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A multi-objective bi-level stochastic programming for water sustainable supply and allocation problem

Mostafa Ekhtiari[1], Mostafa Zandieh[1*]

[1]Department of Industrial Management, Management and Accounting Faculty, Shahid Beheshti University, Tehran, Iran

m_ektiari@yahoo.com, m_zandieh@sbu.ac.ir

Abstract

In recent years, the existence of some challenges in the water industry has led organizations to design and implement various solutions. This paper seeks to propose a methodology to address some of the most important challenges such as water sustainable supply and allocation (WSSA) problem, type of decision-making approach, coordination, sustainability, and uncertainty. The proposed methodology focuses on solving the WSSA problem, by considering these challenges in the problem. Concerning the conflict between sectors benefits of water resources and consumption and the need for coordinating between them, in this paper the type of decision-making approach is based on coordination and because of the existence of conflicting goals in important areas of water management decision making, a multi-objective bi-level programming model is presented. At the model leader level, the water supply management problem and the follower level, the water allocation management problem with multiple objectives is formulated, so that some of the parameters are assumed to be random and normally distributed. Also, a hybrid model based on chance-constrained programming (CCP) and nadir compromise programming (NCP) models as a deterministic transformation to bi-level stochastic programming model is proposed and a bi-level genetic algorithm is used to solve it. The proposed model is illustrated to solve a real problem in water resources and consumption management of Tehran city and based on several scenarios, the results are analyzed. The results show that the proposed methodology presents a suitable solution for addressing the mentioned challenges in the decision-making and planning process in the water management.

Keywords: Water sustainable supply and allocation, multi-objective bi-level stochastic programming, bi-level genetic algorithm

1- Introduction

Activities such as supply and demand planning, materials supply, production planning, distribution and customer service, which all performed at the level of an organization in the past, have now transferred to the supply chain level consisting of several organizational units responsible for converting raw materials into final products. Organizations have mainly conflicting interests and goals and operate in functional areas of the supply chain. Therefore, adopting a correct decision-making approach in the functional areas of the supply chain can be considered as the prerequisite for the survival and success of today's supply chains.

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*Corresponding author
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Researchers have categorized various types of supply chain decision-making approaches into three categories of centralized decision-making approach, decentralized decision-making approach, and coordination-based decision-making approach (Yang et al., 2014). Concerning the centralized decision-making approach, it is assumed that a central decision-maker (DM) controls the entire supply chain and the whole chain system operates as an integrated unit. In this approach, the performance of a supply chain is at its best state theoretically, which is called a centralized supply chain. This type of supply chain is only a theoretically ideal state, and therefore, real supply chains are not managed according to this approach in practice, as utilizing a centralized decision-making approach to manage a supply chain faces obstacles such as increasing operating costs and maintenance and reducing system reliability (Ertogral and Wu, 2000).

In the decentralized decision-making approach, each member of the supply chain is assumed as an independent economic entity that independently seeks to optimize its profits and interests. In other words, a decision that is optimal for a member of the chain may lead to high costs for other members of the chain. This decision-making approach can be sought in the decentralized supply chain, in which conflict in the interests, goals, and priorities of chain members is at its maximum possible level, leading to weakened supply chain performance and inefficiency, reduced customer service levels, and ultimately, increased product production costs in the supply chain. However, the bullwhip effect and bilateral finalization can be considered as adverse phenomena in the decentralized supply chain.

Although the above two approaches are the ultimate scenarios of decision-making approaches in today's supply chains, the coordination-based decision-making approach is an intermediate state between the two approaches. The issue of supply chain coordination is mainly concerned with the decentralized structure of the supply chain and its purpose is to create coordination and cooperation in the decisions and prioritization of supply chain members, in order to encourage them to work together and improve the overall performance of the supply chain. In other words, supply chain coordination aims to improve the performance of the decentralized supply chain, so that the performance of the decentralized chain is as close to a centralized one as possible. So far, various studies have been conducted on the issue of supply chain coordination, which highlights the importance and necessity of supply chain coordination. However, the procedure of supply chain coordination is now a fundamental issue, especially in the Iranian water supply and distribution chain in decision-making levels.

The geographical location of Iran in the arid region, the occurrence of numerous droughts, limited water resources, lack of observation of consumption patterns and problems like these have made Iran one of the countries with water problem. Reviewing the latest research on per capita water consumption in each country reveals that despite of the limitation of water resources, Iran with 190 liters of household drinkable water consumption per day is one of the largest water consumers in the world and ranks tenth in per capita household water consumption among the countries. While the average household water consumption in the world is 150 liters per inhabitant per day, this amount in Tehran is estimated 220 to 276 liters per citizen and has reached 400 liters per day in the recent water crisis in Tehran, according to water and sewage officials in this province.

Generally, the most important challenges in managing the country's water resources and consumption are as follows:

Demand management

The rapid population growth and the increasing demand for resources and products, especially non-renewable resources such as water, has leaded to paying more attention to planning in consumer demand control. The critical level of water resources per capita in each country has highlighted the importance of this field of management. Demand management in the water sector pursues the following objectives:

- Providing an optimal allocation of water among consumers,
- Increasing revenues of the water management,
- Establishing a balance between the amount of supplied and consumed water,
- Designing a sustainable development,
- Reducing unnecessary losses and expenses,
- Controlling water quality,
- Developing drought management.

Environmental management and water refinement

The optimization of ecological systems, ecosystem conservation, ecological integration of groundwater, rivers, lakes, and coastal areas, and urban and agricultural wastewater refinement are all among measures that should be considered in the field of environmental management and water refinement activities.

Economic management and financial resources of water

The difference between the costs of supply, transmission, refinement, and allocation of water and the return on capital has made the government to pay subsidies in this regard. However, the issue of price restraint and payment of costs, as significant axes in economic management and water resources, should be on the planning agenda of this sector.

In recent years, the decreased annual rainfall compared to the global average, limited freshwater resources in Iran, non-standard extraction of groundwater, inability to control surface water, increase in water pollution due to domestic, agricultural, and industrial wastewater, lack of long-term plans in water resources management, problems caused by economic and financial failures, lack of water research, scientific, and study centers, and lack of accurate databases of statistics on water reservoirs, resources, and consumption are among other challenges in managing the country's water resources and consumption (FAO, 2017).

To overcome these challenges, the country's water management structure should adopt the necessary planning and arrangements to address the challenges in this field, considering the modern management theories and known scientific models, as well as the requirements of sustainable development. The concept of sustainability refers to using available resources to meet the needs of the current generation without compromising the ability of the next generation (Linton et al., 2007). This concept should be examined in the management of sustainable water supply chains from technical, environmental, economic, and social dimensions. The sustainability of the water supply chain refers to the social, environmental, economic, and technical goals of the water supply and water allocation with the effective coordination of intra-organizational processes. Considering the concept of sustainability in the water supply chain allows addressing and reducing the adverse environmental and social effects, in addition to considering financial profitability. Nowadays, the concept of supply chain sustainability is recognized as a new and effective issue that has been considered by many researchers in the field of supply chain management. Thus, it is necessary to design measures for achieving sustainable development and planning a sustainable paradigm in managing the country's water resources and consumption.

This article mainly focuses on modeling some of the challenges in water supply and allocation management, which can be quantified to provide a scientific solution to reduce the negative effects of the current situation of the country's water industry. Regarding the operational capabilities of multi-level programming models in establishing coordination between different levels of decision-making and achieving a feasible solution for each level, this research seeks to develop a multi-level multi-objective programming model based on sustainability indicators for water supply and distribution system. Concerning the proposed model, the water supply problem is formulated to decrease the cost and level of water supply pollution at the leader level while the water allocation problem is formulated to increase revenue and reduce the cost and the pollution of water allocation at the follower level. In this way, some of the problem parameters are considered non-deterministic. To deal with the uncertainty conditions of the problem, a model called chance-constrained compromise programming is used and the transformed problem is solved by using a bi-level genetic algorithm. After adjusting the parameters of the bi-level genetic algorithm (GA), the efficiency of the algorithm in solving several random sampling problems is compared and evaluated by using the extreme solutions method (ESM). The bi-level genetic algorithm is used to solve a problem with the data of the water supply and distribution system in Tehran city. Finally, the results are analyzed and evaluated based on different scenarios.

Therefore, this paper is organized as follows: Section 2 presents a literature review related to this paper topic. In section 3 is reviewed the most important methods employed in this paper. The proposed methodology is presented in section 4. The case study of this paper is explained in section 5 and the results obtained are analyzed in this section. Finally, section 6 presents the conclusions.

2- Literature review

Table 1 presents a detailed classification of the literature related to the subject of this paper. As presented in Table (1), concurrent attention to issues of coordination-based multi-objective decision making, uncertainty, sustainability and considering bi-level programming approach in modeling the water sustainable supply and allocation (WSSA) problems are the main differences of the problem compared to those discussed in the literature. Moreover, there are several approaches in the literature to deal with problems related to supply and allocate water, despite a few studies conducted on WSSA by considering a multi-objective bi-level programming approach.

Table 1. A brief review on the research literature

Researcher(s)	Approach: Centralized	Approach: Decentralized	Approach: Coordination-based	Water supply problem: Single-level programming (Single-objective (●) Multi-objective (■))	Water supply problem: Bi-level programming (Single-objective (●) Multi-objective (■))	Water allocation problem: Single-level programming (Single-objective (●) Multi-objective (■))	Water allocation problem: Bi-level programming (Single-objective (●) Multi-objective (■))	Water supply and allocation problem: Single-level programming (Single-objective (●) Multi-objective (■))	Water supply and allocation problem: Bi-level programming (Single-objective (●) Multi-objective (■))	Conditions: Certainty	Conditions: Uncertainty	Indicators: Sustainability	Indicators: Others	Modeling and solution approach
Li et al. (2009)	✓					■					✓		✓	Fuzzy stochastic programming
Aviso et al. (2010)			✓		●						✓		✓	Fuzzy programming- Game theory
Lu et al. (2010)	✓			■							✓		✓	Fuzzy linear programming- Interval numbers
Wang and Huang (2011)	✓					●					✓		✓	Two stage stochastic fuzzy programming
Kucukmehmetoglu (2012)		✓	✓				●			✓			✓	Multi-objective linear programming-game theory
Zarghami and Hajykazemian (2013)	✓			■							✓	✓		Compromise programming-Genetic algorithm-Particle swarm optimization algorithm
Gu et al. (2013)	✓					●					✓		✓	Multi-stage stochastic integer programming
Britz et al. (2013)	✓					■				✓			✓	Multi-objective programming
Grosso et al. (2014)	✓					●					✓		✓	Chance constrained programming-Quadratic programming
Roozbahani et al. (2015)	✓					■				✓		✓		Compromise programming
Cai et al. (2016)	✓			●							✓	✓		Interval programming-Fuzzy numbers
Sun et al. (2016)	✓			■						✓		✓		Analytical Hierarchy Process
Zhang and Vesselinov (2016)			✓		●						✓		✓	Two-level programming-Fuzzy theory
Lewis and Randall (2017)	✓			■						✓			✓	Multi-objective programming-NSGA II
Chen et al. (2017)		✓	✓		●						✓	✓		Bi-level programming- Interactive approach
Ren et al. (2017)	✓			■							✓	✓		Multi-objective programming-Fuzzy numbers
Xiong et al. (2018)	✓							■			✓	✓		Multi-objective programming-Simulation
Li et al. (2018)	✓						■				✓		✓	Interval linear multi-objective programming-Fuzzy programming
Xie et al. (2018)	✓					■					✓	✓		Interval programming-Two stage stochastic programming
Uen et al. (2018)			✓	■						✓			✓	Multi-objective programming-NSGA II
Pérez-Uresti et al. (2019)	✓							■		✓			✓	Multi-objective programming
Thi Bui et al. (2019)	✓			■						✓		✓		Analytical Hierarchy Process
Tirupathi et al. (2019)	✓			■							✓	✓		Fuzzy programming
Yao et al. (2019)		✓					■				✓	✓		Game theory-Fuzzy number-Genetic algorithm
Tianhong et al. (2019)	✓			●							✓	✓		System dynamics
Zhang et al. (2019)	✓			●							✓		✓	Chance constrained programming-Interval programming

3- Methods overview

The proposed methodology of this paper is based on three main methods and one proposed method as follows:

3-1- Bi-level programming

As presented in section 1, the coordination-based approach for the WSSA problem is an acceptable solution when there are different stakeholders and DMs in a sustainable supply chain. Accordingly, the present study aims to propose a mechanism for coordinating in WSSA process. To establish coordination in a sustainable supply chain, different mechanisms have been presented which include (Arshinder and Deshmukh, 2008):

- **Contracts:** Designing contracts in a sustainable supply chain is an agreement among various members of the chain that encourages them to cooperate and work together to increase profitability and reduce costs of the whole system.
- **Information technology:** This mechanism improves intra-organizational coordination and creates necessary coordination between units of production, distribution and delivery. Information technology can plan and predict times of product delivery.
- **Information sharing:** Sustainable supply chain members can coordinate the chain by sharing information on demand, orders, and inventories. The timely sharing of information related to customers' demand leads to an increase in the profitability of the system, in addition to reducing inventory costs and increasing customers' service level.
- **Joint decision:** Given the joint decision-making mechanism, a decision-making process is established through cooperation between members of a sustainable supply chain system that addresses interest conflicts of each member and gives each member of the chain a clear view of the activities and sustainable supply chain decisions. In this regard, mathematical programming models such as Game theory (Leng and Parlar, 2005; Cachon and Netessine, 2004) are among the common decision-making tools. Bilateral problems defined at levels of the leader (first) and a follower (second) are close to Stackelberg games in the Game theory, as both of them have two levels of optimization problems. In such cases, the space of higher-level problem constraints is implicitly defined by the lower-level optimization problem, the mathematical decision-making model of which is called the bi-level programming (Colson et al., 2007).

Assuming that the DM controls variable x at the leader level and can determine its value, and the DM controls variable y at the follower level, it can be said that $x \in X \subset R^n, y \in Y \subset R^m, F: X \times Y \to R^1$. With this assumption, the bi-level programming model can be defined as equation (1):

$$\mathcal{P}_1: \min_{x \in X}/\max f_1(x,y) = a_1 x + b_1 y, \tag{1-1}$$

$$\mathcal{P}_2: \min_{y \in Y}/\max f_2(x,y) = a_2 x + b_2 y, \tag{1-2}$$

s.t

$$Ax + By \le c, \tag{1-3}$$

Where $a_1, a_2 \in R^n$, $b_1, b_2 \in R^m$, $c \in R^p$, $A \in R^{p \times n}$, and $B \in R^{p \times m}$ are the parameters of the model and $\mathcal{P}_1$ and $\mathcal{P}_2$ represent DMs at leader and follower levels, respectively. The objective functions (1-1) and (1-2), respectively are concerned with the problems of leader and follower levels that are related to each other through the system constraint (1-3). In general, two variables of control and decision are defined in the bi-level programming model (Kuo and Han, 2011). Concerning the control variable, the DM of leader/follower levels can determine a value for it while the decision variable is an unknown variable, the value of which is determined after solving the problem, such that the control variable of one level can be as decision variable of another level. In Program (1), the decision variable of leader and follower levels are y and x and the control variable of leader and follower levels are x and y, respectively.

To achieve an optimal solution in Program (1) that can simultaneously supply the maximum interests of leader and follower levels, the overall form of the decision-making process is as follows (Shih et al., 1996):

Step 1: The leader determines a value for his/her preferences for decision variable y and presents it to the follower.

Step 2: The variable y in the follower problem is a control variable and has a constant and known value. Therefore, the follower simultaneously provides the leader's control goals and priorities as much as possible, by optimizing his/her objective, which is $\min/\max_{y \in Y} f_2(y) = a_2 x + d$ (d is a constant value).

Step 3: The follower knows that regardless of the leader's wishes, his/her proposed solution will most likely be rejected and the process of reaching the final solution will be lengthy. Thus he/she presents his/her proposed value for variable x to the leader.

Step 4: If the follower's proposed solution is accepted by the leader, then the final solution of the problem is the value of decision variable y defined at the leader level and the value of decision variable x obtained from the problem-solution at the follower level.

Step 5: If the leader rejects the follower's proposed solution, then the leader should re-evaluate the value of decision variable x so that the decision-making process leads to the final solution.

Step 6: Go to Step 1.

In the bi-level programming problems, there is a hierarchical structure between the levels of the leader and follower, causing them to be considered as NP-hard problems (Shih et al., 1996; Kuo and Han, 2011; Wee et al., 2013; Naimi Sadigh et al., 2012). So far, researchers have attempted to use the bi-level programming models to solve various problems of the supply chain, some of which have been cited in Roghanian et al., (2007), Lan et al., (2011), Kuo et al., (2015), and Guo et al., (2016).

Suppose that each of the problems $\mathcal{P}_1$ and $\mathcal{P}_2$ in Program (1) have not only one but also several objective functions. This type of bi-level programming problem, in which multiple objective functions are considered for leader/follower level problems, is called a multi-objective bi-level programming model.

Regarding the capabilities of the multi-objective bi-level programming models, including the participation of different levels of the supply chain in the decision-making process and considering the conflict objectives of supply chain members, a few research has been carried out to find an optimal solution for supplying the common interests of all members and increasing the level of chain coordination. Therefore, the multi-objective bi-level programming models should further focus on modeling and solving problems of today's supply chains.

3-2- Nadir compromise programming (NCP)

NCP is one of the models to solve multi-objective mathematical programming problems. This model, proposed by Amiri et al.(2011), concerns with maximizing the distance between the achievement levels and the nadir values associated with each objective. If the objective k for $k = 1, \dots, K$ should be maximized, then the nadir values (Z_{k*}) can be obtained as follows:

$$
\begin{aligned}
&\min\ Z_k(\mathbf{x}),\ \ k = 1, \dots, K, \\
&\text{s.t.} \\
&\mathbf{x} \in S,
\end{aligned}
\tag{2}
$$

Considering the preference weights of objectives (w_k), the final model of NCP is formulated as follows:

$$
\begin{aligned}
&\max \left\{ \textstyle\sum_{k=1}^{K} w_k (\lambda_k)^p \right\}^{\frac{1}{P}}, \\
&\text{s.t.} \\
&Z_k(\mathbf{x}) - \lambda_k = Z_{k*}, \quad k = 1, \dots, K, \\
&\lambda_k \geq 0, \quad k = 1, \dots, K, \\
&\mathbf{x} \in S,
\end{aligned}
\tag{3}
$$

Where P depicts the parameter of the final utility function with the values of metrics $\{1,2, \dots\} \cup \{\infty\}$ and λ_k indicates the deviation value between $Z_k(\mathbf{x})$ and Z_{k*}.

Furthermore, if the objective l for $l = 1, \dots, L$ should be minimized, then the nadir values (Z_{l*}) can be obtained as follows:

$$
\begin{aligned}
&\max\ Z_l(\mathbf{x}), \quad l = 1, \dots, L,\\
&\text{s.t.}\\
&\mathbf{x} \in S.
\end{aligned}
\tag{4}
$$

By considering the preference weights of objectives (w_l), the final model of NCP is formulated as follows:

$$
\begin{aligned}
&\max\left\{\sum_{l=1}^{L} w_l (\lambda_l)^p\right\}^{\frac{1}{P}},\\
&\text{s.t.}\\
&Z_l(\mathbf{x}) + \lambda_l = Z_{l*}, \quad l = 1, \dots, L,\\
&\lambda_l \geq 0, \quad l = 1, \dots, L,\\
&\mathbf{x} \in S.
\end{aligned}
\tag{5}
$$

Generally, if we maximize K objective functions and minimize L objectives, the final model of NCP can be written as follows (Amiri et al., 2011):

$$
\begin{aligned}
&\max\left\{\sum_{k=1}^{K} w_k (\lambda_k)^p + \sum_{l=1}^{L} w_l (\lambda_l)^p\right\}^{\frac{1}{P}},\\
&\text{s.t.}\\
&Z_k(\mathbf{x}) - \lambda_k = Z_{k*}, \quad k = 1, \dots, K,\\
&Z_l(\mathbf{x}) + \lambda_l = Z_{l*}, \quad l = 1, \dots, L,\\
&\lambda_k, \lambda_l \geq 0, \quad k = 1, \dots, K, \quad l = 1, \dots, L,\\
&\mathbf{x} \in S.
\end{aligned}
\tag{6}
$$

Where $\sum_{k=1}^{K} w_k + \sum_{l=1}^{L} w_l = 1$ ($w_k, w_l > 0$, for $k = 1, \dots, K$ and $l = 1, \dots, L$).

3-3- The chance constrained programming (CCP)

Stochastic programming deals with a class of optimization models and algorithms, in which all or some of the parameters may be subjected to significant uncertainties. The models of stochastic programming yield a plan to deal with losses and catastrophic failures better (Sen, 2001). Because of these properties, the stochastic programming models have been developed for a variety of applications, including manpower allocation (Ekhtiari and Ghseiri, 2013), financial planning (Carino et al., 1994), flexible manufacturing systems (Ip et al., 1999), supply chain management (Sheikh Sajadieh and AkbariJokar, 2009), and aggregate production planning (Mirzapour Al-e-Hashem et al., 2011). In this regard, the CCP approach, as the most popular approach to solve the stochastic programming problems (Charnes and Cooper, 1959), attempts to maximize the expected value of random objectives, in addition to securing a given confidence level of satisfaction for random constraints. The CCP approach transforms the stochastic programming problem into a deterministic equivalent problem, which can be easily solved by an appropriate optimization technique.

Let $\tilde{c}_{kj}$, $\tilde{a}_{ij}$ and $\tilde{b}_i$be uncertain parameters. If we maximize the objectives $\sum_{j=1}^{n} \tilde{c}_{kj} x_j$ (for $k = 1, \dots, K$), the stochastic programming problem can be written as follows:

$$
\begin{aligned}
&\max\ f_k(\mathbf{x}): \sum_{j=1}^{n} \tilde{c}_{kj} x_j, \quad k = 1, \dots, K,\\
&\text{s.t.}\\
&\sum_{j=1}^{n} \tilde{a}_{ij} x_j \leq \tilde{b}_i, \ i = 1, \dots, m,\\
&\mathbf{x} \in S,
\end{aligned}
\tag{7}
$$

Where $\mathbf{x} = (x_1, \dots, x_n)$ represents th e vector of decision variables and S indicates the solution space. In the CCP approach, Program (7) is converted into a deterministic program as follows (Prekopa, 1995):

$$\max \ E\left(\sum_{j=1}^{n} \tilde{c}_{kj} x_j\right), \quad k = 1, \dots, K,$$
s.t.
$$\text{Prob}\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j \le \tilde{b}_i\right) \ge 1 - \alpha_i, \quad i = 1, \dots, m, \tag{8}$$
$$\mathbf{x} \in S.$$

3-4- Nadir compromise constrained programming (NCCP)

In this paper, a combined approach of CCP and NCP models is proposed to convert Program (7) to a deterministic programming problem as follow:

a) Random objectives are handled in the CCP approach: $\tilde{c}_{kj}$ are random and normally distributed parameters and c_{kj*} is the least value observed for objective$k$. Thus:

$$c_{kj*} = \min \tilde{c}_{kj} \tag{9}$$

It is assumed that K objectives should be maximized. Therefore, the nadir value of objective k (f_{k*}) is obtained by equation (10):

$$\min \sum_{j=1}^{n} c_{kj*} x_j, \quad k = 1, \dots, K, \tag{10}$$
s.t:
$$\mathbf{x} \in S.$$

It can be said:

$$\sum_{j=1}^{n} \tilde{c}_{kj} x_j \ge f_{k*}, \quad k = 1, \dots, K, \tag{11}$$

Where f_{k*} $k = 1, \dots, K$ is the nadir value or the worst solution of the objective function kth subject to system constraints.

Based on CCP, the objective is maximizing λ_k subject to:

$$\text{Prob}\left(\sum_{j=1}^{n} \tilde{c}_{kj} x_j \le f_{k*} + \lambda_k\right) \ge 1 - \alpha_k, \quad k = 1, \dots, K, \tag{12}$$

Where $\alpha_k k = 1, \dots, K$ is the threshold value of the objective kth.

$$\text{Prob}\left(\sum_{j=1}^{n} \tilde{c}_{kj} x_j - f_{k*} \le \lambda_k\right) \ge 1 - \alpha_k, \quad k = 1, \dots, K. \tag{13}$$

Let $\tilde{A}_i(\mathbf{x}) = \sum_{j=1}^{n} \tilde{c}_{kj} x_j - f_{k*}, \tilde{A}_k(\mathbf{x})$ be normally distributed and $E(\tilde{A}_k(\mathbf{x}))$ and $Var(\tilde{A}_k(\mathbf{x}))$ be the mean and the variance, respectively. Thus we have:

$$\text{Prob}(\tilde{A}_k(\mathbf{x}) \le \lambda_k) \ge 1 - \alpha_k, \quad k = 1, \dots, K, \tag{14}$$

$$\text{Prob}\left(\frac{\tilde{A}_k(\mathbf{x}) - E(\tilde{A}_k(\mathbf{x}))}{\sqrt{Var(\tilde{A}_k(\mathbf{x}))}} \le \frac{\lambda_k - E(\tilde{A}_k(\mathbf{x}))}{\sqrt{Var(\tilde{A}_k(\mathbf{x}))}}\right) \ge 1 - \alpha_k, \quad k = 1, \dots, K, \tag{15}$$

$$\frac{\lambda_k - E(\tilde{A}_k(\mathbf{x}))}{\sqrt{Var(\tilde{A}_k(\mathbf{x}))}} \ge \Phi^{-1}(1 - \alpha_k), \quad k = 1, \dots, K, \tag{16}$$

$$\lambda_k \ge E\left(\tilde{A}_k(\mathbf{x})\right) + \Phi^{-1}(1 - \alpha_k)\sqrt{Var(\tilde{A}_k(\mathbf{x}))}, \quad k = 1, \dots, K, \tag{17}$$

$$E\left(\sum_{j=1}^{n} \tilde{c}_{kj} x_j - f_{k*}\right) + \Phi^{-1}(1 - \alpha_k)\sqrt{Var\left(\sum_{j=1}^{n} \tilde{c}_{kj} x_j - f_{k*}\right)} - \lambda_k \le 0, \quad k = 1, \dots, K. \tag{18}$$

If $\delta_k^- k = 1, \dots, K$ is slack variable kth and the objective is to minimize δ_k^-(or maximize $-\delta_k^-$), then the standard form of equation (18) is as follows:

$$E\left(\sum_{j=1}^{n} \tilde{c}_{kj} x_j\right) + \Phi^{-1}(1-\alpha_k)\sqrt{\sum_{j=1}^{n} Var(\tilde{c}_{kj} x_j)} - \lambda_k + \delta_k^- = f_{k*}, \quad k = 1, \dots, K. \tag{19}$$

b) Random constraints are handled in the CCP approach: $\tilde{a}_{ij}$ and $\tilde{b}_i$ represent random and normally distributed parameters, respectively. The related chance constraint to $\sum_{j=1}^{n} \tilde{a}_{ij} x_j \leq \tilde{b}_i,\ i = 1, \dots, m$, is:

$$\text{Prob}\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j \leq \tilde{b}_i\right) \geq 1 - \alpha_i, \quad i = 1, \dots, m, \tag{20}$$

Where $\alpha_i i = 1, \dots, m$ indicates the threshold value of constraint ith.

Let $\tilde{B}_i(\mathbf{x}) = \sum_{j=1}^{n} \tilde{a}_{ij} x_j - \tilde{b}_i, \tilde{B}_i(\mathbf{x})$ be normally distributed and $E(\tilde{B}_i(\mathbf{x}))$ and $Var(\tilde{B}_i(\mathbf{x}))$ are the mean and the variance, respectively. Thus we have:

$$\text{Prob}(\tilde{B}_i(\mathbf{x}) \leq 0) \geq 1 - \alpha_i, \quad i = 1, \dots, m, \tag{21}$$

$$\text{Prob}\left(\frac{\tilde{B}_i(\mathbf{x}) - E(\tilde{B}_i(\mathbf{x}))}{\sqrt{Var(\tilde{B}_i(\mathbf{x}))}} \leq \frac{-E(\tilde{B}_i(\mathbf{x}))}{\sqrt{Var(\tilde{B}_i(\mathbf{x}))}}\right) \geq 1 - \alpha_i,\ i = 1, \dots, m, \tag{22}$$

$$\frac{-E(\tilde{B}_i(\mathbf{x}))}{\sqrt{Var(\tilde{B}_i(\mathbf{x}))}} \geq \Phi^{-1}(1-\alpha_i), \quad i = 1, \dots, m, \tag{23}$$

$$E\left(\tilde{B}_i(\mathbf{x})\right) + \Phi^{-1}(1-\alpha_i)\sqrt{Var(\tilde{B}_i(\mathbf{x}))} \leq 0,\ i = 1, \dots, m, \tag{24}$$

$$E\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j - \tilde{b}_i\right) + \Phi^{-1}(1-\alpha_i)\sqrt{Var\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j - \tilde{b}_i\right)} \leq 0, \quad i = 1, \dots, m. \tag{25}$$

If $\delta_i^- i = 1, \dots, m$ is slack variable ith and the objective is to minimize δ_i^-(or maximize $-\delta_i^-$), then, the standard form of equation (25) is as follow:

$$E\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j\right) + \Phi^{-1}(1-\alpha_i)\sqrt{Var\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j - \tilde{b}_i\right)} + \delta_i^- = E\left(\tilde{b}_i\right), \quad i = 1, \dots, m. \tag{26}$$

The equivalent model to Program (5) that is formulated based on NCCP, can be stated as follows:

$$\begin{aligned}
&\max\left\{\sum_{k=1}^{K} w_k(\lambda_k - \delta_k^-)^P + \sum_{i=1}^{m} w_i(-\delta_i^-)^P\right\}^{\frac{1}{P}},\\
&\text{s.t.}\\
&E\left(\sum_{j=1}^{n} \tilde{c}_{kj} x_j\right) + \Phi^{-1}(1-\alpha_k)\sqrt{\sum_{j=1}^{n} Var(\tilde{c}_{kj} x_j)} - \lambda_k + \delta_k^- = f_{k*}, \quad k = 1, \dots, K,\\
&E\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j\right) + \Phi^{-1}(1-\alpha_i)\sqrt{Var\left(\sum_{j=1}^{n} \tilde{a}_{ij} x_j - \tilde{b}_i\right)} + \delta_i^- = E\left(\tilde{b}_i\right), \quad i = 1, \dots, m,\\
&\lambda_k, \delta_k^-, \delta_i^- \geq 0, \quad k = 1, \dots, K,\ i = 1, \dots, m,\\
&\mathbf{x} \in S.
\end{aligned} \tag{27}$$

4- Proposed methodology

4-1- Problem statement

The WSSA system shown in figure (1) is a bi-level system consisting of two levels of leader and follower. The first level addresses water supply management based on m water sources and current goals and constraints while the second level concerns with water allocation management based on n consumer type, and goals and constraints of the system. The existence of examples of conflict of interest, such as several stakeholders, several DMs, and several goals between the leader and follower levels, necessitates considering the issue of coordination between levels to manage the system better. Furthermore, the existence of uncertainty conditions and the need to pay attention to sustainability indicators in the sustainable management of water supply and allocation are among the issues that affect the performance of both levels. Therefore, the present study aims to achieve a solution that ensures reaching maximum benefits for different levels of decision-making in water supply and allocation management, in addition to addressing the limitations of the system.

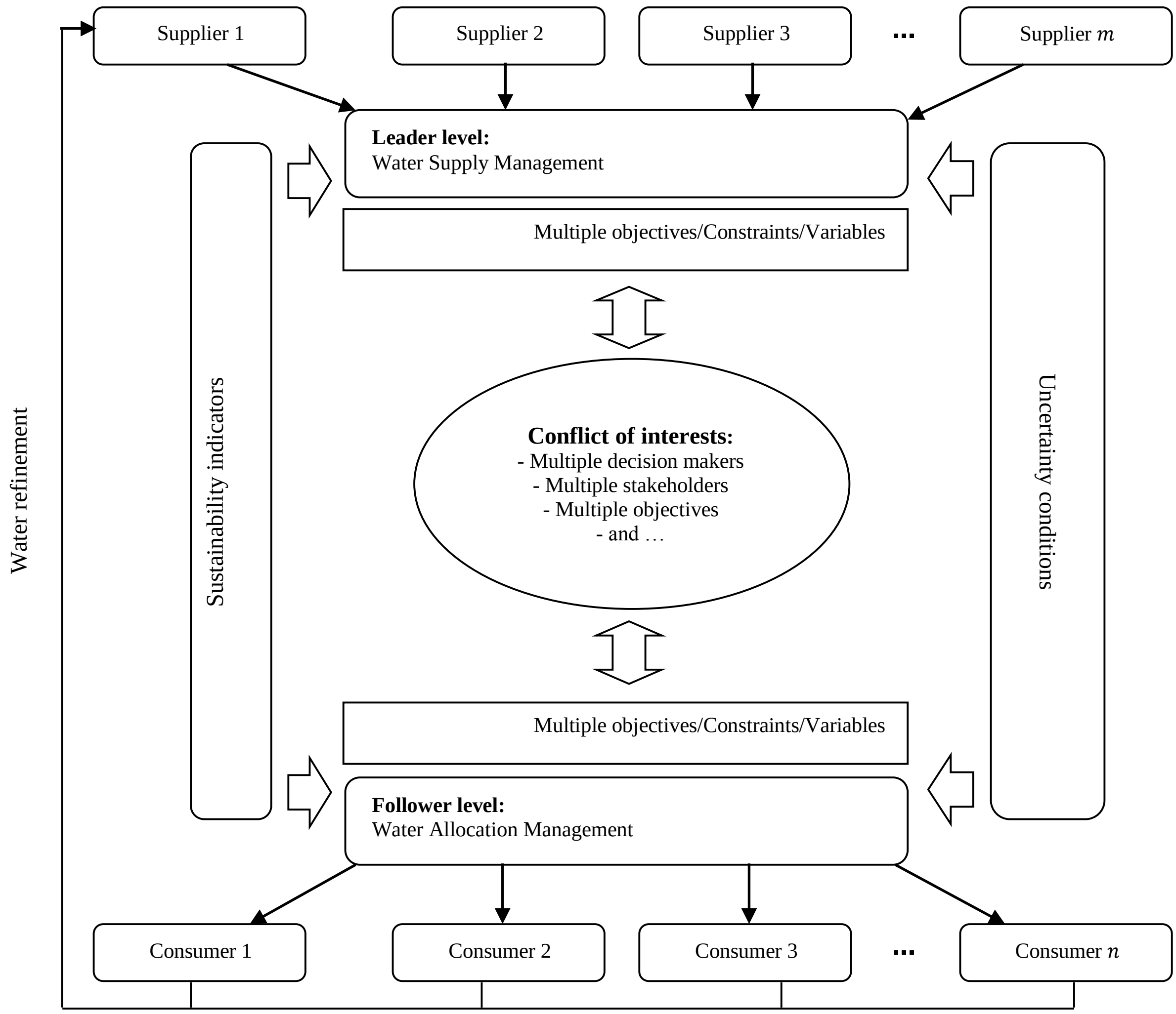


Fig. 1. The WSSA system studied in this paper

4-2- Solution approach

Figure (2) illustrates the flowchart of the proposed methodology.

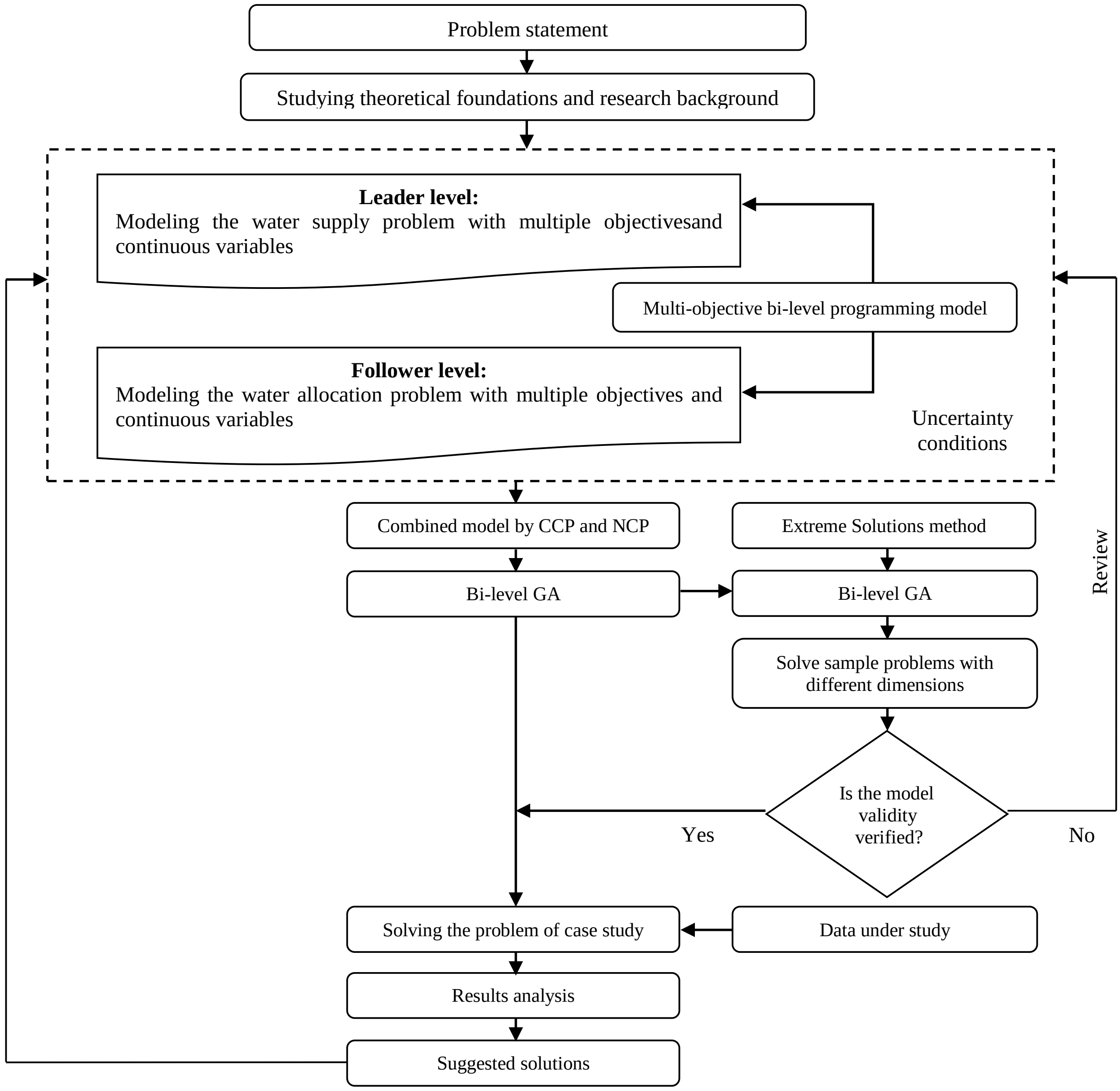


Fig. 2. Proposed methodology of this paper

In the following, we present the steps and explanation of the implementation stages of the proposed methodology:

Step 1: Modeling the non-deterministic problem of WSSA based on the bi-level programming model and sustainability indicators

***Step 1-1*:** Modeling the water supply problem with multiple objectives at the leader level

In this research, the water supply problem is formulated according to equation (28):

$$f_{11}(\mathbf{x}) = \min \sum_{i=1}^{m} \widetilde{pe}_i \, x_i, \tag{28-1}$$

$$f_{12}(\mathbf{x}) = \min \sum_{i=1}^{m} c_i \, x_i, \tag{28-2}$$

s.t: (28-3)

$x_i \leq A_i, \quad i = 1, \dots, m,$ (28-4)
$x_i \leq S_i, \quad i = 1, \dots, m,$ (28-5)
$A_1 = \sum_{j=1}^{n} v_j y_j,$ (28-6)
$\sum_{i=1}^{m} (1 - \gamma_i) x_i = \sum_{j=1}^{n} y_j,$ (28-7)
$\theta_i cap_i \leq x_i \leq cap_i, \ i = 1, \dots, m.$

where:
m: number of water suppliers,
n: number of water consumers,
$\widetilde{pe}_i$: The amount of greenhouse gas pollution caused by the unit volume of water supply from source i ($\frac{kgco_2-eq}{m^3}$),
c_i: The cost of supplying each unit volume of water from the source i ($\frac{Rials}{m^3}$),
A_i: The level of access to the water source i ($\frac{m^3}{Month}$),
S_i: The capacity of water supplying infrastructure from the source i ($\frac{m^3}{Month}$),
v_j: The rate of water wastage from consumer j,
γ_i: Water leakage rate from source i (such as water lost through desalination plants and water distribution pipes) ($\frac{m^3}{Month}$),
cap_i: Water supply capacity by the source i ($\frac{m^3}{Month}$),
θ_i: The minimum amount of water in the source i,
x_i: The decision variable of the amount of water supplied from source i,
y_j: The decision variable of the amount of water allocated to the consumer j.

Equations (28-1) to (28-7) are respectively as follows:
Minimization of the total greenhouse gas pollution from the water supply (environmental indicator), minimization of the total cost of water supply (economic indicator), access and withdrawal of water from source i (technical indicator), the capacity of water supplying infrastructure from source i (technical indicator), access to refined water from total water wastes (environmental indicator), the balance between the total supplied and distributed water (technical indicator), and the limitation of the minimum and maximum water supply capacity through the source i (technical indicator).

***Step 1-2*:** Modeling the water allocation problem with multiple objectives at the follower level

After supplying water from resources, the allocation of water to each consumer should be considered. Therefore, the water allocation problem is formulated under equation (29):

$$
\begin{aligned}
& f_{21}(\mathbf{y}) = \max \textstyle\sum_{j=1}^{n} b_j \, y_j, && \text{(29-1)} \\
& f_{22}(\mathbf{y}) = \min \textstyle\sum_{j=1}^{n} \widetilde{de}_j \, y_j, && \text{(29-2)} \\
& f_{23}(\mathbf{y}) = \min \textstyle\sum_{j=1}^{n} dc_j \, y_j && \text{(29-3)} \\
& \text{s.t:} \\
& y_j \geq \widetilde{D}_j, \ \ j = 1, \dots, n && \text{(29-4)} \\
& y_j \leq \omega_j \widetilde{D}_j, \ \ j = 1, \dots, n. && \text{(29-5)}
\end{aligned}
\qquad (29)
$$

Where:
b_j: The amount of revenue from allocating a unit of water to the consumer j,
dc_j: The cost of distributing water to the consumer j,
$\widetilde{D}_j$: The amount of water demand from the consumer j,
ω_j: The average of geometric growth rate of annual water demand in the consumer j,
$\widetilde{de}_j$: The amount of greenhouse gas pollution caused by the unit volume of water distribution to the consumer j ($\frac{kgco_2-eq}{m^3}$).

Equations (29-1) to (29-5) are respectively as follows:
Maximizing the revenue from water allocation to consumers (economic indicator), minimizing the total pollution of greenhouse gases due to water allocation (environmental indicator), minimizing the total

cost of water allocation (economic indicator), not having shortage in supplying the demand of water consumers (social indicator), and the maximum demand of water consumers (social indicator).

Finally, to solve the WSSA problem, the proposed multi-objective bi-level stochastic programming model is written in accordance with equation (30):

$$
\begin{array}{l}
f_{11}(\mathbf{x}) = \min \sum_{i=1}^{m} \widetilde{pe}_i \, x_i, \\
f_{12}(\mathbf{x}) = \min \sum_{i=1}^{m} c_i \, x_i, \\
\text{s.t:} \\
\quad x_i \le A_i, \quad i = 1, \dots, m, \\
\quad x_i \le S_i, \quad i = 1, \dots, m, \\
\quad A_1 = \sum_{j=1}^{n} v_j y_j, \\
\quad \sum_{i=1}^{m} (1-\gamma_i) x_i = \sum_{j=1}^{n} y_j, \\
\quad \theta_i cap_i \le x_i \le cap_i, \ \ i = 1, \dots, m, \\
\quad f_{21}(\mathbf{y}) = \max \sum_{j=1}^{n} b_j \, y_j, \\
\quad f_{22}(\mathbf{y}) = \min \sum_{j=1}^{n} \widetilde{de}_j \, y_j, \\
\quad f_{23}(\mathbf{y}) = \min \sum_{j=1}^{n} dc_j \, y_j, \\
\quad \text{s.t:} \\
\qquad y_j \ge \widetilde{D}_j, \ \ j = 1, \dots, n, \\
\qquad y_j \le \omega_j \widetilde{D}_j, \ \ j = 1, \dots, n.
\end{array}
\tag{30}
$$

Step 2: Converting the non-deterministic Program (30) into a deterministic form using the NCCP model.

In Program (30), $\widetilde{pe}_i$, $\widetilde{de}_j$ and $\widetilde{D}_j$(for $i = m$) are assumed random and normally distributed parameters. Thus, Program (30) is a non-deterministic problem, which is solved using the Program (27).

The Program (31), which is equivalent to Program (30), with assumption $P = 1$ can be stated as:

$$
\begin{array}{l}
D_1 = \max \left(w_{11}(\lambda_{11} - \delta_{11}^{+}) + w_{12}\lambda_{12} \right), \\
\text{s.t:} \\
\quad E\left(\sum_{i=1}^{m} \widetilde{pe}_i x_i\right) + \Phi^{-1}(1-\alpha_{11}) \sqrt{Var\left(\sum_{j=1}^{n} \widetilde{pe}_i x_i - f_{11*}\right)} + \lambda_{11} - \delta_{11}^{+} = f_{11*}, \\
\quad \sum_{i=1}^{m} c_i \, x_i + \lambda_{12} = f_{12*}, \\
\quad x_i \le A_i, \quad i = 1, \dots, m, \\
\quad x_i \le S_i, \quad i = 1, \dots, m, \\
\quad A_1 = \sum_{j=1}^{n} v_j y_j, \\
\quad \sum_{i=1}^{m} (1-\gamma_i) x_i = \sum_{j=1}^{n} y_j, \\
\quad \theta_i cap_i \le x_i \le cap_i, \ \ i = 1, \dots, m, \\
\quad D_2 = \max \ \left(w_{21}\tau_{21} + w_{22}(\lambda_{22} - \delta_{22}^{+}) + w_{23}\lambda_{23} - \sum_{j=1}^{n} w_j \delta_j^{-} + \sum_{j=1}^{n} w_j \delta_j^{+} \right), \\
\quad \text{s.t:} \\
\qquad \sum_{j=1}^{n} b_j y_j - \tau_{21} = f_{21*}, \\
\qquad E\left(\sum_{i=1}^{m} \widetilde{de}_j y_j\right) + \Phi^{-1}(1-\alpha_{22}) \sqrt{Var\left(\sum_{j=1}^{n} \widetilde{de}_j y_j - f_{22*}\right)} + \lambda_{22} - \delta_{22}^{+} = f_{22*}, \\
\qquad \sum_{j=1}^{n} dc_j \, y_j + \lambda_{23} = f_{23*}, \\
\qquad E(\widetilde{D}_j) + \Phi^{-1}(1-\alpha_j) \sqrt{Var(\widetilde{D}_j - y_j)} + \delta_j^{-} = y_j, \quad j = 1, \dots, n, \\
\qquad \omega_j E(\widetilde{D}_j) - \Phi^{-1}(1-\alpha_j) \sqrt{Var(y_j - \omega_j \widetilde{D}_j)} - \delta_j^{+} = y_j, \quad j = 1, \dots, n.
\end{array}
\tag{31}
$$

Step 3: Solving the deterministic Program (31) by using the bi-level GA

Genetic Algorithm (GA) is regarded as one of the most important population-based random search techniques and uses genetic evolution as a problem-solving model (Holland, 1975). Given that program

(31) is in the form of a single objective bi-level programming model and continuous variables exist at the leader and follower levels, the GA used in this paper is in a bi-level structure. This algorithm combines two continuous GAs in a hierarchical structure. Further, two decisions are simultaneously derived in each implementation of this algorithm:

- deciding on supplying water (at the leader level);
- deciding on allocating water (at the follower level).

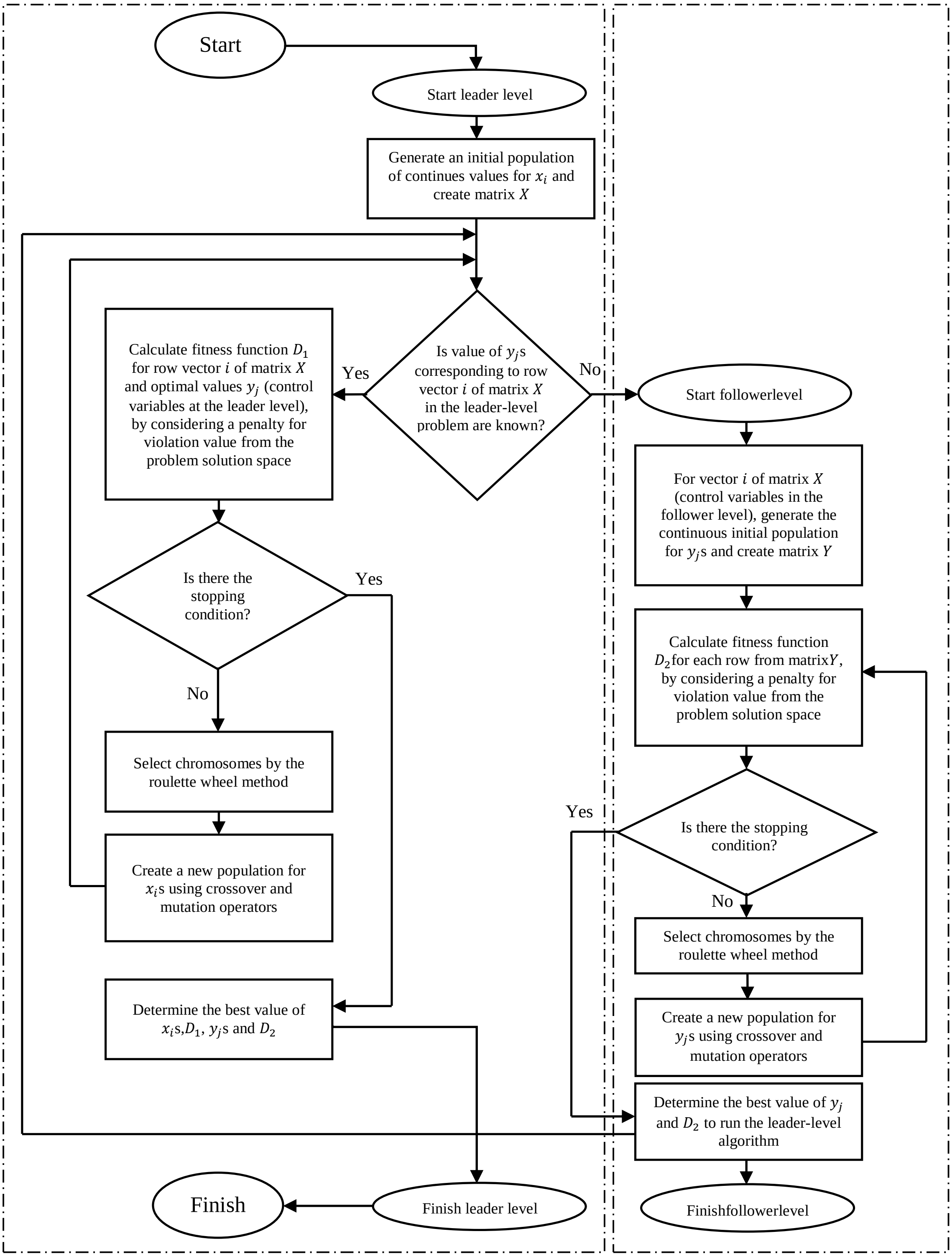


Fig.3. Steps to run the bi-level GA

Figure (3) displayed the process of running bi-level GA for the problem formulated in equation (31). As observed, the follower-level GA loop is completely run for each solution generated at the leader level GA loop and the best solution obtained at the follower-level problem is entered to the leader level GA to evaluate the solution generated at this level. The specifications of bi-level GA shown in figure (3) are as follows:

4-2-1- Solutions representation

For a four-stage sustainable supply chain system that includes n_1 raw material suppliers, n_2 producers, n_3 distributors, and n_4 retailers, figure (4) shows how to display solutions in bi-level GA of the problem formulated in equation (31).

The water supply problem at leader level:

x_1	x_2	x_3	x_4	x_5	x_6	x_7

The water allocation problem at follower level:

y_1	y_2	y_3	y_4	y_5	y_6	y_7

Fig 4. An example of solutions representation of bi-level programming problem in a four-stage sustainable supply chain system

As shown in figure (4), solutions representation for variables x_i and y_j in the WSSA problem is as continuous values based on the interval defined for each variable.

4-2-2- Generation of initial solutions

Based on the interval defined for decision variables x_i and y_j, the initial solutions are generated randomly for unknown variables x_i (at the leader level) and y_j (at the follower level).

4-2-3- Calculation of solutions fitness

The decision (unknown) and control (known) variables of the leader and follower levels in bi-level GA are defined following table (2).

Table 2. Decision and control variables in bi-level GA

Level	Control variable	Decision variable
Leader	y_j	x_i
Follower	x_i	y_j

After each generation of decision variables x_i at the leader level, the algorithm enters the follower level. After fully executing max_iter2 iteration and evaluating solutions generated by the fitness function of the follower problem, the best possible value for the decision variable y_j is determined and then, the algorithm returns to the leader's level loop.

Finally, since the values of variables x_i and y_j are known, the solutions are evaluated through the fitness function of the leader-level problem. In this paper, the fitness functions of the leader and follower level problems in bi-level GA are objective functions of leader and follower levels in the formulated problem of equation (31), respectively. To avoid generating infeasible solutions, a value, as the average penalty of violation from constraints of the leader (follower)-level problem, is deducted from the fitness function of the leader (follower)-level problem. Regarding the evolutionary and gradual approach of the GA algorithm, the process of solving problems at the leader and follower levels is such that the bi-level algorithm leads to feasible solutions for these problems and ultimately, the values of violation and penalty will be zero. However, when solving the problem by algorithm, if all solutions are infeasible, then this run of the algorithm is not considered and can be neglected.

4-2-4- Selection operator

The selection operator of solutions at the leader and follower levels of bi-level GA is based on the roulette wheel method, in which the selection pressure parameter is used for selecting parent chromosomes in the crossover and mutation operators. The concept of selection pressure is the desirability rate that presents a better solution. The greater the value of this parameter, the higher the desirability of solutions with high fitness (Sivanandam and Deepa, 2008). If the value of the pressure parameter is low, then the algorithm convergence will be long and the unnecessary time to reach the final solution is spent. If the value of this parameter is high, then the algorithm will have a premature convergence and the probability that the algorithm is trapped in the local optimal solutions will increase (Sivanandam and Deepa, 2008). If the selection pressure parameter is displayed with $\beta (\beta \geq 0)$, the selection probability of solution i is obtained from equation (32):

$$\Pr(i) = \frac{Fit(i)^{\beta}}{\sum_{i=1}^{nPop} Fit(i)^{\beta}}, \qquad i = 1, \dots, nPop \tag{32}$$

Where:

$$\Pr(i) = \begin{cases} \frac{1}{nPop}, & \text{if } \beta = 0 \\ 1, & \text{if } \beta = \infty \text{ and solution } i \text{ is the best solution} \\ 0, & \text{if } \beta = \infty \text{ and solution } i \text{ is not the best solution} \end{cases} \tag{33}$$

and $nPop$ is the number of solutions and $Fit(i)$ is the fitness value of solution i.

4-2-5- Crossover operator

Because solutions of the WSSA problem are continuous, the type of crossover operator for the GA of leader and follower levels is arithmetic. In each iteration of the leader and follower level GA, the number N_{c1} and N_{c2} solutions from current populations are selected using the roulette wheel method for arithmetic crossover operators, respectively. If P_{c1} and P_{c2} are the probability of arithmetic crossover at the leader and follower level algorithm, then $N_{c1}$and N_{c2} are obtained from equations (34) and (35), respectively.

$$N_{c1} = 2 \times \left\lceil \frac{P_{c1} \times nPop1}{2} \right\rceil, \tag{34}$$

$$N_{c2} = 2 \times \left\lceil \frac{P_{c2} \times nPop2}{2} \right\rceil. \tag{35}$$

For example, if $y_1 = (\mathrm{y}_{11}, \mathrm{y}_{12}, \dots, \mathrm{y}_{1\mathrm{n}})$ and $y_2 = (\mathrm{y}_{21}, \mathrm{y}_{22}, \dots, \mathrm{y}_{2\mathrm{n}})$, are the chromosomes of parents 1 and 2 with n genes at the follower level, respectively and a random value is selected as $\lambda_j \in [0,1]$ for each gene, then the child's chromosomes 1 and 2 are generated following equations (36) and (37) (Köksoy and Yalcinoz, 2008).

$$\hat{y}_{1j} = \lambda_j \mathrm{y}_{1j} + (1 - \lambda_j) \mathrm{y}_{2j}, \qquad j = 1, \dots, n \tag{36}$$

$$\hat{y}_{2j} = \lambda_j \mathrm{y}_{2j} + (1 - \lambda_j) \mathrm{y}_{1j}, \qquad j = 1, \dots, n \tag{37}$$

Obviously, by a random selection of $\lambda_j \in [0,1]$, each gene of the child's chromosomes will have a value between the gene values of their parent chromosomes. In this paper, to increase the diversification of new solutions, the value λ_j is randomly chosen from interval $[-\gamma_j, 1 + \gamma_j] (\gamma_j \geq 0)$. By choosing a larger γ_j, it is possible to generate values less or more than the parent's chromosomes, and the diversification of solutions is increased and the intensification decreases.

4-2-6- Mutation operator

In each iteration of the leader and follower level GA, the number of N_{m1} and N_{m2} solutions (parent chromosomes) of the current populations are selected using the roulette wheel method to perform a mutation operator. If the mutation probability at the leader and follower level algorithm is displayed by $P_{m1}$and P_{m2}, then N_{m1} and N_{m2} are obtained from equations (38) and (39).

$$N_{m1} = \lceil P_{m1} \times nPop1 \rceil, \quad (38)$$
$$N_{m2} = \lceil P_{m2} \times nPop2 \rceil. \quad (39)$$

For each of the parent's chromosome$i$, the number of genes affected by mutation operator at the leader and follower levels is calculated by equations (40) and (41).

$$n_{m1(\mathrm{i})} = \pi_{m1(\mathrm{i})} \times n, \quad i = 1, \dots, N_{m1} \quad (40)$$
$$n_{m2(\mathrm{i})} = \pi_{m2(\mathrm{i})} \times n, \quad i = 1, \dots, N_{m2} \quad (41)$$

Where $\pi_{m1(\mathrm{i})}$ and $\pi_{m2(\mathrm{i})}(\pi_{m1(\mathrm{i})}, \pi_{m2(\mathrm{i})} \in [0,1])$ represent the impact rate of mutation for parent chromosome i at the leader and follower levels, respectively. The value of each gene affected by the mutation operator in parent chromosome changes at the leader and follower levels during the mutation process and takes a new random variable within the allowed range of variations x_i and y_j.

4-2-7- Generation of a new population and stop condition

The new population of solutions in both leader and follower levels of bi-level GA is based on the elitism approach (merging the current and generated solutions by crossover and mutation operators and selecting $nPop$ better solution). Furthermore, the stop condition of GA at the leader and follower levels is achieved by max_iter1 and max_iter2 number of iterations.

4-2-8- Tuning parameters

To tune parameters of bi-level GA, the combinational designs of Taguchi $L_{36}(2^1 \times 3^5)$ in MINITAB17 software were used for GA of leader and follower levels. For each of 36 experiments in each design, we run four replications of small problems, 3 replications of medium problems, and 2 replications of large problems by using bi-level GA in MATLAB R2015b software environment under Windows 10 with specifications of Intel (R) Core i5-7500 CPU, 3.40 GHz, and RAM 8.00 GB. Table (3) reports the considered levels for the algorithm parameters for small, medium, and large problems so that the values of parameters P_m and P_c are determined based on the steady state genetic algorithm (SSGA).

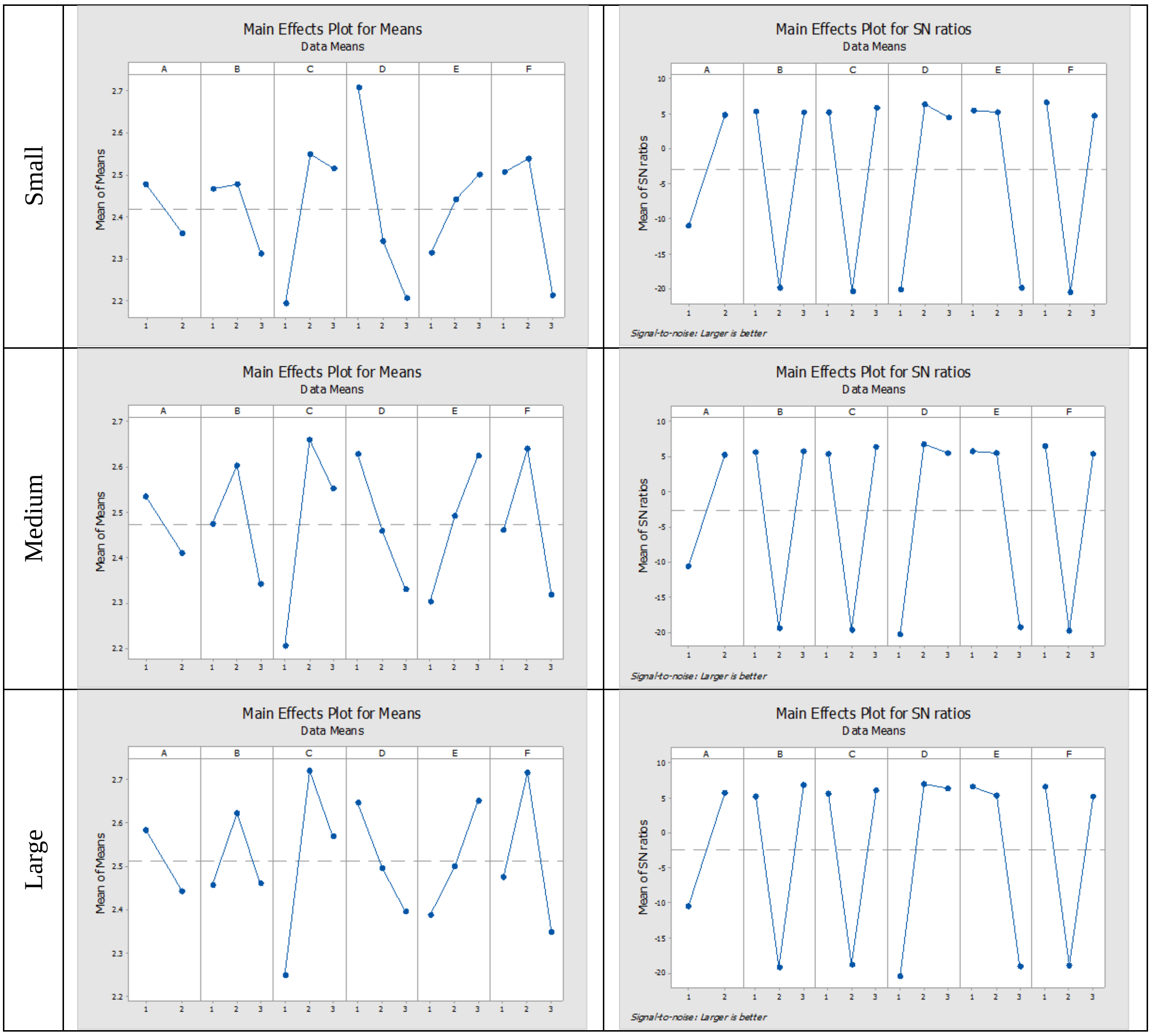
Table 3. Levels of parameters of bi-level GA under study

Type of problem	Level of algorithm	Level of experiment	Parameters					
			$A = (nPop, max\_iter)$	$B = P_c$	$C = P_m$	$D = \beta$	$E = \pi_m$	$F = \gamma$
Small	Leader	1	(30,100)	0.6	0.45	1	0.15	0.05
		2	(40,75)	0.7	0.55	1.5	0.2	0.1
		3	-	0.8	0.6	2	0.25	0.2
	Follower	1	(40,75)	0.5	0.45	1	0.15	0.05
		2	(50,60)	0.6	0.55	1.5	0.2	0.1
		3	-	0.7	0.6	2	0.25	0.2
Medium	Leader	1	(30,200)	0.6	0.45	1	0.15	0.05
		2	(40,150)	0.7	0.55	1.5	0.2	0.1
		3	-	0.8	0.6	2	0.25	0.2
	Follower	1	(50,120)	0.5	0.45	1	0.15	0.05
		2	(60,100)	0.6	0.55	1.5	0.2	0.1
		3	-	0.7	0.6	2	0.25	0.2
Large	Leader	1	(40,250)	0.6	0.45	1	0.15	0.05
		2	(50,200)	0.7	0.55	1.5	0.2	0.1
		3	-	0.8	0.6	2	0.25	0.2
	Follower	1	(50,200)	0.5	0.45	1	0.15	0.05
		2	(100,100)	0.6	0.55	1.5	0.2	0.1
		3	-	0.7	0.6	2	0.25	0.2

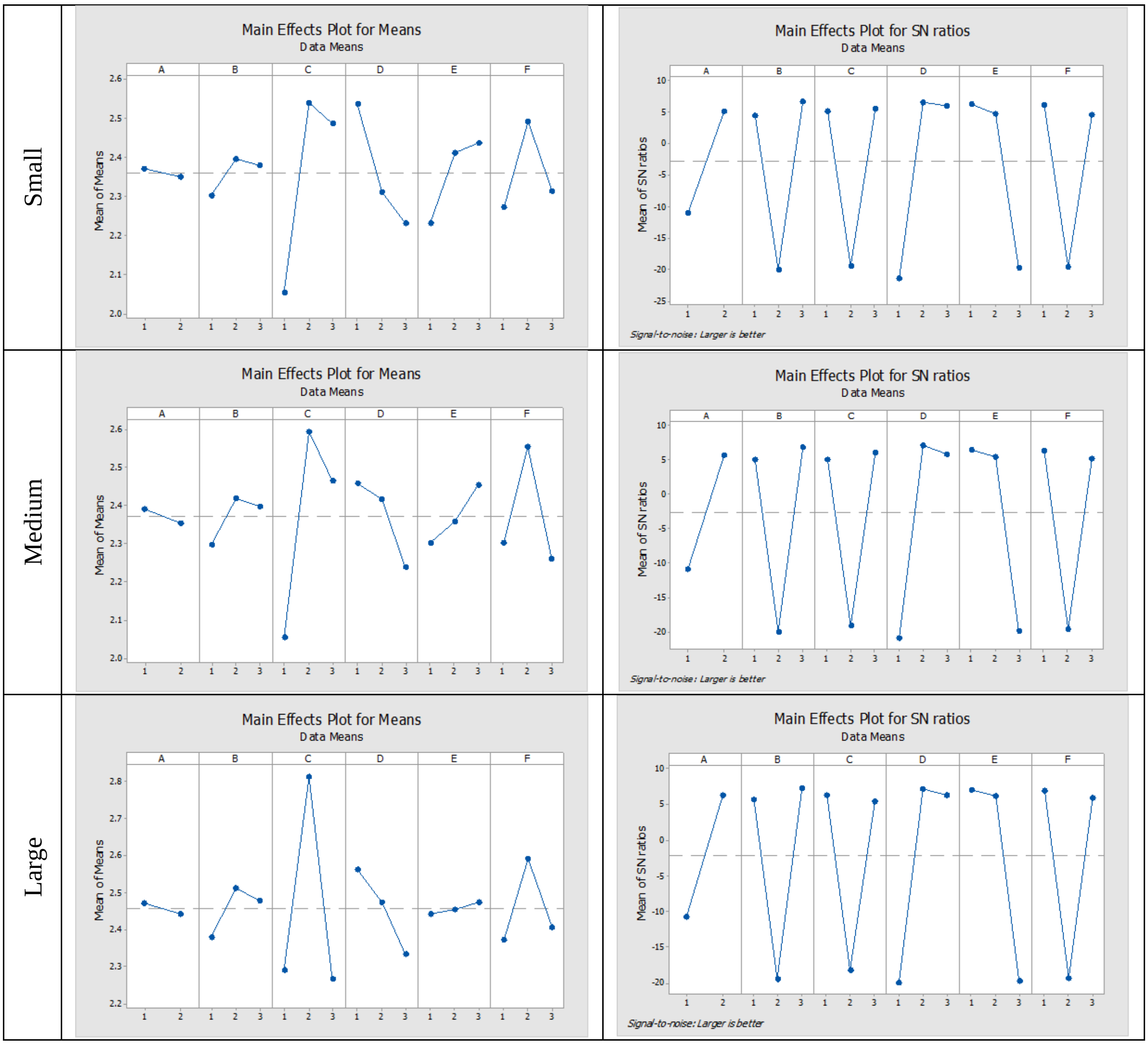
The results of experiments implemented after normalization were evaluated by the related percentage deviation (RPD) based on two criteria of RPD and S/N ratios. Since the follower-level GA depends on the value of decision variables in the leader-level GA, parameters of the leader-level algorithm are tuned in each experiment after tuning parameters of the follower-level algorithm based on parameters random values of the leader-level algorithm. Table (4) and figure (5) present the results of tuning the parameters of bi-level GA.

Table 4. Value of tuned parameters in bi-level GA

Level of algorithm	**Type of problem**	**Parameters**					
		$(nPop, max\_iter)$	P_c	P_m	β	π_m	γ
Leader	Small	(30,100)	0.7	0.55	1	0.25	0.1
	Medium	(30,200)	0.7	0.55	1	0.25	0.1
	Large	(40,250)	0.7	0.55	1	0.25	0.1
Follower	Small	(40,75)	0.6	0.5	1	0.25	0.1
	Medium	(50,120)	0.6	0.5	1	0.25	0.1
	Large	(50,200)	0.6	0.5	1	0.25	0.1



(a)



(b)

Fig. 5. Variations of mean of RPD and S/N ratio for sample problems of small, medium and large in GA of leader (a) and follower (b) levels

4-2-9- Performance evaluation of bi-level GA

In this paper, the ESM was used to evaluate the performance of the bi-level genetic algorithm. Accordingly, several sample problems with small dimensions and random parameters were defined and solved independently by using the ESM and the bi-level genetic algorithm. Finally, the results were analyzed and evaluated. In the ESM, two extreme optimistic and pessimistic solutions are considered for the problem formulated in equation (31) (Alves et al., 2019): (1) Optimistic solution: This solution aims to achieve an optimal solution at the leader level based on the best solution suggested by the follower, (2) Pessimistic solution: This solution seeks to achieve an optimal solution at the leader level based on the worst solution suggested by the follower.

In this research, several sample problems based on the information given in table (5) are considered to validate the results of the bi-level genetic algorithm. Table (5) presents the value of the parameters of the problem formulated in equation (31) in a uniform distribution form for the sample problems, each of which is solved 10 times and finally, the average optimal value of the problem objectives is considered and the results are compared and evaluated. Table (6) reports the average results of 10 times the solution of each of the sample problems by the bi-level genetic algorithm and the ESM based on the objectives of the problem formulated in equation (31).

Table 5. Value of parameters in the experimental sample problems

Parameter	Scale of problem				
	$m = 2, n = 2$ (P1)	$m = 2, n = 3$ (P2)	$m = 3, n = 2$ (P3)	$m = 3, n = 3$ (P4)	$m = 4, n = 4$ (P5)
c_i	$[2 \times 10^3, 3 \times 10^3]$	$[3 \times 10^3, 4 \times 10^3]$	$[4 \times 10^3, 5 \times 10^3]$	$[5 \times 10^3, 6 \times 10^3]$	$[6 \times 10^3, 7 \times 10^3]$
A_i	$[2, 5]$	$[5,7]$	$[7,9]$	$[9,12]$	$[12,15]$
S_i	$[10, 20]$	$[20,30]$	$[30,40]$	$[40,50]$	$[50,60]$
γ_i	$[5 \times 10^{-4}, 10^{-3}]$	$[10^{-3}, 2 \times 10^{-3}]$	$[2 \times 10^{-3}, 3 \times 10^{-3}]$	$[4 \times 10^{-3}, 6 \times 10^{-3}]$	$[7 \times 10^{-3}, 9 \times 10^{-3}]$
θ_i	$[0.05, 0.06]$	$[0.07, 0.08]$	$[0.09, 0.12]$	$[0.13,0.15]$	$[0.15,0.17]$
cap_i	$[10, 13]$	$[13,20]$	$[20,30]$	$[30,40]$	$[40,50]$
$\widetilde{pe}_i$	$[N(3,0.5), N(5,0.7)]$	$[N(6,0.8), N(10,0.9)]$	$[N(11,1.0), N(15,1.5)]$	$[N(16,1.5), N(18,1.7)]$	$[N(18,1.7), N(20,2.0)]$
b_j	$[10^3, 3 \times 10^3]$	$[3 \times 10^3, 5 \times 10^3]$	$[5 \times 10^3, 8 \times 10^3]$	$[8 \times 10^3, 10 \times 10^3]$	$[10 \times 10^3, 12 \times 10^3]$
$\widetilde{de}_j$	$[N(0.2,0.5), N(0.4,0.7)]$	$[N(0.5,0.8), N(0.7,0.9)]$	$[N(0.8,1.0), N(1.5,1.0)]$	$[N(1.1,1.5), N(1.3,1.7)]$	$[N(1.3,1.7), N(1.5,2.0)]$
dc_j	$[10^2, 2 \times 10^2]$	$[2 \times 10^2, 4 \times 10^2]$	$[4 \times 10^2, 6 \times 10^2]$	$[6 \times 10^2, 8 \times 10^2]$	$[8 \times 10^2, 10 \times 10^2]$
$\widetilde{D}_j$	$[N(10,0.5), N(20,0.7)]$	$[N(20,0.8), N(30,0.9)]$	$[N(30,1.0), N(40,1.5)]$	$[N(40,1.5), N(50,1.7)]$	$[N(50,1.7), N(60,2.0)]$
ω_j	$[0.5,0.6]$	$[0.6,0.8]$	$[0.8,0.9]$	$[0.9,1.0]$	$[1.0,1.1]$
v_j	$[0.001,0.007]$	$[0.008,0.014]$	$[0.015,0.022]$	$[0.023,0.03]$	$[0.03,0.035]$

Table 6. Average results of solving sample problems

Problem	Situation	ESM					Bi-level GA				
		f_{11}	f_{12}	f_{21}	f_{22}	f_{23}	f_{11}	f_{12}	f_{21}	f_{22}	f_{23}
P1	**Optimistic**	5.2	3406.9	50192.4	0.7	224.9	6.3	3497.3	49889.3	1.2	227.8
	Pessimistic	84.9	54975.2	3059.4	8.1	3709.8					
P2	**Optimistic**	7.8	5541.1	92134.2	2.1	346.2	8.3	5587.4	91789.4	2.4	355.1
	Pessimistic	122.3	80138.6	5148.8	10.2	3846.5					
P3	**Optimistic**	10.7	7977.1	134450.3	3.9	480.8	11.2	8149.3	133894.8	4.3	487.4
	Pessimistic	165.2	104510.4	6959.2	13.6	3988.7					
P4	**Optimistic**	13.8	11171.9	185796.8	5.2	754.8	14.5	11257.2	185045.7	5.9	765.2
	Pessimistic	203.9	135007.8	8997.2	16.6	4137.9					
P5	**Optimistic**	17.2	13486.6	224942.5	8.1	684.2	17.8	13767.1	224167.1	9.2	692.5
	Pessimistic	249.6	169133.5	10964.3	19.5	4516.7					

In table (6), the results obtained by the genetic algorithm reveal a slight difference with those of the optimistic approach, regarding the range of partially optimistic and pessimistic solutions. The reason for this difference is the existence of coordination and interaction mechanisms between the leader and follower levels and the achievement of an optimal and common solution, by taking into account the limitations and resources of both levels. Further, the proximity of the solutions obtained in the optimistic approach of the ESM and the bi-level genetic algorithm and the definition of a coordination mechanism between decision-making levels for solving the bi-level programming problem justify the slight difference and confirm the performance of the bi-level genetic algorithm.

Based on the results, the performance of the bi-level genetic algorithm has the required validity in terms of proximity to optimistic solutions and avoidance of pessimistic solutions simultaneously and includes a coordination-based interactive approach between the leader and follower levels. This issue is considered as one of the capabilities of the bi-level genetic algorithm in solving bi-level programming problems and simultaneously follows the process of optimization and problem-solving at both leader and follower levels.

5- Case study

The geographical location of Iran in the arid region, the occurrence of numerous droughts, limited water resources, lack of observation of consumption patterns and problems like these have made Iran one of the countries with water problem. Water industry in the country has faced challenges; however, the methodology of this research has been proposed in line with fields of the study as well as to address them. Table (7) presents some of the most important challenges in Iran's water industry, along with suggested solutions.

Table 7. The most important challenges in the Iranian water industry

Row	Challenge	Proposed approach	Field of the study
1	Improper withdrawal of groundwater resources that leads to irreversible loss of groundwater resources	- Optimal management of water supply (production) from the country's water resources, considering the capacity of withdrawal from any source and the costs of supply and withdrawal from resources	- Simultaneous management of water supply and allocation - Mathematical modeling to maintain the balance and simultaneous management of water resources and consumption of the country
2	Unhealthy condition of groundwater resources and over-withdrawal of these resources		
3	Improper consumption of water, especially in the agricultural and drinking sectors	- Optimal management of water allocation to consumer units, considering the consumption demand of each consumer, water distribution and transportation costs, and revenue from water sales	- Simultaneous management of water supply and allocation - Mathematical modeling to maintain the balance and simultaneous management of water resources and consumption of the country
4	Entrance of various pollutants into water resources which make part of water resources unusable due to loss of quality	- Integration of water resources and consumption management, and simultaneous attention to sustainability (environmental, social, economic, and technical) indicators, with the purpose of sustainable development of water supply and distribution system in the country	- Planning based on sustainability indicators
5	Lack of establishment of integrated management for water and other environmental resources		
6	Environmental problems of water bodies and pollution of water resources		
7	Lack of appropriate and necessary structure and mechanisms for simultaneous management of supply and demand and lack of necessary social connections	- Developing a specific action plan for simultaneous management of water supply and demand to prevent shortages and meet the demand of consumer units, reducing costs, and increasing revenue - Simultaneous attention to water supply management from resources and allocation of water among consumers	- Simultaneous management of water supply and allocation - Mathematical modeling to maintain the balance and simultaneous management of water resources and consumption of the country
8	Lack of balance in the resources and expenditures of water companies and lack of financial resources to supply drinking water to cities and villages of the country		
9	Climate change, droughts, and per capita decline of renewable resources	- Planning and developing preventive measures within the framework of a specific operational plan to estimate indicators such as rainfall, growth rate of catchments, and demand for water-consuming units	- Planning under uncertainty conditions (such as stochastic programming)
10	Local water resources management, regardless of the requirements of integrated water resources management and sustainable development	- Holism in the whole water cycle and the principles of sustainable development - Realizing integrated management of water resources with mutual coordination between sustainability (environmental, social, economic, and technical) indicators and a water area - Decentralizing the country's water management structure in implementation and operation - Increasing the role of public participation and local organizations and holism in the water cycle	- Planning based on sustainability indicators - Decision-making approaches in supply and distribution systems - Coordination between the responsible units of water supply and allocation management, aiming to decentralize the management structure and increase stakeholder participation - Utilizing multi-objective bi-level programming models

5-1- Data

In this research, the water supply and distribution system include seven water supply sources in Tehran and seven types of consumers (domestic, educational and religious places, free and construction, industrial, public (governmental), commercial, and others). Table (8) provides the historical data obtained, as well as the status of the water supply and distribution system in Tehran city at the end of May 2020. Concerning the random parameters $\widetilde{pe}_i$, $\widetilde{de}_j$, and $\widetilde{D}_j$ (for $i, j = 1, \dots, 7$), a set of past historical data related to each parameter was first collected and then, the normality of the data was tested in Minitab 17.0 software. Based on the results, the hypothesis of normality of historical data related to each of the random parameters could not be confirmed. Consequently, the data collected by Johnson Transformation in Minitab 17.0 software were converted to normal data, and the resulted conversion function was used to calculate the mean and variance values of each random parameter. Further, the minimum amount of water in each water source was considered equal to 10% of the water capacity of each source.

Table 8. The data under study

Supplier (i)	x_i	γ_i	c_i	A_i	S_i	Cap_i	$\widetilde{Pe}_i$
Water wastes	x_1	---	12911	---	---	---	$N(9.005,1.146)$
Amirkabir	x_2	0.003	7373	9.3	17.1	12.6	$N(9.538,0.987)$
Mamlu	x_3	0.002	7866	10.7	20.8	15.3	$N(9.5,1.173)$
Latian	x_4	0.004	6875	3.2	7.9	3.8	$N(9.409,1.049)$
Lar	x_5	0.087	8461	12.8	80.0	14.8	$N(9.558,0.987)$
Taleghan	x_6	0.001	7957	8.3	35.0	24.1	$N(9.424,0.96)$
Underground wells	x_7	0.0003	13800	38.1	190.5	38.1	$N(287.147,1.044)$
Consumer (j)	y_j	v_j	ω_j	b_j	dc_j	$\widetilde{D}_j$	$\widetilde{de}_j$
Domestic	y_1	0.089	0.98	5500	623	$N(50.4,0.969)$	$N(0.795,1.215)$
Educational	y_2	0.003	1.00	3880	478	$N(1.97,0.982)$	$N(0.644,0.943)$
Free	y_3	0.0003	0.98	12800	1541	$N(0.11,0.905)$	$N(0.812,0.996)$
Industrial	y_4	0.002	0.98	9350	1365	$N(0.98,1.032)$	$N(0.679,1.034)$
Public	y_5	0.009	0.97	8760	1326	$N(5.00,1.033)$	$N(0.681,1.088)$
Commercial	y_6	0.006	1.03	10972	1246	$N(2.45,1.106)$	$N(0.778,1.077)$
Others	y_7	0.001	0.98	3440	319	$N(0.47,0.903)$	$N(0.771,0.978)$

5-2- Solving the case study problem

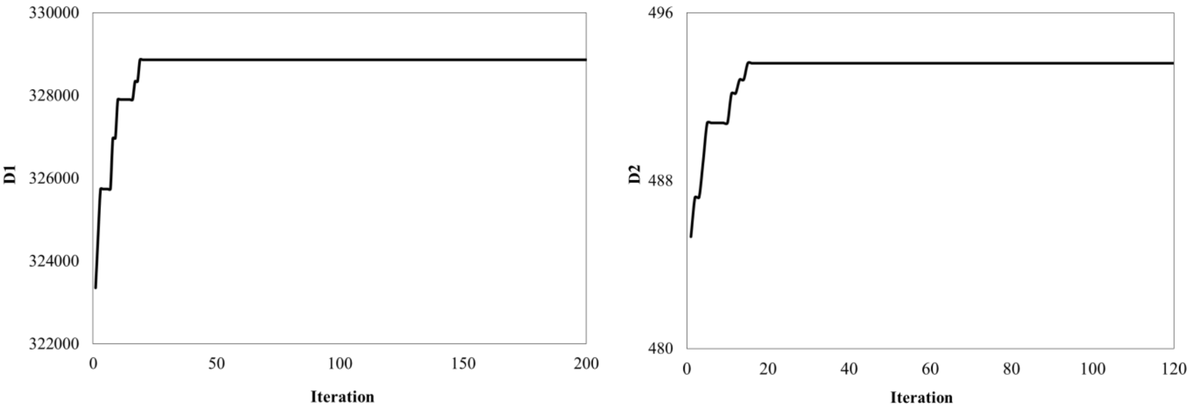
Regarding the dimensions of the studied problem, the problem formulated in equation (31) is a medium problem. Therefore, the value of parameters of bi-level GA is in accordance with the values tuned for medium problems in table (4). To solve this problem, the bi-level GA is run five times. Table (9) presents the best obtained solution compared with the current situation of this supply chain system after comparing the results by normalization criterion of D_1 and D_2 in equation (42).

$$L = \min\left(\epsilon_1 \times \left(\frac{{D_1}^{+} - D_1}{{D_1}^{+} - {D_1}^{-}}\right) + \epsilon_2 \times \left(\frac{{D_2}^{+} - D_2}{{D_2}^{+} - {D_2}^{-}}\right)\right). \tag{42}$$

In equation (42), ${D_1}^{+}$ and ${D_1}^{-}$ indicate the highest and lowest values obtained for D_1, and ${D_2}^{+}$and ${D_2}^{-}$ represent the highest and lowest D_2 during five repetitions. Additionally, $\epsilon_1$and ϵ_2 are the preference weights of D_1 and D_2 objectives, respectively. In this paper, the value of each parameter is equal to 0.5. Figure (6) shows the convergence diagrams of D_1 and D_2 related to the best solution for each iteration.

Table 9. Current and optimal situations of the system

Water supply problem			Water allocation problem		
Parameter	Optimal situation (Million m^3)	Current situation (Million m^3)	Parameter	Optimal situation (Million m^3)	Current situation (Million m^3)
x_1	2.23	1.39	y_1	57.79	65.40
x_2	12.09	13.49	y_2	2.63	2.18
x_3	10.76	8.58	y_3	0.15	1.27
x_4	3.65	2.42	y_4	1.17	3.14
x_5	10.41	9.74	y_5	6.74	8.37
x_6	23.42	18.94	y_6	3.25	5.26
x_7	10.85	20.35	y_7	0.68	1.07
Sum	73.42	74.91	Sum	72.41	86.69
$f_{11}(\mathbf{x})$	3715.61	6363.68	$f_{21}(\mathbf{y})$	437.95	548.49
$f_{12}(\mathbf{x})$	651.93	715.43	$f_{22}(\mathbf{y})$	56.20	67.18
---	---	---	$f_{23}(\mathbf{y})$	52.29	66.02



(a) (b)

Fig. 6. Convergence diagram of (a) D_1-iteration, and (b) D_2-iteration

5-3- Analyzing the status of water resources supply

According to table (9), the total volume of water resources supplied in the current conditions shows a 2% growth compared to the optimal situation. However, the volume of water utilized from wasted water resources (Mamlu, Latian, Lar, and Taleghan dams) shows a declining trend compared to the optimal situation, although the volume of water supplied in the current conditions in Amirkabir dam and underground wells is greater than that of the optimal condition. However, the current situation presents worse results than that of the optimal situation in terms of the achievement level of the objectives suggested in this research, such that the current situation shows a growth of 71% and 9% in the objectives of pollution rate and water supply costs compared to the optimal situation, respectively. The results presented in table (9) indicates that the lack of attention to cost units and pollution per cubic meter of water resources leads to an increase in pollution levels and the cost of water supply, although the current situation shows a lower level in the operation of five water sources compared to the optimal situation. To implement the results presented in the optimal situation, it is suggested to determine and formulate executive mechanisms for the exploitation of water resources, considering the system limitations and capacities, as well as the factors affecting the objectives.

5-4- Analyzing the status of water resources allocation

Based on table (9), the total volume of water distributed in the current situation reveals a 19% growth compared to the optimal situation. Moreover, the volume of water resources allocated to domestic, free, industrial, public, commercial, and other uses shows an increasing trend compared to the optimal situation and a decreasing trend in educational consumption. The results indicate that the highest volume of water demand in the current and optimal situations is related to household uses while the lowest volume of water demand in the current situation is for other uses.

Evaluating the results from the perspective of achieving the desired goals confirms that all three objectives of the level of revenue from water sales, pollution level, and distribution costs indicate an increasing trend compared to the optimal situation, in addition to increasing the volume of water resources allocated to water consumption in the current situation. Regarding the planning and operational process, it is suggested to specify different and sometimes conflicting goals on water supply and allocation management dynamically and variably, and then, prioritize them following the strategies formulated in the relevant and decision-making organizations. Ultimately, the results should be analyzed and evaluated based on priorities and avoided focusing on a one-dimensional approach to the problem of water supply and allocation management.

5-5- Analyzing the effect of changes of importance weight and uncertainty level on the results of the problem

Table (10) presents a set of vectors of the importance weights for evaluating the effect of changes in the importance weight and the uncertainty level of on the results and objectives of the problem.

Table 10. Set of importance weight vectors

Importance weight	w_{11}	w_{12}	w_{21}	w_{22}	w_{23}	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}
W_1	0.1	0.9	0.1	0.1	0.8	0.3	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078
W_2	0.2	0.8	0.2	0.2	0.6	0.078	0.3	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078
W_3	0.3	0.7	0.3	0.3	0.4	0.078	0.078	0.3	0.078	0.078	0.078	0.078	0.078	0.078	0.078
W_4	0.4	0.6	0.4	0.4	0.2	0.078	0.078	0.078	0.3	0.078	0.078	0.078	0.078	0.078	0.078
W_5	0.5	0.5	0.5	0.25	0.25	0.078	0.078	0.078	0.078	0.3	0.078	0.078	0.078	0.078	0.078
W_6	0.5	0.5	0.5	0.4	0.1	0.078	0.078	0.078	0.078	0.078	0.3	0.078	0.078	0.078	0.078
W_7	0.6	0.4	0.6	0.3	0.2	0.078	0.078	0.078	0.078	0.078	0.078	0.3	0.078	0.078	0.078
W_8	0.7	0.3	0.7	0.2	0.3	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.3	0.078	0.078
W_9	0.8	0.2	0.8	0.1	0.4	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.3	0.078
W_{10}	0.9	0.1	0.9	0.05	0.5	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.3

Tables (11) and (12) present the changes in the values of the objective functions of the leader and follower level problems, respectively, along with the changes in the importance weight of the objectives and the uncertainty level.

Table 11. The values of the objectives of the leader-level problem with changes in the importance weights and the uncertainty level

Uncertainty level	Objective	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}
$\alpha = 0.01$	f_{11}	3928.0	3847.5	3773.7	3682.7	3607.2	3565.7	3469.6	3364.5	3273.4	3206.8
	f_{12}	677.5	670.3	652.2	642.9	632.5	628.6	609.9	599.6	590.7	576.4
$\alpha = 0.025$	f_{11}	3988.5	3902.9	3810.9	3724.5	3659.3	3617.5	3532.5	3438.7	3334.5	3248.2
	f_{12}	690.2	678.7	662.0	653.2	642.3	636.1	623.3	609.8	600.8	584.6
$\alpha = 0.05$	f_{11}	4030.2	3967.5	3854.2	3794.3	3693.9	3638.6	3552.7	3467.1	3366.6	3304.6
	f_{12}	699.3	685.1	669.3	662.3	650.3	643.9	631.7	616.3	610.0	592.1
$\alpha = 0.1$	f_{11}	4068.3	4009.6	3923.5	3874.0	3782.4	3699.3	3628.1	3486.3	3424.9	3371.9
	f_{12}	707.0	693.7	679.7	672.7	657.8	655.1	639.8	624.0	619.4	599.4

Table 12. The values of the objectives of the follower-level problem with changes in the importance weights and the uncertainty level

Uncertainty level	Objective	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}
$\alpha = 0.01$	f_{21}	350.3	369.9	377.8	409.7	426.8	443.7	478.2	495.6	525.7	555.1
	f_{22}	45.7	46.5	48.6	49.8	51.0	51.9	53.6	56.0	57.8	58.8
	f_{23}	18.8	22.6	32.6	40.2	43.8	49.4	52.5	62.1	64.1	73.5
$\alpha = 0.025$	f_{21}	319.3	340.7	359.6	386.3	410.4	424.6	455.7	478.1	497.6	527.7
	f_{22}	48.9	49.7	51.8	52.7	54.1	55.4	56.8	58.8	60.6	62.2
	f_{23}	21.2	25.8	34.0	44.5	47.2	52.1	58.1	65.2	68.9	79.8
$\alpha = 0.05$	f_{21}	296.1	314.5	340.6	366.2	391.3	400.3	425.6	450.0	471.4	507.2
	f_{22}	52.3	53.0	55.9	56.9	57.8	59.1	60.9	63.0	64.2	66.3
	f_{23}	24.3	30.0	37.4	46.9	49.1	55.8	61.7	66.9	73.5	86.1
$\alpha = 0.1$	f_{21}	274.7	284.4	320.5	347.0	371.8	379.2	399.2	421.2	452.0	482.9
	f_{22}	56.6	57.6	60.7	61.0	62.7	64.0	66.1	68.3	69.4	70.6
	f_{23}	29.4	37.2	41.3	49.6	53.0	63.9	67.8	70.3	80.6	92.5

According to table (11), the costs of water supply increases (decreases) at each level of uncertainty by increasing (decreasing) the pollution level of water supplied from water sources. Since the functions in the leader level problem have a linear relationship with the variable x_i (for $i = 1, \ldots, 7$), increasing (decreasing) the level of water withdrawal from water sources increases (decreases) the level of pollution and therefore, increases (decreases) the total cost of providing water resources.

On the other hand, for each importance weight vector, an increase (decrease) in the uncertainty level puts the objectives of the leader-level problem in a deterioration (improvement) state. In other words, an increase (decrease) in the uncertainty level of the problem puts the value of the objectives of the leader level problem in a worse (better) state than before. This issue can be interpreted due to the uncertainty conditions prevailing in the problem area so that the amounts of pollution level and the cost of supply increase to cover the risks and dangers arising from planning under uncertainty conditions.

According to table (12), increasing (decreasing) the level of revenue from the sale of water supplied from water sources at each uncertainty level increases (decreases) the amount of water distribution costs and the pollution level simultaneously. Regarding the linear relationship between the functions in the leader level problem and the variable y_j (for $j = 1, \ldots, 7$), an increase (decrease) in the level of water consumption demand increases (decreases) the level of sales revenue and the pollution level, resulting in increasing (decreasing) the total cost of water distribution. Concerning the efficient and effective management of water supply and allocation, it is suggested to first set the desired goals and then consider a set of priorities of individuals and decision-making units in the planning process. Next, various solutions should be evaluated and analyzed following each of the priorities. It is worth noting that paying attention to participatory culture and consensus on achieving a common solution, examining the problem from different angles, and avoiding a one-dimensional approach are among the advantages of implementing this proposal. Table (11) reports different priorities based on a set of importance weights of objectives.

Similar to the results of the leader level problem, increasing (decreasing) the uncertainty level worsens (improves) the objectives of the follower level problem for each importance weight vector. In other words, an increase (decrease) in the uncertainty level of the problem worsens (improves) the amount of objectives of the follower-level problem compared to the previous state. This finding can be interpreted by the uncertainty conditions prevailing in the problem area so that the level of pollution and distribution costs are increased and the level of revenue from water sales is reduced to cover the risks and dangers of planning under uncertainty conditions.

6- Conclusion

Considering the importance of supply chain coordination, a multi-objective bi-level programming model was proposed in this research to solve the WSSA problem. To this aim, the water supply problem and water allocation problem were formulated based on sustainability indicators in a multi-objective bi-level programming model. In the proposed model, some of the parameters were considered as a non-deterministic and random parameter, so that a combined model of CCP and NCP models was proposed to solve the problem under uncertainty conditions.

Since the proposed model was formulated in the form of multi-objective bi-level programming and such problems are NP-hard, a bi-level GA was used for achieving solutions in this research. The proposed model was implemented for several sample problems using a bi-level GA and the obtained solutions were evaluated with results of the complete count method. Then, the proposed model was illustrated to solve the case study problem and the obtained results were analyzed under various scenarios. The most important findings of this research are as follows:

- As mentioned, considering the participatory culture and consensus on achieving a common solution, examining the issue from different perspectives, and focusing on a multi-dimensional approach in decision-making are among efficient approaches in line with the issue of coordination in the field of water supply and allocation management. This issue can be considered by formulating a set of priorities of individuals and relevant organizations in the decision-making process, aiming to evaluate and analyze different solutions in accordance with each of the priorities.
- Regarding the studied problem, decreasing (increasing) the volume of water extracted from water sources provides favorable (unfavorable) conditions for the intended purposes in the field of water supply. However, this issue reduces (increases) the volume of water allocation among consumption areas and affects the intended objectives in the field of water allocation. Therefore, coordination between supply and distribution sectors should be established to maximize the benefits and objectives of the whole system in the problem-solving process.
- In the case study, each level seeks to achieve its maximum benefits, and their goals conflict with each other. Thus, the goal is to create a logical balance between the goals defined at the leader and follower levels through interaction and coordination between the two levels.
- Since the pollution caused by water supply and distribution is unavoidable, adopting a proper strategy is of great importance for managing and controlling the effects of greenhouse gases on the environment. Although an increase in the volume of water supply and allocation reduces the shortage of the system and increases the supply level of consumer demand and the system revenue level, it increases the level of pollution and costs.
- It should be noted that decreasing the volume of supplied water resources can reduce the level of pollution, water supply, and distribution costs, although it declines the level of revenue from the sale of water. Therefore, considering multiple and conflicting goals in the decision-making process allows assessing the sensitivity of the issue from different dimensions.

Future research can focus on the development of the model proposed in this paper in modeling and solving other fields and applied problems.

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