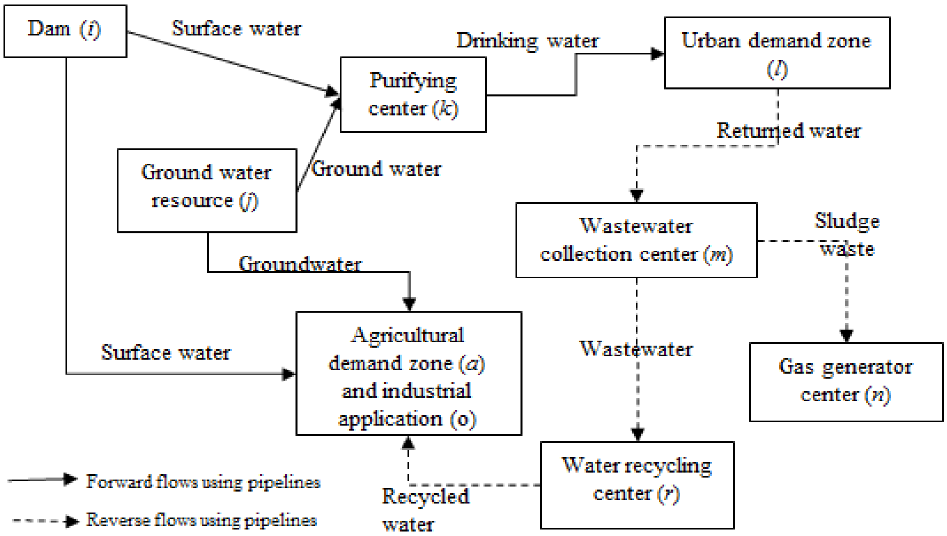


Figure 1. Proposed water network system [9]

assessed and then divided into sludge waste and wastewater. The sludge waste is transformed into biogas generator centers to create energy. The wastewater is evaluated by the water recycling centers. After recycling the wastewater, the recycled water is applicable to agricultural and industrial zones. All these mentioned operations are processed in our water network system.

The proposed water network system is evaluated by the triple bottom line approach for contributing to economic, environmental and social criteria, simultaneously. We are making the location, allocation and inventory decisions based on economic criteria to minimize the expected total cost. To address the environmental criteria, we have considered a maximum upper bound for environmental emissions generated by location, transition and processing different types of the water in our network. To consider the social sustainability, a minimal lower bound is considered for the number of jobs generated by the proposed water network system. In addition, a maximum upper bound is considered for lost working days in the water network system.

This water network is formulated by the concept of robust optimization proposed by Mulvey et al. [32]. The robust optimization aims to address the uncertainty and to control the possibility of worst-case scenarios. To illustrate this tool for the optimization, consider a minimization objective function $Z_s = fy + c_s x_s$, where Z_s is the objective function for each scenario, f denotes the coefficients of location decisions, y is the binary variable, c_s indicates the coefficients of allocation and inventory decisions, and x_s is the continuous variable for each scenario. Using this definition, the robust optimization model is as follows:

$$\min\left(\lambda \sum_{s\in S} \pi_s Z_s + (1-\lambda) \sum_{s\in S} \pi_s \left(Z_s - \sum_{s'\in S} \pi_{s'} Z_{s'}\right)^2\right) \quad (1)$$

where λ shows the importance of each part of the total cost and π_s is the occurrence probability of each scenario $(s\ s' \in S)$, The constraints of the above objective function, are:

$$Ty + Ax_s \le b_s \quad \forall s \in S \quad (2)$$

where T is the technical coefficient of locational decisions, A denotes the technical coefficient of allocation decisions and b_s is the budget. The robust optimization is generally an extension to the two-stage stochastic programming to control the worst-case scenarios in an efficient way. The robust optimization model proposed by Mulvey et al., [32], is more complex than a general type of a two-stage stochastic programming which is a mixed integer linear approach. It is because of the non-linearity in the objective function. This robust optimization model is linearized by Leung *et al.* [33] using one auxiliary variable. The objective function of this revised robust optimization model is:

$$Min \sum_{s\in S} \pi_s Z_s + \lambda \sum_{s\in S} \pi_s \left(Z_s - \sum_{s'\in S} \pi_{s'} Z_{s'} + 2\theta_s\right) \quad (3)$$

where θ_s is an auxiliary variable. This model is limited to the following constraints:

$$Ty + Ax_s \le b_s \quad \forall s \in S \quad (4)$$

$$Z_s - \sum_{s'\in S} \pi_{s'} Z_{s'} + \theta_s \ge 0 \quad \forall s \in S \quad (5)$$

Equation (4) defines the budget constraint with regards to each scenario and Equation (5) ensures the deviation of scenarios must be positive based on statistical properties.

All in all, based on the description of the proposed water network and the concept of robust optimization model, this study follows the following assumptions:

- The proposed integrated network for the water supply and wastewater collection is a single-objective, multi-level, multi-period, scenario-based network design to address the triple bottom line concept.
- The proposed mode makes the location of facilities and their right allocation and the inventory status in each time period. These decisions are considered in an uncertain environment using the concept of robust optimization.
- The economic dimensions include the fixed establishment, transition, processing, holding and shortage costs.
- The environmental dimensions are to consider the effects of facilities establishment, processing, water transition by pipelines and extraction of groundwater on the environment. These environmental impacts are limited by a maximum upper bound.
- The social dimensions are to model the employment and lost workdays aspects.
- The water shortage is considered in the proposed model as an uncertain factor.
- It is assumed that there is one demand point in support of all industrial applications employed different types of water.
- Some parameters are multiplied by scenarios and considered the sign factor for these parameters.

To formulate the proposed water network using the robust optimization, the notations are defined according to litertature. In the mathematical model, the objective function aims to minimize the expected total cost including the shortage costs (Z^{SC}), holding costs (Z^{HC}), processing costs (Z^{PC}), transition costs (Z^{TC}) and the fixed opening costs (Z^{FC}) as well as the cost of each scenario given (f_s). This objective function is limited by a set of constraints including envioronmental and social constraints, inventory statuses, balance network constraints, capacity limitations, pipline assignment and locational constraints.

3. PROPOSED METAHEURISTIC ALGORITHMS

Since the water network design is a complex optimization problem and the exact solver is not able to handle large-scale problems [9], heuristics and metaheuristics are an alternative answer. The high performance of recent metaheuristics like RDA and KA, is a motivation for us to employ them in the area of water supply planning. This study for the first time applies RDA and KA and compares them with GA and PSO. Here, in this section, an encoding plan is proposed to show that how our metaheuristics can handle the constraints and decision variables. Then, the main loop for RDA and KA is explained. Since GA and PSO are well-known algorithms, more details about them are not provided and referred to [37, 38].

3. 1. Encoding Plan Metaheuristic algorithms use a continuous search space and the decision variables are continuous. However, in the proposed optimization model, we have integer and binary decision variables. These decision variables must get a feasible value to meet the constraints. Our encoding plan is planned by the random-key method [39]. Here, we firstly show that how we can find feasible values for the location decisions.

Consider that metaheuristics generate random continuous values between zero and one for location variables ($Y_k^K, Y_m^M, Y_n^N, Y_r^R, Y_p^P$). In our encoding plan, we sort these variables and select the lowest values based on the constraints (59) to (62). Figure 2 is an example for one of the decision variables (Y_k^K). Assume that we have five candidate points for purifying centers and three of them should be selected. In this regard, the lowest values are selected and they are one and other variables are zero.

For allocation and inventory decision variables, we need to do first the allocation decisions and the inventory decisions are repeated by each period. In our example, we want to allocate these selected purifying centers to urban demand zones. Figure 3 shows a priority-based representation to do the allocation decisions. Similar to location decisions, a set of random uniform distributed numbers for both contributions of assignment has been generated. Their sequence separately has been computed from the lowest amount to the highest one. Subsequently, the allocation based on this sequence and also their general order has been considered as detailed in this figure.

3. 2. RDA RDA is a recently-proposed algorithm by Fathollahi-Fard et al. [33]. RDA is an evolutionary algorithm and inspired by amazing behaviors of red deers for roaring, fighting and mating activities during the breading season. The RDA has been applied to many optimization models in different fields like pharmaceutical supply chains [40] and sustainable supply chains applied to aluminum industry [41], glass industry [42] and tire industry [43]. However, as far as we know, no study has applied this metaheuristic to the water supply and wastewater collection network models.

0.35	0.65	0.71	0.48	0.24

1	0	0	1	1

Figure 2. Encoding plan for locational variables

	0.34	0.11	0.86	0.94	0.٠٨	0.٦١	0.٣2
Sequence:	2	1	3	4	1	3	2
Order:	1	2	3	1	2	3	4
	Purifying centers			Urban demand zones			

The procedures of assignment based on priority-based representation is as follows:

2	3	4	3	2
1	3	1	3	4

The second urban zone supports its demand from the second purifying center

3	4	3
3	1	3

The fourth urban zone supplies its demand from the first purifying center

The third urban zone supports customers purchase from third purifying center

The first urban demand zone has been considered as a shortage

Figure 3. Encoding plan for the allocation decisions

Having a definition for the main loop of RDA, it starts with a set of random solutions (*nPop*). Based on the cost function, they are sorted and the best solutions are considered as male red deers (*Nm*) and the rest is hinds (*Nh*). In the first step, the male roars loudly to attract hinds and show their power to other males. In fact, the roar operator does a local search for each male. In the next step, the cost function of each male is reassessed. Then, the males are divided into two groups. Gamma percent of males are selected as male commanders and others are selected as stags. The fighting process is now done. In the fighting process, each commander fights with a stag randomly. This operator is an extension to the crossover operator in a greedy approach. In this regard, the winner is selected as the commander and the loser is selected as the stag. Each commander forms his harem which is a group of hinds. Each harem is the territory of the commander. The final step is to apply the mating operator. The commander mates with alpha percent of hinds in their harem. Then, the commander to promote its territory attacks to a harem randomly and mates with betta percent of hinds in this harem. Finally, the stags who have no harem, mates with his nearest hind. This mating creates some for commanders and stags. The selection of next generation is based on the best males and other solutions are selected by the roulette wheel selection to give a chance to all hinds and offspring randomly. All these steps are repeated per iteration once the maximum number of iterations (*MaxIt*) is satisfied. Having more details for implementation of RDA, the pseudo-code is given in Figure 4.

```
Set the parameters of RDA including nPop, MaxIt, Nm, Nh, alpha,
betta and gamma.
Generate a set of random solutions.
Sort them and divide them into Nm and Nh.
It=0;
While It< MaxIt
For each Nm
      MaleRD= Roaring (MaleRD);
End
Sort MaleRDs.
Select gamma percent of them as male commanders.
For each male commander
      Select one stag randomly.
      [winner, loser]= Fighting (male commander, stag);
      Male commander is the winner.
End
Generate harems for each male commander.
For each male commander
       Select alpha percent of hinds in his harem randomly.
       Select a harem randomly.
       Mate with betta percent in this harem.
End
For each stag
      Find the nearest hind to this stag.
      Mate this hind to this stag.
End
Save the best males and select the next generation.
Find the best solution.
It=It+1;
End
```

Figure 4. Pseudo-code for the RDA

3. 3. KA Keshtel is a dock in Anas family who is living in the north of Iran. Every year, this dock migrates from northern lands in Russia to the southern lands in the Caspian Sea. KA is inspired by an amazing feeding behavior of this dock. Hajiaghaei-Keshteli and Aminnayeri [34] proposed KA as a swarm-based optimization algorithm. The high performance of KA for solving complex optimization models like production scheduling [34], facility location [44] and closed-loop supply chains [42]. As far as we reviewed in the literature review, no study has applied this optimization algorithm for the water supply planning.

KA considers the search space as a lake. Like other metaheuristics, KA generates a set of random solutions as the initial population (*nPop*). They are landed in the lake. KA divides this set of solutions into three groups, i.e., *N1*, *N2* and *N3*. The first group is *N1* who is the best set of solutions. They are named as lucky Keshtels. They are lucky because they found a good source of foods. They are swirling around each other. This operator aims to improve the exploitive behavior of the algorithm. *N2* does a local search and they move around two nearest luck Keshtels. The last group is *N3* and they are flying and landing in other parts of the lake. It means that they are generated randomly per iteration. For the selection of next generation, we update *N1*, *N2* and *N3* and the best solution ever found. These activities are done per iteration to satisfy the maximum number of iterations (*MaxIt*). Having more details about the proposed algorithm, the pseudo-code is provided in Figure 5.

4. INTRODUCED CASE STUDY

Our case study evaluates the North Khorasan province in Iran. A geographical map for this province is depicted in Figure 6. North Khorasan province, which was formed in 2003 as a result of the division of the former Khorasan province into the center of Bojnord, is located in the northeast of Iran with an area of about 28434 square kilometers and constitutes 1.7% of the total area and is the 15th largest province in Iran. This share is more than the share of the province's population in the whole country, because the population of this province in 2010 was equal to 867727 people, i.e., 1.15 percent of the total population of Iran. Thus, the share of the province is larger than the share of its population in the country, and as a result, the population density in it with about 31 people is less than the average density of the country with 46 people in the same year. The characteristics of the area and units of the country divisions of North Khorasan province are shown in Table 1.

```
Set the parameters of KA including nPop, MaxIt, N1, N2 and N3.
Generate a set of random solutions.
Sort them and divide them into N1, N2 and N3.
It=0;
While It< MaxIt
For each N1
    Do the swirling operator and update it.
End
For each N2
    Move each search agent randomly with regards to the nearest lucky Keshtel.
End
For each N3
    Generate each search agent randomly.
End
Merge N1, N2 and N3 and update them.
Find the best solution.
It=It+1;
End
```

Figure 5. Pseudo-code of KA

Given the strategic nature of the water resources allocation debate in North Khorasan province, a 25-year horizon for resource planning will be considered. Hence, 100 periods when each period will be considered as a chapter containing 90 days. Therefore, the timing horizon will include 7776000 seconds. To solve the scenarios of the developed model as a possible model, three general scenarios will be drawn: realistic, optimistic and pessimistic. In this regard, the probability of each scenario will be considered equal to one third. Possible scenarios have a direct effect on the theoretical parameters of demand, rainfall rate, steam rate and water loss rate, as well as the percentage of water return flows that are evaluated in energy recycling and conversion centers. To better understand these scenarios, consider that summer demand is naturally much higher than the rest of the seasons as a pessimistic scenario, but this demand is greatly reduced in the winter and is considered an optimistic demand. Spring and autumn demand rates can be thought of as realistic demand. This situation can be developed and generalized for other parameters such as steam, rainfall and surface water loss. Demand-related parameters for urban and ago-industrial applications will be estimated using previous studies and statistical analyzes. It should be noted the range of other parameters were simulated by the data set from the literature review [9]. Finally, the coefficient of robust optimization is set as 0.5. The upper bound for the environmental emissions is set as 188000 kg. The minimum number of jobs which is expected from the water network, is 3000 jobs and the maximum number of lost working days is expected to be 60000 days maximally.

5. COMPUTATIONAL RESULTS

Here, the model is implemented on a laptop using Intel(R) Core (TM) i7-10850H CPU @ 2.70GHz 2.71

TABLE 1. Characteristics of our case study

Demand zone	Area (km^2)	Number of cities	Capacity of dams ($10^6 \times M^3$)
Esfarayen	5019	2	232
Bojnord	3619	3	196.7
Jajrarm	3486	3	112
Shirvan	3945	4	85
Faruj	1615	2	3.3
Garmeh	2159	3	220.3
Maneh and Samalqan	6053	4	40
Raz and Jargalan	2538	1	67
Total	28434	22	956.3

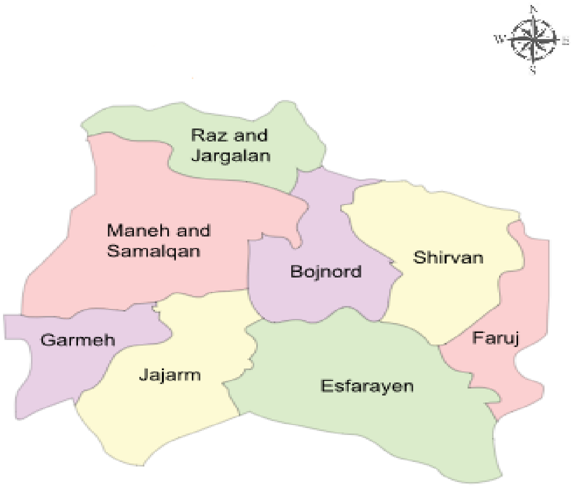


Figure 6. Map of North Khorasan

GHz processor with 32.0 GB RAM. Metaheuristics were coded in MATLAB software. The CPLEX solver was used for GAMS 24.7.4 for finding the exact solution. Here, we firstly tune the algorithms and then, compare them based on different criteria. Finally, our case study is evaluated by some sensitivity analyses.

5. 1. Tuning Tuning the parameters of metaheuristics, plays a significant role in their performance [45]. If the algorithms are not tuned well, the comparison would be biased [46, 47]. There are some methods for tuning like Taguchi and response surface method. Here, we apply the Taguchi design method [48]. The main benefit of this approach is to reduce the number of tests to find the appropriate level for each parameter. We have considered three candidate values for each algorithm. Table 2 shows the parameters of each algorithm.

TABLE 2. Candidate values for each parameter

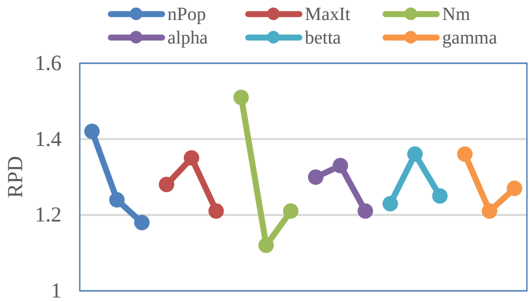
Algorithm	**Parameter**	**Candidate values**		
		Level 1	**Level 2**	**Level 3**
RDA	*nPop*	50	100	150
	MaxIt	100	150	200
	Nm (Nh= nPop- Nm)	10	20	30
	alpha	0.5	0.7	0.8
	betta	0.3	0.5	0.7
	gamma	0.6	0.7	0.8
KA	*nPop*	50	100	150
	MaxIt	100	150	200
	N1	0.2	0.3	0.4
	N2 (N3=1- N1- N2)	0.3	0.4	0.5
GA	*nPop*	50	100	150
	MaxIt	100	150	200
	Pc	0.5	0.6	0.7
	Pm	0.1	0.15	0.2
PSO	*nPop*	50	100	150
	MaxIt	100	150	200
	C1	1.75	2	2.25
	C2	1.75	2	2.25

For RDA, Taguchi suggests L_{27} as the orthogonal array and L_9 is considered for KA, GA and PSO. To tune the algorithms, we have considered the relative percentage deviation (RPD) index as formulated below:

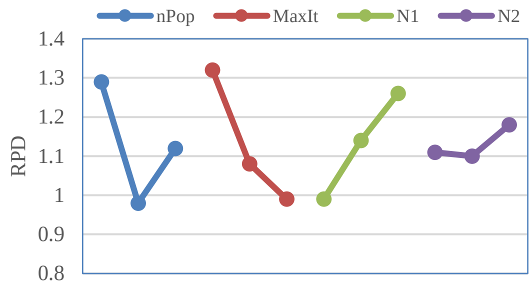
$$RPD = \frac{Alg_{sol} - Best_{sol}}{Best_{sol}} \tag{6}$$

where Alg_{sol} is the output of each algorithm in each test and $Best_{sol}$ is the best solution ever found by this algorithm. As known, a lower value for the RPD brings a better performance of candidate values for algorithms' parameters. We have calculated the average of RPD for each algorithm and the results are given in Figure 7.

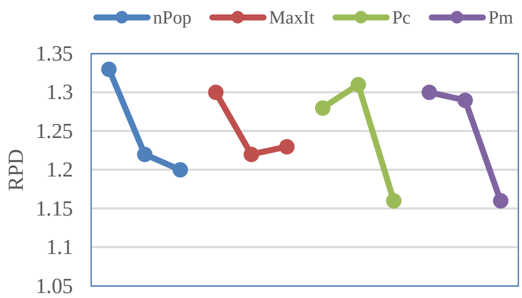
5. 2. Comparison Here, we do an extensive comparison among different criteria. In this regard, we first generate 20 different random test problems as given in Table 4. 10 small and 10 large instances were generated to analyze the complexity of our optimization model.



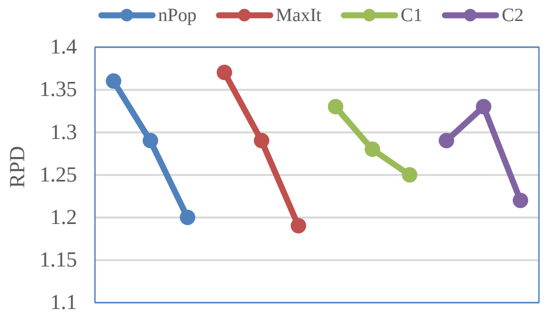
(a)



(b)



(c)



(d)

Figure 7. Results for mean RPD: (a) for RDA, (b) for KA, (c) for PSO and (d) for GA

TABLE 3. Tuned values for algorithms' parameters

Algorithm	Tuned parameters
RDA	*nPop=150; MaxIt=200; Nm=20; Nh=130; alpha=0.8; betta=0.3; gamma=0.7;*
KA	*nPop=100; MaxIt=200; N1=0.2; N2=0.4; N3=0.4;*
GA	*nPop=150; MaxIt=150; Pc=0.7; Pm=0.2;*
PSO	*nPop=150; MaxIt=200; C1=2.25; C2=2.25;*

TABLE 4. Our test problems

Complexity	Number of tests	(I, J, K, L, M, N, R, A, P, T)
Small	P1	(3, 6, 4, 4, 2, 2, 2, 4, 3, 4)
	P2	(3, 8, 6, 4, 2, 2, 2, 5, 3, 8)
	P3	(3, 8, 6, 6, 4, 2, 4, 6, 3, 8)
	P4	(5, 8, 6, 6, 4, 2, 4, 7, 3, 16)
	P5	(5, 12, 8, 8, 6, 2, 4, 8, 3, 3, 24)
	P6	(5, 12, 8, 8, 6, 4, 6, 9, 3, 3, 24)
	P7	(7, 14, 10, 9, 6, 4, 6, 10, 3, 3, 32)
	P8	(7, 14, 10, 9, 6, 4, 6, 5, 11, 5, 3, 32)
	P9	(9, 18, 12, 10, 8, 4, 6, 5, 12, 5, 3, 32)
	P10	(9, 18, 12, 10, 8, 4, 6, 5, 12, 5, 3, 48)
Large	P11	(12, 24, 16, 16, 12, 8, 10, 16, 6, 3, 64)
	P12	(12, 24, 16, 18, 14, 8, 10, 17, 6, 3, 64)
	P13	(12, 24, 18, 20, 18, 10, 14, 18, 6, 3, 72)
	P14	(12, 24, 18, 20, 18, 10, 14, 19, 6, 3, 72)
	P15	(15, 28, 20, 22, 18, 12, 16, 20, 6, 3, 80)
	P16	(15, 28, 20, 22, 20, 14, 18, 20, 8, 3, 80)
	P17	(15, 28, 24, 24, 20, 14, 18, 22, 8, 3, 84)
	P18	(18, 32, 24, 24, 20, 14, 18, 24, 8, 3, 92)
	P19	(18, 32, 28, 28, 22, 14, 20, 28, 8, 3, 100)
	P20	(18, 32, 28, 32, 24, 14, 22, 32, 8, 3, 112)

Results of the comparison are provided in Appendix (Table A1). We have run algorithms for 10 times and the best, the worst, the average and standard deviations for solutions are noted. The optimality gap from the exact solver and the CPU time are also noted in this table.

For the criteria of the best, worst and the average solutions, the RDA can be selected as the best algorithm in these metrics. After RDA, KA is highly efficient than PSO and GA. At the end, PSO is slightly better than GA.

Based on the criterion of optimality gap, Figure 8 shows a comparison among algorithms. It should be noted that the exact solver was not able to solve the test problem P9 to P20. From the criterion of optimality gap, RDA shows the best performance. KA and PSO are not better than RDA. Vice versa, the GA was the weakest performance.

Based on the CPU time for algorithms, there is a great similarity between the performance of algorithms. The behavior of algorithms is the same. However, GA is faster than other algorithms. Conversely, RDA needs more time in comparison with other metaheuristics. Finally, based on the standard deviation of algorithms, a statistical test using the interval plot is done. This analysis is provided in Figure 10. In this regard, we first normalize the standard deviation of metaheuristics and then run MINITAB software to calculate the interval plot based on 95% confidence level. As can be seen, RDA is highly better than other metaheuristics and shows a robust behavior in this comparison. After RDA, KA is better than GA and PSO. At the end, PSO shows the weakest performance in this comparison.

5. 3. Sensitivity Analysis Here, we analyze our case study by some sensitivity analyses. These analyses were run on GAMS software. First, the values of robust optimization coefficient are analyzed and changed from 0 to 1. The results were given in Table 5.

Results given in Table 5, indicate that an increase in the robust optimization coefficient not only increases the total cost uniformly, but also increases the complexity as the computational time is generally increased during variations.

In addition to the sensitivity analysis on the robust optimization, some sensitivity analyses are done to implement sustainable development goals. In this regard, the bounds for environmental emissions, job opportunities and lost working days are analyzed. In addition, we do sensitivity analyses for the maximal amount of environmental emissions. This bound is changed from 175000 to 200000 kg. Five tests are designed and analyses are reported. Accordingly, the behavior of total cost and computational time of these solutions, is reported in Table 6.

The results in Table 6 indicate that there is no feasible solution if we reduce the maximum bound of environmental emissions to 175000 kg. An increase to this factor provides two advantages. First, the total cost would be reduced and it shows that the total cost and environmental emissions have a conflict for finding the optimal solution. Another advantage is the reduction of time complexity and when this factor increases, the environmental constraints would be relaxed.

Another sensitivity analysis is done on the constraint of job opportunities. The minimum number of job opportunities is increased from 2000 to 4000. Five tests are considered. Table 7 shows the behavior of criteria. From results given in Table 7, there is no feasible solution for the minimum number of job opportunities which is equaled to 4000. While the number of job opportunities increases, the computational time increases and the

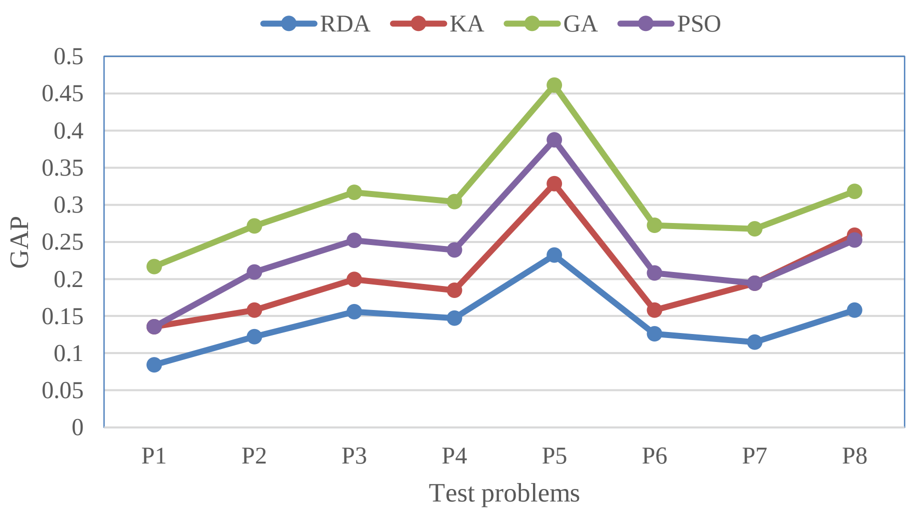


Figure 8. Comparison of algorithms based on the optimality gap

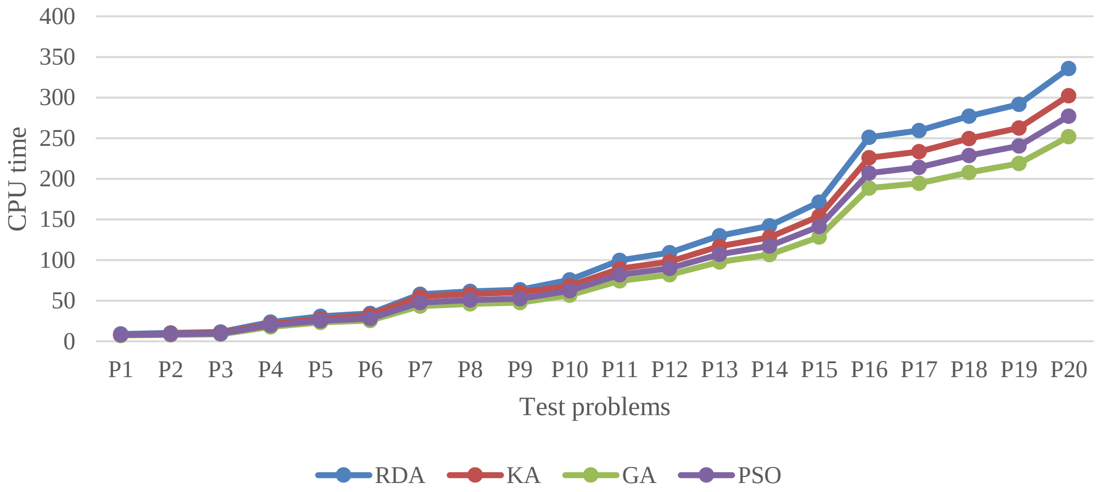


Figure 9. Comparison of algorithms based on the CPU time

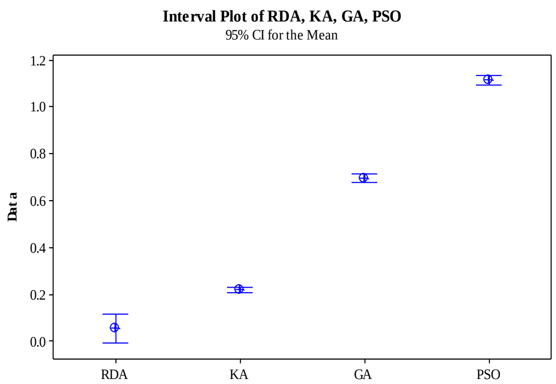


Figure 10. Interval plot for analyzing the metaheuristics

optimality is limited. Finally, the maximum number of lost working days is analyzed. This factor is changed from 40000 to 80000 days. Five tests are studied and results are reported in Table 8.

As given in Table 8, there is no feasible solution if we want to limit the number of lost working days to 40000. While the number of lost working days increases, the total cost is reduced and the optimality is improved. It goes without saying that an increase to the bound of lost working days, releases this social constraint and reduces the time complexity of the proposed optimization model.

TABLE 5. Results for the sensitivity analysis on the robust optimization

Robust optimization coefficient	Total cost	CPU time
0	8.42E+07	630.43
0.1	1.13E+11	784.25
0.2	2.26E+11	912.54
0.3	3.39E+11	892.75
0.4	4.52E+11	864.62
0.5	5.65E+11	899.54
0.6	6.78E+11	903.72
0.7	7.91E+11	913.62
0.8	9.04E+11	905.71
0.9	1.02E+12	907.13
1	1.13E+12	911.48

TABLE 6. Results for the sensitivity analysis on the environmental emissions

Maximum upper bound for environmental emissions	Total cost	CPU time
175000	Infeasible	0
180000	1.4562E+13	1000
188000	5.6534E+11	899.54
195000	2.7418E+11	912.28
200000	4.8219E+10	865.19

TABLE 7. Results for the sensitivity analysis on the job opportunities

Minimum number of job opportunities	Total cost	CPU time
2000	7.5843E+09	912.56
2500	3.2871E+10	987.39
3000	5.6534E+11	899.54
3500	7.9124E+11	1000
4000	Infeasible	0

TABLE 8. Results for the sensitivity analysis on the lost working days

Maximum number of lost working days	Total cost	CPU time
40000	Infeasible	0
50000	7.8324E+13	1000
60000	5.6534E+11	899.54
70000	6.8319E+11	912.33
80000	2.1743E+10	845.27

There are some limitations to this study and some recommendations can be suggested for future works. One suggestion is to develop a multi-objective decision-making framework and algorithms for our robust and sustainable water supply network design problem [49]. Other uncertainty models like fuzzy logic can be applied to our optimization model in comparison with the proposed robust optimization [50]. Finally, different recent and state of the art metaheuristics like social engineering optimizer [51] and adaptive evolutionary algorithm [52] should be tested on our optimization problem in comparison with our applied algorithms.

6. CONCLUSION AND FUTURE WORKS

In this paper, a robust optimization model was developed to address a comprehensive water network design problem. A sustainable water supply and wastewater collection network design problem was proposed and applied to the case study of North Khorasan province, Iran. The main novelty was the development a set of metaheuristics for the proposed sustainable water supply model. In this regard, RDA and KA were applied to this research area for the first time. We have compared these algorithms with two traditional metaheuristics, namely, GA and PSO. In this regard, their encoding plan was presented and then, the algorithms were tuned by Taguchi method. At the end, an extensive comparison based on different criteria was done and one finding was the high performance of RDA in comparison with KA, PSO and GA.

It goes without saying that the proposed robust optimization model as different from other similar models in the literature. The proposed optimization model aimed to minimize the total cost while the environmental pollution, job opportunities and lost working days were limited as new constraints to the model in addition to the constraints of water network design, inventory statuses, capacity limitations, pipeline assignments and locational decisions. The case study of North Khorasan province, Iran was solved and some sensitivity analyses were performed. Results confirm that the robust optimization coefficient is very important to manage the time complexity and solution quality. In addition, the role of environmental and social constraints, is highlighted to improve the optimality and solution time.

7. REFERENCES

1. Fathollahi-Fard, A.M., Hajiaghaei-Keshteli, M., Tian, G. and Li, Z., "An adaptive lagrangian relaxation-based algorithm for a coordinated water supply and wastewater collection network design problem", ***Information Sciences***, Vol. 512, (2020), 1335-1359, https://doi.org/10.1016/j.ins.2019.10.062
2. Yazdani, M., Kabirifar, K., Frimpong, B.E., Shariati, M., Mirmozaffari, M. and Boskabadi, A., "Improving construction and demolition waste collection service in an urban area using a simheuristic approach: A case study in sydney, australia", ***Journal of Cleaner Production***, Vol. 280, (2021), 124138, https://doi.org/10.1016/j.jclepro.2020.124138
3. Ali, S.M., Paul, S.K., Chowdhury, P., Agarwal, R., Fathollahi-Fard, A.M., Jabbour, C.J.C. and Luthra, S., "Modelling of supply chain disruption analytics using an integrated approach: An emerging economy example", ***Expert Systems with Applications***, Vol. 173, (2021), 114690, https://doi.org/10.1016/j.eswa.2021.114690
4. Shabbir, M.S., Mahmood, A., Setiawan, R., Nasirin, C., Arshad, M.A., Khan, S. and Batool, F., "Closed-loop supply chain network design with sustainability and resiliency criteria", Petra Christian University, (2021),
5. Yang, F., Fan, X.-Y., Jia, X., Klemeš, J.J. and Liu, Z.-Y., "An iterative design approach for water networks with multiple regeneration units", ***Journal of Cleaner Production***, Vol. 271, (2020), 122483, doi: 10.1002/apj.2420.
6. Fathollahi-Fard, A.M., Ahmadi, A. and Karimi, B., "Multi-objective optimization of home healthcare with working-time balancing and care continuity", ***Sustainability***, Vol. 13, No. 22, (2021), 12431, https://doi.org/10.3390/su132212431
7. Fathollahi-Fard, A.M., Dulebenets, M.A., Tian, G. and Hajiaghaei-Keshteli, M., *Sustainable supply chain network design*. 2022, Springer.1-3.
8. Fathollahi-Fard, A., Hajiaghaei-Keshteli, M. and Tavakkoli-Moghaddam, R., "A lagrangian relaxation-based algorithm to solve a home health care routing problem", ***International Journal of Engineering***, Vol. 31, No. 10, (2018), 1734-1740, https://www.magiran.com/paper/1901827?lang=en
9. Fathollahi-Fard, A.M., Ahmadi, A. and Al-e-Hashem, S.M., "Sustainable closed-loop supply chain network for an integrated water supply and wastewater collection system under uncertainty", ***Journal of Environmental Management***, Vol. 275, (2020), 111277, doi: 10.1016/j.jenvman.2020.111277.
10. Sakib, N., Hossain, N.U.I., Nur, F., Talluri, S., Jaradat, R. and Lawrence, J.M., "An assessment of probabilistic disaster in the oil and gas supply chain leveraging bayesian belief network", ***International Journal of Production Economics***, Vol. 235, (2021), 108107, doi: 10.1016/j.ijpe.2021.108107.
11. Goulter, I. and Morgan, D., "An integrated approach to the layout and design of water distribution networks", ***Civil Engineering Systems***, Vol. 2, No. 2, (1985), 104-113, https://doi.org/10.1080/02630258508970389
12. Goldman, N. and Saykally, R., "Elucidating the role of many-body forces in liquid water. I. Simulations of water clusters on the vrt (asp-w) potential surfaces", ***The Journal of Chemical***

Physics, Vol. 120, No. 10, (2004), 4777-4789, doi: 10.1063/1.1645777.

13. Samani, H.M. and Mottaghi, A., "Optimization of water distribution networks using integer linear programming", ***Journal of Hydraulic Engineering***, Vol. 132, No. 5, (2006), 501-509, https://doi.org/10.1061/(ASCE)0733-9429(2006)132:5(501)

14. Wang, L., Fang, L. and Hipel, K.W., "Basin-wide cooperative water resources allocation", ***European Journal of Operational Research***, Vol. 190, No. 3, (2008), 798-817, doi: 10.1016/j.ejor.2007.06.045.

15. Samani, H.M. and Zanganeh, A., "Optimisation of water networks using linear programming", in Proceedings of the Institution of Civil Engineers-water management, Thomas Telford Ltd. Vol. 163, (2010), 475-485.

16. Fattahi, P. and Fayyaz, S., "A compromise programming model to integrated urban water management", ***Water Resources Management***, Vol. 24, No. 6, (2010), 1211-1227, doi: 10.1007/s11269-009-9492-4.

17. Verleye, D. and Aghezzaf, E.-H., "Modeling and optimization of production and distribution of drinking water at vmw", in International Conference on Network Optimization, Springer. (2011), 315-326.

18. Eum, H.-I., Vasan, A. and Simonovic, S.P., "Integrated reservoir management system for flood risk assessment under climate change", ***Water Resources Management***, Vol. 26, No. 13, (2012), 3785-3802, doi: 10.1007/s11269-012-0103-4.

19. Kang, D. and Lansey, K., "Scenario-based robust optimization of regional water and wastewater infrastructure", ***Journal of Water Resources Planning and Management***, Vol. 139, No. 3, (2013), 325-338, https://doi.org/10.1061/(ASCE)WR.1943-5452.0000236

20. Zhang, W., Chung, G., Pierre-Louis, P., Bayraksan, G. and Lansey, K., "Reclaimed water distribution network design under temporal and spatial growth and demand uncertainties", ***Environmental Modelling & Software***, Vol. 49, (2013), 103-117, http://dx.doi.org/10.1016/j.envsoft.2013.07.008

21. Steinbrueckh, E., "Water scarcity and international conflict in africa, a game theory approach”", Università degli Studi di Perugia, Scienze Politiche, (2014),

22. Pérez, R., Sanz, G., Cugueró, M.-À., Blesa, J. and Cugueró, J., "Parameter uncertainty modelling in water distribution network models", ***Procedia Engineering***, Vol. 119, (2015), 583-592, doi: 10.1016/j.proeng.2015.08.911.

23. Mortazavi-Naeini, M., Kuczera, G., Kiem, A.S., Cui, L., Henley, B., Berghout, B. and Turner, E., "Robust optimization to secure urban bulk water supply against extreme drought and uncertain climate change", ***Environmental modelling & software***, Vol. 69, (2015), 437-451, https://doi.org/10.1016/j.envsoft.2015.02.021

24. Mo, S., Duan, H., Shen, B. and Wang, D., "Interval two-stage stochastic integer programming for urban water resource management under uncertainty", ***Journal of Coastal Research***, Vol., No. 73 (10073), (2015), 160-165, https://doi.org/10.2112/SI73-028.1

25. Degefu, D.M., He, W., Yuan, L. and Zhao, J.H., "Water allocation in transboundary river basins under water scarcity: A cooperative bargaining approach", ***Water Resources Management***, Vol. 30, No. 12, (2016), 4451-4466, doi: 10.1007/s11269-016-1431-6.

26. Schwartz, R., Housh, M. and Ostfeld, A., "Least-cost robust design optimization of water distribution systems under multiple loading", ***Journal of Water Resources Planning and Management***, Vol. 142, No. 9, (2016), 04016031, doi: 10.1061/(ASCE)WR.1943-5452.0000670.

27. Naderi, M. and Pishvaee, M., "Robust bi-objective macroscopic municipal water supply network redesign and rehabilitation", ***Water Resources Management***, Vol. 31, No. 9, (2017), 2689-2711, doi: 10.1007/s11269-017-1655-0.

28. Naderi, M.J. and Pishvaee, M.S., "A stochastic programming approach to integrated water supply and wastewater collection network design problem", ***Computers & Chemical Engineering***, Vol. 104, (2017), 107-127, doi: 10.1016/j.compchemeng.2017.04.003.

29. Ghelichi, Z., Tajik, J. and Pishvaee, M.S., "A novel robust optimization approach for an integrated municipal water distribution system design under uncertainty: A case study of mashhad", ***Computers & Chemical Engineering***, Vol. 110, (2018), 13-34, doi: 10.1016/j.compchemeng.2017.11.017.

30. Sahebjamnia, N. and Fathollahi-Fard, A., "A lagrangian relaxation-based algorithm to solve a collaborative water supply chain network design problem", ***International Journal of Emerging Trends in Engineering Research***, Vol. 6, (2018), 40-45, doi: 10.30534/ijeter/2018/01672018.

31. Abdul Ghani, L., Ali, N.a., Nazaran, I.S. and Hanafiah, M.M., "Environmental performance of small-scale seawater reverse osmosis plant for rural area water supply", ***Membranes***, Vol. 11, No. 1, (2021), 40, https://doi.org/10.3390/membranes11010040

32. Wolpert, D.H. and Macready, W.G., "No free lunch theorems for optimization", ***IEEE Transactions on Evolutionary Computation***, Vol. 1, No. 1, (1997), 67-82, doi: 10.1109/4235.585893.

33. Fathollahi-Fard, A.M., Hajiaghaei-Keshteli, M. and Tavakkoli-Moghaddam, R., "Red deer algorithm (RDA): A new nature-inspired meta-heuristic", ***Soft Computing***, Vol. 24, No. 19, (2020), 14637-14665, https://doi.org/10.1007/s00500-020-04812-z

34. Hajiaghaei-Keshteli, M. and Aminnayeri, M., "Solving the integrated scheduling of production and rail transportation problem by keshtel algorithm", ***Applied Soft Computing***, Vol. 25, (2014), 184-203, https://doi.org/10.1016/j.asoc.2014.09.034

35. Wang, S.-C., "Interdisciplinary computing in java programming, Springer Science & Business Media, Vol. 743, (2003).

36. Kennedy, J. and Eberhart, R., "Particle swarm optimization", in Proceedings of ICNN'95-international conference on neural networks, IEEE. Vol. 4, (1995), 1942-1948.

37. Altiparmak, F., Gen, M., Lin, L. and Karaoglan, I., "A steady-state genetic algorithm for multi-product supply chain network design", ***Computers & Industrial Engineering***, Vol. 56, No. 2, (2009), 521-537, https://doi.org/10.1016/j.cie.2007.05.012

38. Mousavi, S.M., Bahreininejad, A., Musa, S.N. and Yusof, F., "A modified particle swarm optimization for solving the integrated location and inventory control problems in a two-echelon supply chain network", ***Journal of Intelligent Manufacturing***, Vol. 28, No. 1, (2017), 191-206, doi: 10.1007/s10845-014-0970-z.

39. Zheng, J.-N., Chien, C.-F. and Gen, M., "Multi-objective multi-population biased random-key genetic algorithm for the 3-d container loading problem", ***Computers & Industrial Engineering***, Vol. 89, (2015), 80-87, https://doi.org/10.1016/j.cie.2014.07.012

40. Delfani, F., Kazemi, A., Seyedhosseini, S. and Niaki, S., "A green hazardous waste location-routing problem considering the risks associated with transportation and population", ***International Journal of Engineering***, Vol. 33, No. 11, (2020), 2272-2284, doi: 10.5829/IJE.2020.33.11B.18.

41. Yuan, G., Yang, Y., Tian, G. and Fathollahi-Fard, A.M., "Capacitated multi-objective disassembly scheduling with fuzzy processing time via a fruit fly optimization algorithm", ***Environmental Science and Pollution Research***, (2022), 1-18, doi: 10.21203/rs.3.rs-1075510/v1.

42. Hajiaghaei-Keshteli, M. and Fathollahi Fard, A.M., "Sustainable closed-loop supply chain network design with discount

supposition", ***Neural computing and applications***, Vol. 31, No. 9, (2019), 5343-5377, https://doi.org/10.1007/s00521-018-3369-5

43. Fathollahi-Fard, A.M., Dulebenets, M.A., Hajiaghaei–Keshteli, M., Tavakkoli-Moghaddam, R., Safaeian, M. and Mirzahosseinian, H., "Two hybrid meta-heuristic algorithms for a dual-channel closed-loop supply chain network design problem in the tire industry under uncertainty", ***Advanced Engineering Informatics***, Vol. 50, (2021), 101418, https://doi.org/10.1016/j.aei.2021.101418

44. Fard, A.M.F. and Hajaghaei-Keshteli, M., "A tri-level location-allocation model for forward/reverse supply chain", ***Applied Soft Computing***, Vol. 62, (2018), 328-346, https://doi.org/10.1016/j.asoc.2017.11.004

45. Mojtahedi, M., Fathollahi-Fard, A.M., Tavakkoli-Moghaddam, R. and Newton, S., "Sustainable vehicle routing problem for coordinated solid waste management", ***Journal of Industrial Information Integration***, Vol. 23, (2021), 100220, doi: 10.1016/j.jii.2021.100220.

46. Fathollahi-Fard, A.M., Woodward, L. and Akhrif, O., "Sustainable distributed permutation flow-shop scheduling model based on a triple bottom line concept", ***Journal of Industrial Information Integration***, Vol. 24, (2021), 100233, https://doi.org/10.1016/j.jii.2021.100233

47. Pasha, J., Dulebenets, M.A., Fathollahi-Fard, A.M., Tian, G., Lau, Y.-y., Singh, P. and Liang, B., "An integrated optimization method for tactical-level planning in liner shipping with heterogeneous ship fleet and environmental considerations", ***Advanced Engineering Informatics***, Vol. 48, (2021), 101299, doi: 10.1016/j.aei.2021.101299.

48. Karna, S.K. and Sahai, R., "An overview on taguchi method", ***International Journal of Engineering and Mathematical Sciences***, Vol. 1, No. 1, (2012), 1-7, https://www.researchgate.net/publication/265282800

49. Fazli, M., Fathollahi-Fard, A.M. and Tian, G., "Addressing a coordinated quay crane scheduling and assignment problem by red deer algorithm", ***International Journal of Engineering***, Vol. 32, No. 8, (2019), 1186-1191, doi: 10.5829/ije.2019.32.08b.15.

50. Moosavi, J., Fathollahi-Fard, A.M. and Dulebenets, M.A., "Supply chain disruption during the covid-19 pandemic: Recognizing potential disruption management strategies", ***International Journal of Disaster Risk Reduction***, (2022), 102983, https://doi.org/10.1016/j.ijdrr.2022.102983

51. Fathollahi-Fard, A.M., Hajiaghaei-Keshteli, M. and Tavakkoli-Moghaddam, R., "The social engineering optimizer (SEO)", ***Engineering Applications of Artificial Intelligence***, Vol. 72, (2018), 267-293, https://doi.org/10.1016/j.engappai.2018.04.009

52. Soleimani, H., Chhetri, P., Fathollahi-Fard, A.M., Mirzapour Al-e-Hashem, S. and Shahparvari, S., "Sustainable closed-loop supply chain with energy efficiency: Lagrangian relaxation, reformulations and heuristics", ***Annals of Operations Research***, (2022), 1-26, https://doi.org/10.1007/s10479-022-04661-z

Appendix A

The comparison of algorithms is provided in the results as reported in Table A1.

TABLE A1. Comparison of algorithms (B=best; W=worst; M=mean; ST=standard deviation; GAP=optimality gap from exact solver; CPU=computational time based on seconds)

Algorithm		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
RDA	B	1.34E+10	5.31E+10	5.62E+10	1.07E+11	1.76E+11	3.18E+11	4.61E+11	6.99E+11	9.38E+11	1.16E+12	1.57E+12	2.22E+12	4.78E+12	5.54E+12	5.75E+12	5.8E+12	6.06E+12	8.31E+12	1.07E+13	1.3E+13
	W	1.49E+10	5.89E+10	6.24E+10	1.19E+11	1.95E+11	3.53E+11	5.12E+11	7.76E+11	1.04E+12	1.29E+12	1.74E+12	2.46E+12	5.31E+12	6.15E+12	6.38E+12	6.44E+12	6.73E+12	9.22E+12	1.19E+13	1.44E+13
	M	1.41E+10	5.60E+10	5.93E+10	1.13E+11	1.86E+11	3.35E+11	4.86E+11	7.37E+11	9.90E+11	1.22E+12	1.66E+12	2.34E+12	5.04E+12	5.84E+12	6.07E+12	6.12E+12	6.39E+12	8.77E+12	1.13E+13	1.37E+13
	ST	5.98E+08	2.31E+09	2.45E+09	4.65E+09	7.69E+09	1.38E+10	2.0921E+10	3.19E+10	4.27E+10	5.29E+10	7.17E+10	1.02E+11	2.18E+11	2.53E+11	2.63E+11	2.65E+11	2.77E+11	3.8E+11	4.91E+11	5.93E+11
	GAP	0.0843	0.1222	0.156	0.147	0.232	0.126	0.115	0.158	-	-	-	-	-	-	-	-	-	-	-	-
	CPU	8.905	10.35556	11.41667	23.655	30.765	34.105	57.845	61.425	63.355	75.46	99.415	109.0045	129.9455	141.9591	171.1	251.144	259.444	277.1	291.564	335.864
KA	B	1.4E+10	5.41E+10	5.73E+10	1.09E+11	1.8E+11	3.24E+11	4.9E+11	7.48E+11	1E+12	1.24E+12	1.68E+12	2.38E+12	5.11E+12	5.93E+12	6.15E+12	6.2E+12	6.49E+12	8.89E+12	1.15E+13	1.39E+13
	W	1.54E+10	5.95E+10	6.30E+10	1.20E+11	1.98E+11	3.56E+11	5.39E+11	8.23E+11	1.10E+12	1.36E+12	1.85E+12	2.62E+12	5.62E+12	6.52E+12	6.77E+12	6.82E+12	7.14E+12	9.78E+12	1.27E+13	1.53E+13
	M	1.47E+10	5.68E+10	6.02E+10	1.14E+11	1.89E+11	3.40E+11	5.15E+11	7.85E+11	1.05E+12	1.30E+12	1.76E+12	2.50E+12	5.37E+12	6.23E+12	6.46E+12	6.51E+12	6.81E+12	9.33E+12	1.21E+13	1.46E+13
	ST	7.37E+08	2.92E+09	3.09E+09	5.89E+09	9.68E+09	1.75E+10	2.54E+10	3.84E+10	5.16E+10	6.38E+10	8.64E+10	1.22E+11	2.63E+11	3.05E+11	3.16E+11	3.19E+11	3.33E+11	4.57E+11	5.89E+11	7.15E+11
	GAP	0.135626	0.157764	0.199498	0.184525	0.328217	0.157804	0.194277	0.258941	-	-	-	-	-	-	-	-	-	-	-	-
	CPU	8.0145	9.32	10.275	21.2895	27.6885	32.39975	54.95275	58.35375	60.18725	67.914	89.4735	98.10409	116.9509	127.7632	153.99	226.0296	233.4996	249.39	262.4076	302.2776
GA	B	1.5E+10	5.94E+10	6.29E+10	1.2E+11	1.98E+11	3.56E+11	5.2E+11	7.83E+11	1.05E+12	1.3E+12	1.76E+12	2.49E+12	5.35E+12	6.21E+12	6.44E+12	6.49E+12	6.79E+12	9.3E+12	1.2E+13	1.46E+13
	W	1.74E+10	6.89E+10	7.30E+10	1.39E+11	2.30E+11	4.13E+11	6.03E+11	9.08E+11	1.22E+12	1.51E+12	2.04E+12	2.89E+12	6.21E+12	7.20E+12	7.47E+12	7.53E+12	7.88E+12	1.08E+13	1.39E+13	1.69E+13

	M	1.62E+10	6.42E+10	6.79E+10	1.30E+11	2.14E+11	3.84E+11	5.62E+11	8.46E+11	1.13E+12	1.40E+12	1.90E+12	2.69E+12	5.78E+12	6.71E+12	6.96E+12	7.01E+12	7.33E+12	1.00E+13	1.30E+13	1.58E+13
	ST	1.02E+09	4.06E+09	4.3E+09	8.2E+09	1.35E+10	2.43E+10	3.5523E+10	5.35E+10	7.17E+10	8.88E+10	1.2E+11	1.7E+11	3.65E+11	4.24E+11	4.4E+11	4.43E+11	4.64E+11	6.35E+11	8.2E+11	9.97E+11
	GAP	0.216742	0.271186	0.316726	0.304064	0.461039	0.272156	0.267396	0.317849	-	-	-	-	-	-	-	-	-	-	-	-
	CPU	7.21305	7.766667	8.5625	17.74125	23.07375	25.57875	43.38375	46.06875	47.51625	56.595	74.56125	81.75341	97.45909	106.4693	128.325	188.358	194.583	207.825	218.673	251.898
PSO	B	1.4E+10	5.65E+10	5.98E+10	1.14E+11	1.88E+11	3.38E+11	4.9E+11	7.44E+11	9.98E+11	1.24E+12	1.67E+12	2.37E+12	5.08E+12	5.9E+12	6.11E+12	6.17E+12	6.45E+12	8.84E+12	1.14E+13	1.38E+13
	W	1.69E+10	6.84E+10	7.24E+10	1.38E+11	2.27E+11	4.09E+11	5.93E+11	9.00E+11	1.21E+12	1.50E+12	2.02E+12	2.87E+12	6.15E+12	7.14E+12	7.39E+12	7.47E+12	7.80E+12	1.07E+13	1.38E+13	1.67E+13
	M	1.55E+10	6.24E+10	6.61E+10	1.26E+11	2.08E+11	3.73E+11	5.41E+11	8.22E+11	1.10E+12	1.37E+12	1.85E+12	2.62E+12	5.61E+12	6.52E+12	6.75E+12	6.82E+12	7.13E+12	9.77E+12	1.26E+13	1.52E+13
	ST	1.26E+09	5.07E+09	5.36E+09	1.02E+10	1.6856E+10	3.03E+10	4.39E+10	6.67E+10	8.95E+10	1.11E+11	1.4973E+11	2.12E+11	4.55E+11	5.29E+11	5.48E+11	5.53E+11	5.78E+11	7.93E+11	1.02E+12	1.24E+12
	GAP	0.135626	0.209125	0.251832	0.238861	0.387249	0.207833	0.194277	0.252209	-	-	-	-	-	-	-	-	-	-	-	-
	CPU	7.934355	8.543333	9.41875	19.51538	25.38113	28.13663	47.72213	50.67563	52.26788	62.2545	82.01738	89.92875	107.205	117.1163	141.1575	207.1938	214.0413	228.6075	240.5403	277.0878

Persian Abstract

چکیده

طراحی کارآمد یک سیستم آبرسانی و جمع آوری فاضلاب برای مقابله با عدم قطعیت طبیعی این سیستم و اهداف توسعه پایدار در کشورهای در حال توسعه مانند ایران اهمیت قابل توجهی دارد. برای پرداختن به عدم قطعیت طبیعی در تامین آب و چالش گرمایش جهانی، این طراحی باید قوی باشد و این انگیزه یک بهینه‌سازی قوی است. برای در نظر گرفتن معیارهای پایداری، این طرح باید تمام اثرات اقتصادی، زیست محیطی و اجتماعی را پوشش دهد. از این رو، این مطالعه راه‌حل‌های نوآورانه‌ای را بر اساس الگوریتم‌های فراابتکاری اخیر و سنتی برای تامین آب و سیستم جمع‌آوری فاضلاب قوی و پایدار توسعه می‌دهد. الگوریتم گوزن قرمز (RDA) و الگوریتم کشتل (KA) به عنوان الگوریتم های اخیر استفاده شده است. این الگوریتم‌های اخیر با روش‌های پیشرفته مانند الگوریتم ژنتیک (GA) و بهینه‌سازی ازدحام ذرات (PSO) مقایسه می‌شوند. کاربرد مدل و الگوریتم های ما، بر روی یک مطالعه موردی در استان خراسان شمالی آزمایش شده است. پس از انجام برخی تحلیل‌ها بر روی عملکرد الگوریتم‌ها و حساسیت‌های ما روی مدل، بحثی برای نتیجه‌گیری بینش‌ها و یافته‌های مدیریتی برای دست اندرکاران در سیستم کاربردی ارائه می‌شود.