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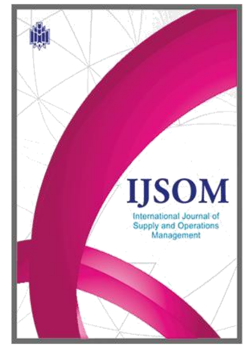

Designing a Sustainable Model for Providing Health Services Based on the Internet of Things and Meta-Heuristic Algorithms

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Abstract

In this article, a health service delivery model based on the Internet of Things (IoT) under uncertainty is presented. The considered model includes a set of patients, doctors, vehicles, and services that should be provided in the shortest time and cost. The most important decisions of the network include the allocation of specialist doctors to patients, the routing of vehicles, and doctors to provide health services. The dataset of the problem has been provided to the hospital and centers using IoT tools and an integration framework has been designed for this problem. The results of solving the numerical examples show that to reduce the service delivery time and the distance traveled by vehicles, the design costs of the model should be increased. Also, the increase in the rate of uncertainty during service delivery leads to an increase in total costs in the health system. In this article, Non-Dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), and Multi-objective imperialist Competitive algorithm (MOICA) were proposed to solve the model, and the results showed that the proposed methods are more efficient than the exact methods. These algorithms have achieved close to optimal results in the shortest possible time. Also, the calculation results in large numerical examples show the high efficiency of the MOICA.

Keywords: Healthcare System; Uncertainty; IoT; Meta-Heuristic Algorithm; Vehicle Routing.

1- Introduction

In recent years, the healthcare industry has become one of the largest branches of the economy of developed countries, and the increase in the population of elderly people worldwide has created many challenges in the policy and development of healthcare services (Fathollahi-Fard et al, 2021). Due to the aging of the population and the preference of these people to stay at home, as well as the spread of the Coronavirus worldwide, the demand for home health care system has increased (Jahangiri et al., 2021; Jahangiri et al., 2023). On the other hand, receiving health care system services at home instead of the hospital reduces the cost of the entire health system and in many cases is more convenient and effective than the care provided in the hospital and solves the lack of resources caused by the limited

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number of hospital beds. (Eguchi, 2019). According to the report presented by the United Nations, about 12.3% of the world's population in 2015 consisted of people over 60 years old, and it is expected that they will occupy more than 21.3% of the population in 2050. Therefore, many countries are facing an increasing population of elderly people (Nikzad et al., 2021). Current policies in the Western world emphasize that older people should live in their homes as much as possible; At the same time, most older people also prefer it (Sixsmith et al., 2014; Olsen et al., 2019). As a result, providing needed healthcare services for the elderly is a challenge for healthcare systems in different countries. Many countries have invested in long-term care to improve the cost and quality of services. If services are provided at home, long-term care is also known as a home health care system (Zhou et al., 2020). Therefore, the provision of health services at home refers to the provision of medical services and various types of health care systems depending on the needs of the patients, which are carried out by the organizations providing these services in the patient's home. Home health care system providers are often staffed by physicians and nurse aides to provide a full range of services.

The services needed by patients at home are very diverse, and as a result, there is a lack of manpower needed to handle them. Today, tools such as the Internet, gadgets, applications, etc., can quickly collect the information and demand for services needed by patients, and information processing systems can analyze the data with high accuracy. Therefore, the IoT in this matter can provide services to patients at home in the shortest possible time, in addition to reducing the personnel costs of hospitals. In addition to paying attention to economic and social aspects, this includes environmental aspects as well. The importance of using the IoT in providing health services to patients at home has led to the presentation of a mathematical model to reduce the cost and time of serving patients based on the IoT. In this model, the main goal is to collect real-time data from patients at home and the type of service requested, to assign doctors specialized in each type of service, and to optimally route the patient's visit at home. On the other hand, in this article, in addition to visiting patients and providing services by doctors, vehicle routing is also included to collect medical samples. The existence of uncertainty in the time of providing services and costs has led to the inclusion of a robust optimization method to control these parameters in the presented framework based on the IoT. Based on the stated content, the main features of the article are as follows:

- Designing a model for providing health services to patients based on the IoT
- Considering the uncertainty in the parameters of the problem
- Considering drug and biological sample delivery services

The structure of the article is as follows. In the second part, the background of the research and its gaps are discussed. In the third part, a model has been designed to provide health services to patients based on the IoT. In the fourth part, the initial solution design for solution methods is discussed. In the fifth section, numerical examples are analyzed and in the sixth section, conclusions and future research suggestions are discussed.

2- Literature Review

In this section, the most important research in health services has been investigated. Issabakhsh et al. (2018) presented a mathematical model for the problem of at-home health services, which at that time was considered an uncertain parameter. In this issue, the main goal was to determine the optimal way to provide services to patients at home. They showed that when the uncertainty is less than 30%, model costs differ from reality by only 1.2%. Shi et al. (2019) designed a model for routing and scheduling a home medical service system considering non-deterministic service and travel times. In this model, they controlled the parameters of the problem using the stable method and solved their model using the SA and TA methods. Luo et al. (2019) used an ACO to optimize the transportation problem in providing home medical services considering greenhouse gas emissions. The results showed that the used algorithm has a higher efficiency than the Gurobi method. Nasir and Kuo (2020) presented a model for providing home health services based on transportation and staff scheduling. In this article, they considered two types of service delivery based on drug delivery and collection of medical samples. Their main goal was to minimize the total costs of providing health services to patients at home. Ratta et al. (2021) examined the application of blockchain and the IoT in the field of medicine and the health system and examined the challenges and prospects future of this field. Goodarzian et al. (2021) modeled a bi-objective problem to balance routing and personnel work time in home healthcare system procurement. They considered two objective functions (OBFs)s of service cost minimization and service time minimization and developed an algorithm called SEO. By comparing their results with FA and BA, they showed that the efficiency of their proposed algorithm is much higher. (2021) investigated the potential impact of the pandemic on IoT adoption in various sectors, including healthcare, smart homes, smart buildings, smart cities, transportation, and industrial IoT. They also explored the challenges of IoT adoption in this research. Ghiasvand Ghiasi et al. (2021) modeled a vehicle routing and home medical care planning problem with two modes of public and private transportation. For this, they proposed a different integer linear programming model, where the OBF was to minimize the sum of travel distance and overtime costs. They used IWO, GOA, and SA to solve their model. Fathollahi-Fard et al. (2022) designed a two-level planning model for the home medical service delivery problem. For this, they considered a Stackelberg game in which the outsourcing of health services was also possible. They also used a meta-heuristic algorithm to validate the designed model and performed some sensitivity analysis on the model. Bahadori-Chinibelagh et al. (2022) proposed a new multi-bay home healthcare routing model assuming overall distance control. In this model, patient care routing decisions and the order of their visits were very important to reduce costs. They also proposed two heuristic algorithms to solve their model and investigated their efficiency in solving their model. Salehi-Amiri et al. (2022) investigated the application of IoT to the home health supply chain problem and proposed a two-stage approach to identify potential patients and collect biological samples. In this model, the presented approach is aimed at determining the optimal path for providing services to patients at home. They also used 4 meta-heuristic algorithms to solve the problem. The results showed that the use of the IoT system helps to maximize overall vehicle occupancy and can effectively optimize the number of trips, thereby minimizing total costs and greenhouse gas emissions. Legato et al. (2022) proposed a multi-level framework that combines a simulation and optimization approach to evaluate the performance of complex IoT service request systems in real time. This conceptual framework focuses on using simulation to mimic the organization, rules, and behavior of the system, while optimization is used to search for the allocation of personnel and equipment to pursue optimization on resource availability.

Based on the conducted research, it can be seen that there is no comprehensive model that includes the provision of drug delivery services and collection of samples from home patients based on the IoT. Therefore, in this research, the designed model fills the research gaps and provides a comprehensive model of providing home health services based on the IoT.

3- Problem definition and modeling

In this part of the research, a framework based on the IoT has been presented to provide health services to patients at home. As stated, the existence of IoT tools provides information to doctors quickly and on time and makes it possible for doctors to provide health services to patients as quickly as possible. 3PL (Third-Party Logistics) plays an important role in the patient health supply chain. 3PL, which are companies that can provide logistics services for other companies and organizations in the field of health, is considered an independent and specialist company in the field of logistics to improve the performance of the patient's health supply chain. In the considered structure, the management of the means of transportation is the responsibility of the 3PL. Responsible for managing the transportation needed for the movement of medicines, medical equipment, and other materials related to the patient's health. They coordinate with transportation companies to transport and distribute materials and ensure that transportation is done on time and safely. Also, in warehouse management, 3PLs are responsible for managing warehouses related to patient health. They undertake the maintenance, monitoring, and distribution of health and pharmaceutical products. Also, they can play a role in managing information systems related to inventory and product tracking. In addition, they also do tracking and follow-up. 3PLs in the patient health supply chain can play an important role in tracking and tracking medical services. Based on this, using IoT tools based on the framework of Figure (1), patients' information and services they need, such as medicine and delivery of medical samples, are sent to the hospital or pharmacy. Then the appropriate doctor with the type of service providers and also the vehicle to collect biological samples is selected and the most appropriate routing of the vehicle is done. This routing is done in terms of two objective functions (OBFs) minimizing the total costs of routing and minimizing the weighted sum of the time of providing services to the patients-the length of the path of providing services. The output of this framework is decisions such as choosing the right doctor to provide services, determining the optimal route to provide services and the start and end time of services.

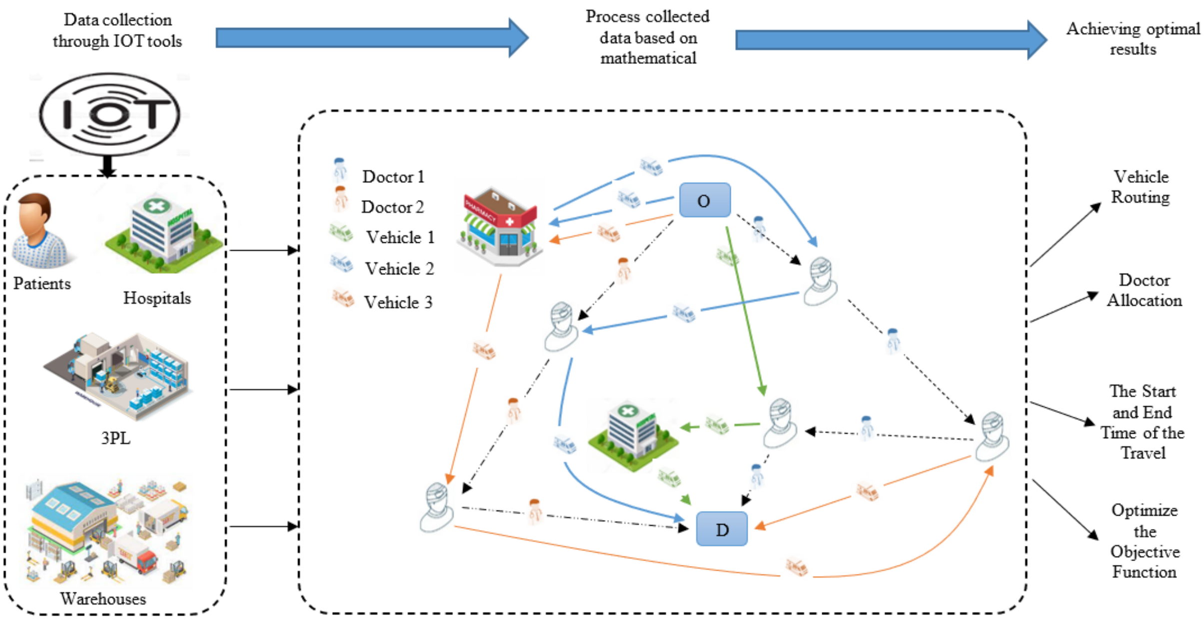

Figure 1- The framework of providing health services to patients based on the IoT

The problem presented above can be modeled and solved by considering the following assumptions:

- It is a single period.
- All services requested by patients must be satisfied.
- A pharmacy and a hospital are planned to supply medicine and collect medical samples.
- Cost parameters, vehicle waiting time, and medical service delivery time are uncertain.
- Multiple vehicles are considered.

According to the stated assumptions, to provide a model of providing health services to patients based on the IoT, the following symbols are defined. Consider $G = (N_0, A)$ where N_0 is the total set of grid nodes and A is the arcs of the model. In the defined nodes, P is the number of patients, $i \in N$ is the number of nurses and $v \in V$ is the number of vehicles. Also, the origin and destination nodes for the movement of doctors and vehicles are defined as O and D respectively. In this model, H is also considered as a hospital, Q as a pharmacy, and R as a collection of service delivery paths by doctors. As a result, the total number of network nodes is equal to $N_0 = P \cup \{O, D, H, Q\}$. In this network, doctors provide a set of $s \in S$ services to patients. Also, $g \in VS$ is a set of services provided to patients by vehicles. In this problem, there are two types of service provision, collection of medical samples and drug delivery, which are indicated by the symbol $g = 1,2$ respectively. All Notation defined follows as:

Indices:

v: *Number of vehicles*

s: *Type of services*

r: *Number of routes*

i: *Number of doctors*

j: *Number of nodes*

Parameters:

$\widetilde{sd}_v$ *Waiting time of vehicle v at each node*

$p_{i,s}$ *If nurse I can provide services, it takes the value of 1, and otherwise, it takes the value of 0.*

$\tilde{T}_s$ *Duration of providing services by each doctor*

$Vq_{g,j}$ *If patient j needs service g, it takes the value 1, otherwise, it takes the value 0.*

$q_{j,s}$ *If patient j needs service s, it takes the value 1, otherwise, it takes the value 0.*

$Vp_{g,v}$ *If vehicle v can provide service g, it takes the value 1, otherwise, it takes the value 0.*

rg_v *Time to start a new route by vehicle v*

$t_{j,k}$ *Travel time between two nodes j and k*

$d_{j,k}$ *The distance between two nodes j and k*

$\tilde{C}$ *Travel cost per kilometer*

F *Fixed cost of using the vehicle*

B *The fixed cost of using a doctor*

$[pe_j, pf_j]$ *The time window for providing health services to patient j by the doctor*

θ *Importance coefficient*

M: *Is a large positive scalar.*

Variables:

$Y_{i,j,k}$ *If nurse I move from node j to node k, it takes the value 1, otherwise, it takes the value 0.*

$X_{r,v,j,k}$ *If vehicle v moves from node j to node k on route r, it takes the value 1, otherwise, it takes the value 0.*

$U_{r,v}$ *If route r is assigned to vehicle v, it takes the value 1, otherwise, it takes the value 0.*

Z_i *It takes the value 1 if doctor i is employed to provide the service and 0 otherwise.*

$ST_{r,v,j}$ *Arrival time of vehicle v on route r to node j*

$S_{i,j}$ *The start time of nurse i at node j*

$SR_{r,v}$ *The start time of vehicle v on route r*

$ER_{r,v}$ *End time of vehicle v on route r*

According to the defined symbols, the two-objective model of the problem of providing health services to patients based on the IoT under uncertainty is as follows:

$$Min\ OBF_1 = \sum_{r\in R}\sum_{v\in V}\sum_{(j,k)\in A} C.d_{j,k}.X_{r,v,j,k} + \sum_{i\in N}\sum_{(j,k)\in A} C.d_{j,k}.Y_{i,j,k} + \sum_{r\in R}\sum_{v\in V} F.U_{r,v} + \sum_{i\in N} B.Z_i \tag{1}$$

$$Min\ OBF_2 = \theta.\sum_{i\in N}\sum_{s\in S}\sum_{(j,k)\in A} T_s.q_{j,s}.Y_{i,j,k} + (1-\theta).\sum_{r\in R}\sum_{v\in V}\sum_{(j,k)\in A} d_{j,k}.X_{r,v,j,k} \tag{2}$$

$s.t.$:

$$\sum_{i \in N} \sum_{(j,k) \in A} Y_{i,j,k} = 1, \qquad j \in P \tag{3}$$

$$\sum_{r \in R} \sum_{v \in V} \sum_{(j,k) \in A} Vp_{g,v}.X_{r,v,j,k} = Vq_{g,j}, \qquad j \in P, g \in VS \tag{4}$$

$$\sum_{(j,h) \in A} Y_{i,j,k} = \sum_{(h,k) \in A} Y_{i,k,j}\,, \qquad h \in P, i \in N \tag{5}$$

$$\sum_{(j,h) \in A} X_{r,v,j,h} = \sum_{(h,k) \in A} X_{r,v,h,k}\,, \qquad h \in N_0(O \cup D), v \in V, r \in R \tag{6}$$

$$ST_{r,v,j} + M.\left(1 - X_{r,v,j,k}\right) \geq S_{i,j}, \qquad i \in N, (j,k) \in A, r \in R, v \in V \tag{7}$$

$$ST_{r,v,j} \leq \sum_{i \in N} S_{i,j} + \sum_{s \in S} T_s.q_{j,s}\,, \qquad j \in P, v \in V, r \in R \tag{8}$$

$$ST_{r,v,j} \leq M.\sum_{(j,k) \in A} X_{r,v,j,k}\,, \qquad j \in P, v \in V, r \in R \tag{9}$$

$$\sum_{v \in V} U_{r,v} \leq 1\,, \qquad r \in R \tag{10}$$

$$-M.\left(1 - X_{r,v,O,j}\right) + SR_{r,v} \leq ST_{r,v,j} - t_{O,j}.X_{r,v,O,j} \leq M\left(1 - X_{r,v,O,j}\right) + SR_{r,v}, \qquad j \in N_0, v \in V, r \in R \tag{11}$$

$$SR_{r,v} \leq M.U_{r,v}, \qquad v \in V, r \in R \tag{12}$$

$$ST_{r,v,j} \leq ER_{r,v} - \left(sd_v + t_{j,D}\right).X_{r,v,j,D} \leq ST_{r,v,j} + M\left(1 - X_{r,v,j,D}\right), \qquad j \in N_0, v \in V, r \in R \tag{13}$$

$$ER_{r,v} + rg_v.U_{r,v} \leq M.\left(1 - U_{r',v}\right) + SR_{r',v}, \qquad v \in V, r < r' \in R \tag{14}$$

$$\sum_{s \in S} \sum_{(j,k) \in A} T_s.q_{j,s}.Y_{i,j,k} \leq M.Z_i, \qquad i \in N \tag{15}$$

$$\sum_{(j,k) \in A} d_{j,k}.X_{r,v,j,k} \leq M.U_{r,v}, \qquad r \in R, v \in V \tag{16}$$

$$p_{i,s}.S_{i,j} \geq pe_j.\sum_{(j,k) \in A} q_{j,s}.Y_{i,j,k}\,, \qquad j \in P, i \in N, s \in S \tag{17}$$

$$S_{i,j} \leq pf_j.\sum_{(j,k) \in A} Y_{i,j,k}\,, \qquad j \in P, i \in N \tag{18}$$

$$X_{r,v,O,Q} = U_{r,v}, \qquad r \in R, v \in \left\{v' \in V : Vp_{2,v'} = 1\right\} \tag{19}$$

$$X_{r,v,H,D} = U_{r,v}, \qquad r \in R, v \in \left\{v' \in V : Vp_{1,v'} = 1\right\} \tag{20}$$

$$Y_{i,j,k}, X_{r,v,j,k}, U_{r,v}, Z_i \in \{0,1\} \tag{21}$$

$$ST_{r,v,j}, S_{i,j}, SR_{r,v}, ER_{r,v} \geq 0 \tag{22}$$

Equation (1) shows the OBF1 of the problem and includes minimizing the total costs of providing health services to patients. Equation (2) is to minimize the weighted sum of the time of providing medical services to patients and also to reduce the distance of the vehicle in providing services. Equation (3) guarantees that each doctor provides services to only one patient. Equation (4) guarantees that patients receive their services from the delivery of medical samples. Equation (5) shows that after providing services to one patient, each doctor visits another patient to continue his work. Equation (6) shows that if the vehicle enters a node, it must leave it. Equation (7) to (8) calculates the doctor's arrival time for each patient. Equation (9) shows that each route cannot be assigned to more than one vehicle. Equation (10) to (14) calculates the start and end time of each route. Equations (15) and (16) specify the type of nurse and route allocation to the vehicle. Equation (17) and (18) calculates the time window for providing services to patients. Equations (19) and (20) show the logical constraints. Equations (21) and (22) show the type of decision variables of the problem. Based on these two constraints, the variables of the problem are binary and positive continuous.

The uncertainty method introduced by Ben-Tal and Nemirevsky (2002), which is called the "Tal-Nemirevsky Uncertainty Method" or "TN method", is an uncertainty analysis method used in complex systems engineering. This method is suitable for modeling and analyzing systems with high uncertainty and complexity. In the TN method, the system is modeled as a connected network. Each element in this network can be a random variable that represents uncertainty. These random variables can be of different types such as continuous, discrete, multiple, or more complex probability distributions. Using the TN method, it is possible to quantitatively model the uncertainty in the system and check its effect on the system outputs. By changing the values of random variables or their probability distributions, different results can be obtained for the system outputs, and in this way, uncertainty analysis can be performed. As an uncertainty analysis method, the TN method provides facilities for modeling and analyzing system complexities. By using this method, it is possible to get a better understanding of the system's behavior under uncertainty and, as a result, make better decisions to improve the system's performance. For this purpose, Ben-Tal et al. (2004) showed that in a limited framework, the robust model can be transformed from a semi-infinite problem to an equilibrate problem in which the set u_{box} is replaced by the bounded set u_{ext}. In this problem, u_{ext} contains the maximum values in the u_{box} x collection. To describe the robust model corresponding to the designed model, the cost parameters, service delivery time by the doctor, and vehicle waiting time are assumed as non-deterministic. It is assumed that each of these uncertain parameters can change within a defined bounded framework. The general form of this framework can be defined as follows (Nahr and Zahedi, 2020):

$$u_{box} = \left\{\xi \in R^n : \left|\xi_t - \bar{\xi}_t\right| \le \rho G_t \; t = 1, \dots, n\right\} \tag{26}$$

where $\bar{\xi}_t$ is the nominal value, ξ_t is the t-th parameter of the vector ξ (it is an n-dimensional vector). Also, 2 positive values of G_t and ρ indicate the degree of uncertainty and the level of uncertainty, respectively. According to the above explanation, the stable model will correspond to the following model:

$$Min\ OBF = Z \tag{27}$$

$s.t.$:

$$fy + cx \le Z, \forall c \in u_{Box}^{c} \tag{28}$$

$$Ax \le dy, \forall A \in u_{Box}^{A} \tag{29}$$

$$y, x \in \{0,1\} \tag{30}$$

Ben-Tal et al (2004), showed that in a limited framework, the robust optimization can be transformed from a semi-infinite problem to an equilibrate problem in which the set u_{box} is replaced by the bounded set u_{ext}. In this problem, u_{ext} contains the maximum values in the u_{box} collection. To show the formability of the above problem, constraints (28) and (29) should be put into their formability. Therefore, for constraint (28) we have:

$$cx \le Z - fy, \forall c \in u_{Box}^{c} | u_{Box}^{c} = \{C \in R^{n_c} : |C_t - \bar{C}_t| \le \rho_c G_t^c \; t = 1, \dots, n_c\} \tag{31}$$

The left side of the inequality (31) has an indeterminate parameter. Now all parameters on the right side are certain. Therefore, the controlled form of the semi-infinite inequality (31) will be in the following form:

$$\sum_t (\bar{C}_t x_t + \eta_t) \le Z - fy \tag{32}$$

$$\rho_c G_t^c x_t \le \eta_t, \qquad t \in \{1, \dots, n_c\} \tag{33}$$

$$\rho_c G_t^c x_t \ge -\eta_t, \qquad t \in \{1, \dots, n_c\} \tag{34}$$

For constraint (29), the semi-infinite controlled equation will be as follows:

$$a_i x \leq d_i y, \qquad i \in \{1, \dots, n_a\}\ \forall a \in u_{Box}^a | u_{Box}^a = \{a \in R^{n_a}: |a_i - \bar{a}_i| \leq \rho_a G_i^a\ i = 1, \dots, n_a\} \tag{35}$$

$$\bar{a}_i + \rho_a G_i^a \leq d_i y, \qquad i \in \{1, \dots, n_a\} \tag{36}$$

The mixed integer non-linear mathematical model is as follows:

$$Min\ OBF_1 = Z \tag{37}$$

$$Min\ OBF_2 = \theta . \sum_{i \in N} \sum_{s \in S} \sum_{(j,k) \in A} (\bar{T}_s + \rho \bar{T}_s) . q_{j,s} . Y_{i,j,k} + (1 - \theta) . \sum_{r \in R} \sum_{v \in V} \sum_{(j,k) \in A} d_{j,k} . X_{r,v,j,k} \tag{38}$$

$s.t.$:

$$\sum_{r \in R} \sum_{v \in V} \sum_{(j,k) \in A} C . d_{j,k} . X_{r,v,j,k} + \sum_{i \in N} \sum_{(j,k) \in A} C . d_{j,k} . Y_{i,j,k} \leq Z - \sum_{r \in R} \sum_{v \in V} F . U_{r,v} - \sum_{i \in N} B . Z_i \tag{39}$$

$$\rho \bar{C} . d_{j,k} . X_{r,v,j,k} \leq \eta_{r,v,j,k}, \qquad r \in R, v \in V, (j,k) \in A \tag{40}$$

$$\rho \bar{C} . d_{j,k} . X_{r,v,j,k} \geq -\eta_{r,v,j,k}, \qquad r \in R, v \in V, (j,k) \in A \tag{41}$$

$$\rho \bar{C} . d_{j,k} . Y_{i,j,k} \leq \eta_{i,j,k}, \qquad i \in N, (j,k) \in A \tag{42}$$

$$\rho \bar{C} . d_{j,k} . Y_{i,j,k} \geq -\eta_{i,j,k}, \qquad i \in N, (j,k) \in A \tag{43}$$

$$S_{i,j} + \left((\bar{T}_s + \rho \bar{T}_s) . q_{j,s} + t_{j,k} \right) . Y_{i,j,k} \leq S_{i,k} + M . \left(1 - Y_{i,j,k}\right), \qquad i \in N, (j,k) \in A, s \in S \tag{44}$$

$$ST_{r,v,j} + \left(\left(\overline{sd}_v + \rho \overline{sd}_v \right) + t_{j,k} \right) . X_{r,v,j,k} \leq ST_{r,v,k} + M . \left(1 - X_{r,v,j,k}\right), \qquad v \in V, (j,k) \in A, r \in R \tag{45}$$

$$ST_{r,v,j} \leq \sum_{i \in N} S_{i,j} + \sum_{s \in S} (\bar{T}_s + \rho \bar{T}_s) . q_{j,s}, \qquad j \in P, v \in V, r \in R \tag{46}$$

$$ST_{r,v,j} \leq ER_{r,v} - \left(\left(\overline{sd}_v + \rho \overline{sd}_v \right) + t_{j,D} \right) . X_{r,v,j,D} \leq ST_{r,v,j} + M \left(1 - X_{r,v,j,D}\right), \qquad j \in N_0, v \in V, r \in R \tag{47}$$

$$\sum_{s \in S} \sum_{(j,k) \in A} (\bar{T}_s + \rho \bar{T}_s) . q_{j,s} . Y_{i,j,k} \leq M . Z_i, \qquad i \in N \tag{48}$$

$$Eqs\ (3,4,5,6,7,10,12,13,14,15,17,19,20,21,22,23,24) \tag{49}$$

$$\eta_{r,v,j,k}, \eta_{i,j,k} \geq 0 \tag{50}$$

4- Solution methods

In this section, problem-solving methods have been investigated. Due to the bi-objective of the developed mathematical model, the epsilon constraint method has been used to solve the problem on small scales and also to perform the sensitivity analysis of the problem. On the other hand, due to the NP-Hard of the mathematical model, NSGA-II, MOPSO, and MOICA have been proposed. In this section, the initial solution to the problem is described.

- *Epsilon-constraint*

The multi-objective approach of the Epsilon Constraint Method is a technique used to solve multi-objective optimization problems. In this approach, the main objective is to find a set of solutions that optimize multiple conflicting objectives simultaneously. The Epsilon Constraint Method introduces epsilon constraints for each objective function to define acceptable ranges or bounds within which the objectives can vary. These epsilon constraints act as thresholds or limits for each objective, allowing some flexibility in achieving the optimal solution (Abolghasemian et al., 2020).

$$min/\max f_i(x) \tag{51}$$

$s.t.$

$f_j \leq \varepsilon_i$

$x \in X$

By introducing these Epsilon constraints, the multi-objective Epsilon Constraint Method transforms the original multi-objective problem into a series of single-objective sub-problems. Each sub-problem focuses on optimizing one objective while considering the epsilon constraints for the remaining objectives. The result of applying the multi-objective Epsilon Constraint Method is a set of Pareto-optimal solutions. These solutions represent the trade-off between different objectives, where no solution can be improved in one objective without sacrificing performance in another objective (Jahangiri et al., 2023). The set of Pareto-optimal solutions forms the Pareto front or Pareto set, which represents the optimal trade-off solutions in the multi-objective problem space. The multi-objective Epsilon Constraint Method provides decision-makers with a range of feasible solutions, allowing them to explore and select the most suitable solution based on their preferences and priorities among the conflicting objectives (Abolghasemian et al., 2022).

- *NSGA-II*

NSGA-II is a multi-objective optimization algorithm that belongs to the class of evolutionary algorithms. It is an extension of the original NSGA algorithm and is widely used for solving problems with multiple conflicting objectives. The main objective of NSGA-II is to find a set of solutions that represents the Pareto front, which is a set of non-dominated solutions. A solution is considered non-dominated if there is no other solution in the population that is better in all objectives and worse in none. NSGA-II operates by maintaining a population of candidate solutions called individuals. The algorithm iteratively evolves this population over generations to improve the quality of solutions. It uses genetic operators such as selection, crossover, and mutation to create new offspring solutions from the existing population (Maadanpour-Safari et al., 2021). The key steps involved in NSGA-II are as follows:

> ***Step 1.*** *Initialization: Generate an initial population of individuals randomly or using some heuristic method.*
>
> ***Step 2.*** *Evaluation: Evaluate the fitness of each individual in the population based on the objective functions.*
>
> ***Step 3.*** *Non-dominated sorting: Sort the individuals into different fronts based on their dominance relationships. Individuals in the first front are non-dominated and have the highest fitness.*
>
> ***Step 4.*** *Crowding distance assignment: Assign a crowding distance to each individual on each front to maintain diversity in the population. The crowding distance measures how close an individual is to its neighboring solutions.*
>
> ***Step 5.*** *Selection: Select individuals from the current population to create the next generation. NSGA-II uses a combination of non-dominated sorting and crowding distance to select the most promising individuals.*
>
> ***Step 6.*** *Variation: Apply genetic operators such as crossover and mutation to create offspring solutions from the selected individuals.*
>
> ***Step 7.*** *Replacement: Replace the least fit individuals in the current population with the newly created offspring solutions.*
>
> ***Step 8.*** *Termination: Repeat steps 2-7 until a termination condition is met, such as reaching a maximum number of generations or convergence of the population.*

By iteratively applying these steps, NSGA-II explores the search space and converges towards a diverse set of non-dominated solutions, providing a trade-off between conflicting objectives. It is widely used in various fields, including engineering, finance, and scheduling, where multiple objectives need to be optimized simultaneously (Chobar et al., 2022).

- *MOPSO*

MOPSO is a metaheuristic optimization algorithm inspired by the behavior of bird flocking or fish schooling. MOPSO is used to solve multi-objective optimization problems, where multiple conflicting objectives need to be optimized simultaneously. In MOPSO, a population of particles represents potential solutions to the optimization problem. Each particle has a position and velocity in the search space, and it moves through the search space to find optimal solutions. The particles communicate with each other to share information about their best positions, called personal bests, and the best positions found by the entire swarm, called global bests. The movement of particles is guided by both their personal bests and the global bests (Ghasemi et al., 2022). By balancing exploration and exploitation, MOPSO aims to converge towards a set of solutions known as the Pareto front, which represents the trade-off between the different objectives. The Pareto front consists of non-dominated solutions, where improving one objective would require sacrificing another. MOPSO has been widely applied to various real-world problems, such as engineering design, scheduling, portfolio optimization, and many others. It offers an effective approach to handling complex optimization problems with multiple conflicting objectives (Maadanpour-Safari et al., 2021).

- *MOICA*

MOICA is a metaheuristic optimization algorithm inspired by the concept of imperialism and competition among empires. It is designed to solve multi-objective optimization problems, which involve optimizing multiple conflicting objectives simultaneously. In MOICA, the optimization problem is modeled as a set of empires, where each empire represents a potential solution or candidate solution to the problem. The empires are composed of colonies, which represent different solutions within an empire. Each colony has a fitness value associated with it, indicating its performance concerning the objectives being optimized. The algorithm starts by initializing a population of empires randomly. These empires compete with each other based on their fitness values. The fitter empires expand their territories by assimilating colonies from weaker empires. This process is known as assimilation, and it aims to improve the overall fitness of the empires (Goodarzian et al., 2021). To maintain diversity in the population, MOICA employs a revolution operator that introduces random changes to the colonies' positions. This helps prevent premature convergence to suboptimal solutions and promotes exploration of the search space. The algorithm also incorporates a selection mechanism to determine the empires that will participate in the assimilation process. This selection is typically based on the dominance relationship between the empires, considering their Pareto dominance or other multi-objective comparison methods. MOICA iteratively repeats the assimilation, revolution, and selection steps until a termination criterion is met, such as reaching a maximum number of iterations or achieving a satisfactory level of convergence. At the end of the algorithm, the non-dominated solutions found during the optimization process form the Pareto front, representing the trade-off between the multiple objectives. Overall, the Multi-Objective Imperialist Competitive Algorithm combines the concepts of imperialism, competition, and evolution to efficiently explore the solution space and find a diverse set of high-quality solutions for multi-objective optimization problems (Ghasemi and Khalili-Damghani, 2020).

4.1- Parameters setting

The most important part of any algorithm is designing the initial solution to the problem. There are different methods of designing the initial solution such as array and matrix. In this section, by presenting a hypothetical example, the design of the initial solution of the proposed model has been discussed considering 2 nurses, 5 patients, 2 vehicles, and 3 routes. Table (1) shows the initial solution of the problem in a matrix. The total number of genes defined in this problem is equal to $3 * |P|$.

Table 1 - The initial solution to the problem

Node	*1*	*2*	*3*	*4*	*5*
The sequence of doctor visits	*2*	*5*	*1*	*3*	*4*
Vehicle visit sequence	*1*	*4*	*3*	*2*	*5*
How to visit	*0.54*	*0.37*	*0.37*	*0.40*	*0.67*

Some important assumptions are needed to decipher Table (1). For example, it is assumed that Doctor 1 provides type 1 services and Doctor 2 provides type 2 services. Also, vehicle 1 is busy collecting biological samples and vehicle 2 is busy delivering medicine. Table (2) shows the need of each patient for the type of service.

Table 2- Each patient's need for various services

Patient	*Doctor services*	*Vehicle services*
1	*1*	*2 " Drug Delivery "*
2	*2*	*1 " Collection of biological samples "*
3	*1*	*2 " Drug Delivery "*
4	*2*	*2 " Drug Delivery "*
5	*1*	*1 "Collection of biological samples "*

To decode Table (2), the following steps must be taken:

Step 1- First, the patients assigned to each doctor and each type of vehicle are determined based on the type of service requested. If more than one doctor can provide services to patients, one doctor will be randomly selected.

- Allocation of patients 1, 3, and 5 with requested service type 1 to doctor 1
- Allocation of patients 2 and 4 with requested service type 2 to doctor 2
- Allocation of patients 2 and 5 with service type "biological sample collection" to vehicle 1
- Allocation of patients 1, 3, and 4 with service type "Drug delivery" to vehicle 2

Step 2- The optimal routing of the doctor's movement toward the patients is determined based on the first line of the initial solution. In this way, based on the sequence of nodes, patients are visited in order. Visits of patients are from the lowest sequence values to the highest sequence values:

- Visiting patients by doctor 1 as O → 3 → 1 → 5 → D
- Visiting patients by doctor 2 as O → 4 → 2 → D

Step 3- Routing of the vehicle is done according to the second line of the matrix and the type of services requested by the patients. In this section, if the patient requests medicine, the vehicle will visit the node (pharmacy) first, and if "biological sample collection" is requested, the vehicle will visit the node (hospital) at the end. Also, the type of route assigned to this problem is based on the random solution of the third row of the matrix:

Main step: After the first patient is visited by the vehicle, a random number between 0 and 1 is generated for visiting or not visiting the next patient. If the generated random number is less than 0.5, it will be visited on the same current route, and if the random number is greater than 0.5, the patient will be visited on the next route by the same vehicle.

- Providing "biological sample collection" services to patients by vehicle 1 on route number 1 as O → 2 → hospital → D
- Providing "biological sample collection" services to patients by vehicle 1 on route number 2 as O → 5 → hospital → D
- Providing drug delivery services to patients by vehicle 2 on route number 3 in the form of O Pharmacy → 3 → 3 → D
- Providing "Drug delivery" services to patients by vehicle 2 on route number 4 as O Pharmacy → 1 → D

Step 4- Determining the starting time of the doctor and the vehicle from the patients based on the parameters of the problem

Step 5- Determining the fine in case of exceeding the time window for doctor's visits to patients

According to the 5 steps mentioned above, the proposed two-objective model can be solved and the values of the decision variables of the problem can be obtained. The initial solution presented in all algorithms is the same and only the operators of each algorithm differ from each other in achieving the solution close to the optimum.

5- Analysis of numerical results

5-1- Analysis of numerical example in small size

In this section, to validate the model and also to check the output variables of the problem, a numerical example is designed considering 5 patients, 2 doctors, 2 types of doctor services, 3 types of vehicle services, 3 routes, and 3 types of vehicles. Also, due to a lack of access to real-world data, random data provided in basic articles based on a uniform distribution function has been used. Table (3) presents the initial data of the problem.

Table 3- Initial data of problem

Parameter	*Range*
x_j, y_j	$\sim U(0,25)$
d_{jk}	$\sqrt{(x_j - x_k)^2 + (y_j - y_k)^2}$
$\tilde{t}_{jk}$	$[3d_{jk}, 2d_{jk}, d_{jk}]$
pe_j	$\min\{1, \lvert pf_j - U(120,240)\rvert\}$
pf_j	$\sim U(1,540)$
T_s	$[\sim U(60,90), \sim U(50,60), \sim U(30,50)]$
c	$[\sim U(4,5), \sim U(5,6), \sim U(6,7)]$
F	500
B	700
rg_v	$\sim U(7,15)$
G	150
G'	2
Sd_v	$[\sim U(5,7), \sim U(7,9), \sim U(9,12)]$

After designing the numerical example and using the Cplex, the set of efficient solutions to the problem has been obtained in the form of a Table (4). Also, in this analysis, the value of the uncertainty in the robust planning method is considered equal to 0.5.

Table 4- The set of efficient solutions for the small-size problem

Efficient Solutions	*OBF1*	*OBF2*
1	*2391.92*	*157.12*
2	*2432.15*	*150.34*
3	*2483.20*	*141.33*
4	*2520.34*	*138.28*
5	*2568.74*	*133.75*
6	*2614.22*	*131.08*
7	*2644.67*	*129.59*

Based on Table (4), by reducing OBF2 and by reducing the weighted sum of the service delivery time and the distance traveled, the costs caused by the routing of health services by doctors and vehicles have increased. To determine the optimal routing, the first efficient solution is selected and its results are shown in Table (5).

Table 5- The optimal way to provide health services in the problem of small size (the first effective solution)

Vehicle	*Doctor*	*Best Routing*	*Service Start Time*
	1	$O \rightarrow p_3 \rightarrow p_6 \rightarrow p_5 \rightarrow D$	$O \rightarrow (22.875) \rightarrow (105.089) \rightarrow (191.351) \rightarrow D$
	2	$O \rightarrow p_7 \rightarrow p_4 \rightarrow D$	$O \rightarrow (39.856) \rightarrow (110.595) \rightarrow D$
1		$O \rightarrow p_5 \rightarrow H \rightarrow D$	$O \rightarrow (246.851) \rightarrow H \rightarrow D$
2		$O \rightarrow Q \rightarrow p_3 \rightarrow p_7 \rightarrow D$	$O \rightarrow Q \rightarrow (77.375) \rightarrow (92.856) \rightarrow D$
3		$O \rightarrow Q \rightarrow p_4 \rightarrow p_6 \rightarrow D$	$O \rightarrow Q \rightarrow (110.595) \rightarrow (159.856) \rightarrow D$

In the following, the sensitivity analysis under the change in the main parameters of the model is discussed. This is due to the effect of changing the parameters on the OBFs. Initially, due to the uncertainty of the parameters, the uncertainty was changed between 0.1 (optimistic) and 0.9 (pessimistic), and the value of OBFs is shown in Table (6).

Table 6- The value of OBFs in different values of the uncertainty

ρ	*OBF1*	*OBF2*
0.1	*2314.13*	*140.28*
0.2	*2331.40*	*144.31*
0.3	*2353.67*	*149.82*
0.4	*2374.95*	*153.24*
0.5	*2391.92*	*157.12*
0.6	*2412.13*	*161.38*
0.7	*2439.33*	*166.97*
0.8	*2472.54*	*171.28*
0.9	*2622.75*	*176.43*

According to Table (6), with the increase in uncertainty, the transfer time and service time in providing services to patients have increased and this issue has led to a change in the optimal time of providing services to patients. As a result of this and due to the increase in transportation costs, the value of the OBF1 has also increased.

In another analysis, the costs of the problem under the change in the upper limit of the time window of providing services to patients have been investigated. By reducing this amount, it is possible to change the optimal route and type of service. The sensitivity analysis of the problem has been performed under the decrease and increase of 10, 20, and 30% in the upper limit of the time window. Table (7) shows the value of the OBFs in different values of the upper limit of the time window.

Table 7- The value of OBFs in different values of the upper limit of the time window

Pf_j%	*OBF1*	*OBF2*
-30%	*2433.60*	*146.35*
-20%	*2422.89*	*149.25*
-10%	*2412.34*	*153.32*
0	*2391.92*	*157.12*
+10%	*2374.77*	*160.27*
+20%	*2354.37*	*164.81*
+30%	*2334.04*	*169.24*

Based on Table (7), by increasing the upper limit of the time window and increasing the solution space of the problem, the optimal value of OBFs has decreased. Therefore, this shows that with the increase in the time window of service provision, the value of the OBF2 has also increased. Figure (2) shows the changes in the values of OBFs as a result of the changes in the parameters of the uncertainty and the upper limit of the time window.

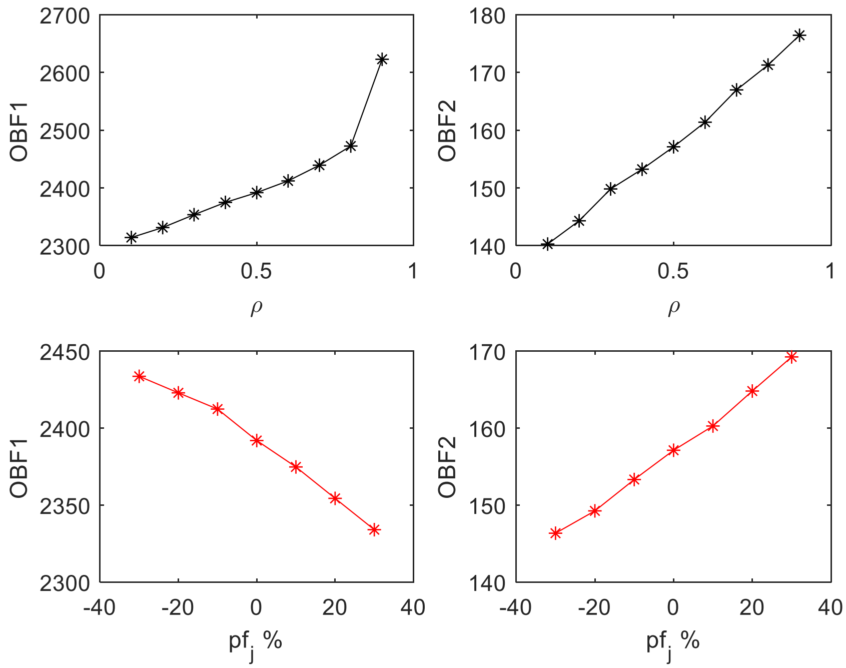

Figure 2- Changes in OBFs due to different values of model parameters

After performing the sensitivity analysis and checking the changes in the value of OBFs in different values of the problem parameters, numerical examples in different sizes have been solved with proposed algorithms such as NSGA II, MOPSO, and MOICA. Before performing the analysis, the initial parameters of the methods have been tuned.

5-2- Parameter setting of meta-heuristic algorithms

Based on Table (8), 3 levels of each parameter are considered. For each algorithm, according to the number of factors and the number of their levels, the design of the test and their implementation are determined. In the last column of Table (8), the optimal values of the parameters of each algorithm are shown after performing the tests.

Table 8- Suggested and optimal parameter levels for parameter tuning

Algorithm	*Parameter*	*Level 1*	*Level 2*	*Level 3*	*Optimum Value*
NSGA II	*Max it*	*50*	*100*	*200*	*200*
	N pop	*50*	*100*	*200*	*200*
	Pc	*0.7*	*0.8*	*0.9*	*0.9*
	Pm	*0.05*	*0.07*	*0.09*	*0.05*
MOPSO	*Max it*	*50*	*100*	*200*	*200*
	N particle	*50*	*100*	*200*	*200*
	C1	*1*	*1.5*	*2*	*1.5*
	C2	*1*	*1.5*	*2*	*1*
	w	*0.7*	*0.8*	*1*	*0.7*
MOICA	*Max it*	*50*	*100*	*200*	*200*
	N Country	*50*	*100*	*200*	*200*
	Beta	*1*	*1.5*	*2*	*2*
	Zeta	*0.1*	*0.2*	*0.3*	*0.2*
	Mu	*0.07*	*0.08*	*0.09*	*0.08*

5-3- Solving numerical examples in different sizes

After tuning the parameter, the analysis of different numerical examples with meta-heuristic algorithms has been done. Therefore, 15 numerical examples in small to large sizes according to Table (9) have been randomly designed. Also, the parameters of the problem have been used randomly and according to Table (3) in the numerical examples. The first numerical example in Table (9) is equal to the numerical example of the small size presented in the previous section.

Table 9- Size of numerical examples in different sizes

Sample Problem	$\|P\|$	$\|N\|$	$\|G\|$	$\|S\|$	$\|R\|$	$\|V\|$
1	*5*	*2*	*3*	*2*	*3*	*3*
2	*10*	*3*	*3*	*3*	*3*	*3*
3	*15*	*4*	*3*	*4*	*3*	*3*
4	*20*	*6*	*4*	*6*	*5*	*4*
5	*25*	*8*	*4*	*8*	*5*	*4*
6	*30*	*10*	*4*	*10*	*5*	*4*
7	*40*	*12*	*6*	*12*	*8*	*6*
8	*50*	*15*	*6*	*15*	*8*	*6*
9	*60*	*18*	*6*	*18*	*8*	*6*
10	*70*	*20*	*8*	*20*	*10*	*8*
11	*80*	*25*	*8*	*25*	*10*	*8*
12	*90*	*30*	*8*	*30*	*10*	*8*
13	*100*	*35*	*10*	*35*	*15*	*10*
14	*120*	*40*	*10*	*40*	*15*	*10*
15	*150*	*45*	*10*	*45*	*15*	*10*

After designing the numerical examples, the Pareto front obtained from the first efficient solution has been compared with the epsilon constraint method as well as the proposed meta-heuristic algorithms. According to the obtained results, it was observed that by decreasing the value of OBF2, the value of OBF1 increased. This shows that the service time has an inverse relationship with the total cost. Figure (3) shows the Pareto front obtained from the solution of the numerical example of small size (example problem 1) with different solution methods. Also, Table (10) compares the comparison indices of the efficient solution such as (NPF, MSI, SM, and CPU-Time).

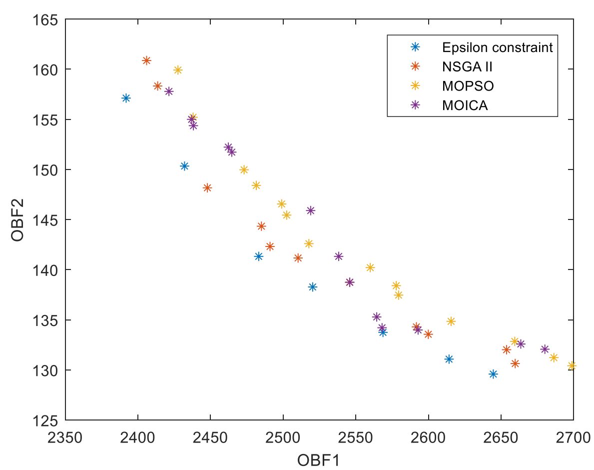

Figure 3- Pareto front obtained from the solution of the numerical example of small size

According to Figure (3), by increasing OBF1, the OBF2 decreases. Therefore, the OBFs conflict with each other.

Table 10- Comparison of comparison indices between efficient solutions

Index	*Epsilon Constraint*	*NSGA II*	*MOPSO*	*MOICA*
NPF	*7*	*11*	*14*	*13*
MSI	*254.24*	*255.51*	*272.76*	*260.065*
SM	*0.121*	*0.448*	*0.560*	*0.678*
CPU-Time	*948.57*	*32.18*	*28.49*	*26.33*

The results of the comparison of efficient solutions show that the highest value of NPF and MSI is related to the MOPSO, the lowest value of SM is related to the NSGA II, and the lowest value of CPU-Time is related to the MOICA.

In Table (11), the optimal routing in the first efficient solution of each of the methods is stated.

After designing the numerical examples, the indices obtained from different solution methods are shown in Table (12). It should be noted that each problem is sampled three times by each algorithm.

The average comparison indices show that the MOICA is the most efficient in terms of problem-solving in large sizes. After that, NSGA-II and MOPSO are the next priority. Finally, Figure (4) shows the average indices of comparison of effective solutions in numerical examples of large size.

Table 11- Comparison of the results of the first effective solution of a small numerical example with different solution methods

Method	*Vehicle*	*Doctor*	*Best Routing*
Epsilon Constraint		*1*	$O \to p_1 \to p_4 \to p_3 \to D$
		2	$O \to p_5 \to p_2 \to D$
	1		$O \to p_3 \to H \to D$
	2		$O \to Q \to p_1 \to p_5 \to D$
	3		$O \to Q \to p_2 \to p_4 \to D$
NSGA II		*1*	$O \to p_1 \to p_3 \to p_4 \to D$
		2	$O \to p_5 \to p_2 \to D$
	1		$O \to p_3 \to H \to D$
	2		$O \to Q \to p_1 \to p_5 \to D$
	3		$O \to Q \to p_2 \to p_4 \to D$
MOPSO		*1*	$O \to p_1 \to p_4 \to p_3 \to D$
		2	$O \to p_5 \to p_2 \to D$
	1		$O \to p_3 \to H \to D$
	2		$O \to Q \to p_5 \to p_1 \to D$
	3		$O \to Q \to p_2 \to p_4 \to D$
MOICA		*1*	$O \to p_1 \to p_4 \to p_3 \to D$
		2	$O \to p_5 \to p_2 \to D$
	1		$O \to p_3 \to H \to D$
	2		$O \to Q \to p_5 \to p_1 \to D$
	3		$O \to Q \to p_4 \to p_2 \to D$

Table 12- Comparison indices of efficient solutions in different numerical examples

Sample Problem	*NSGA II*				*MOPSO*				*MOICA*			
	NPF	*MSI*	*SM*	*CPU-Time*	*NPF*	*MSI*	*SM*	*CPU-Time*	*NPF*	*MSI*	*SM*	*CPU-Time*
1	*11*	*255.51*	*0.448*	*32.18*	*14*	*272.76*	*0.560*	*28.49*	*13*	*260.06*	*0.678*	*26.33*
2	*29*	*329.29*	*0.619*	*36.17*	*17*	*301.31*	*0.383*	*40.66*	*34*	*400.22*	*0.547*	*27.33*
3	*28*	*343.70*	*0.501*	*45.20*	*26*	*250.16*	*0.313*	*50.80*	*13*	*372.92*	*0.507*	*32.54*
4	*29*	*256.63*	*0.452*	*53.94*	*34*	*375.05*	*0.375*	*60.63*	*35*	*338.47*	*0.509*	*38.84*
5	*16*	*375.47*	*0.333*	*63.94*	*24*	*292.41*	*0.428*	*71.87*	*28*	*279.63*	*0.52*	*46.04*
6	*18*	*369.82*	*0.495*	*77.24*	*27*	*299.02*	*0.537*	*86.82*	*16*	*273.29*	*0.683*	*55.61*
7	*35*	*295.42*	*0.36*	*91.04*	*18*	*298.30*	*0.412*	*102.33*	*22*	*330.18*	*0.334*	*65.55*
8	*22*	*277.76*	*0.406*	*110.24*	*22*	*375.41*	*0.472*	*123.91*	*31*	*372.79*	*0.595*	*79.37*
9	*33*	*392.18*	*0.664*	*134.74*	*15*	*270.04*	*0.331*	*151.45*	*22*	*298.17*	*0.699*	*97.01*
10	*16*	*269.21*	*0.314*	*165.38*	*18*	*260.43*	*0.481*	*185.89*	*26*	*250.95*	*0.49*	*119.07*
11	*25*	*262.47*	*0.56*	*197.43*	*13*	*261.92*	*0.311*	*221.91*	*35*	*351.38*	*0.578*	*142.15*
12	*34*	*313.29*	*0.489*	*241.34*	*17*	*262.00*	*0.608*	*271.27*	*16*	*260.51*	*0.699*	*173.76*
13	*18*	*256.43*	*0.581*	*296.57*	*25*	*337.82*	*0.614*	*333.34*	*24*	*353.60*	*0.425*	*213.53*
14	*27*	*267.59*	*0.406*	*356.22*	*34*	*324.92*	*0.486*	*400.39*	*13*	*354.13*	*0.366*	*256.48*
15	*12*	*256.53*	*0.439*	*413.47*	*15*	*251.05*	*0.575*	*464.74*	*19*	*378.14*	*0.344*	*297.70*

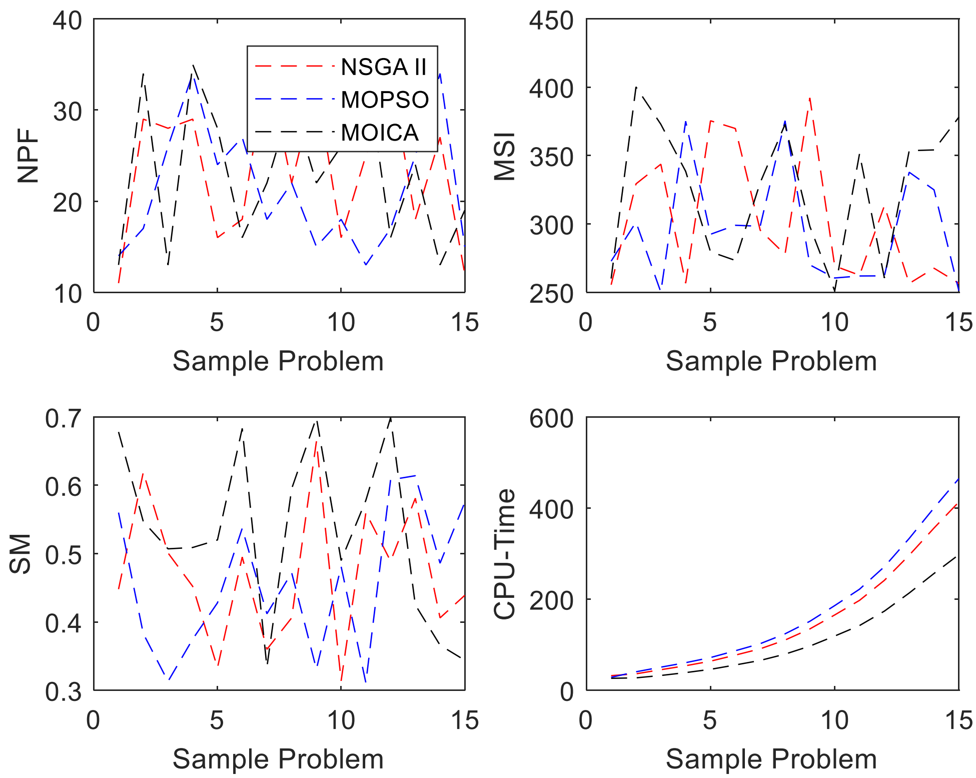

Figure 4- The average indices of the comparison of efficient solutions in large numerical examples

According to the results obtained based on the implementation of numerical examples shown in Table 13, according to the epsilon constraint method and meta heuristic-algorithm methods of MOICA, MOPSO, and NSGA-II, it can be seen that MOICA algorithm has less calculation error than other meta-heuristic methods of MOPSO and NSGA-II. According to the obtained results, the average error in the MOICA method is equal to 0.0358, in the MOPSO method it is equal to 0.1248 and in the NSGA-II method it is equal to 0.2066. Therefore, due to the low calculation error between the MOICA meta-heuristic algorithm and the exact method, the results of this algorithm can be used in the long term and for larger situations.

6- Conclusions and suggestions

In this article, a mathematical model was designed to provide services to patients at home based on the IoT. In the presented framework, the data required to provide services to patients are collected by IoT tools and collected in the database of medical centers such as hospitals. After the data is collected, it is immediately analyzed by data processing tools and based on a two-objective mathematical model, and the best decisions are taken to provide health services to patients. Considering the existence of uncertainty in the real world, a robust programming method was used to control the parameters. The results showed that to reduce the OBF of the weighted sum of service time and the distance traveled by vehicles, the network design costs should be increased. These results also showed that with the increase of the uncertainty in the network and model parameters, the values of OBF1 and OBF2 increase. Also, as much as the time window for providing services to customers decreases, the costs incurred on the network will increase. Based on the solution method used and its inefficiency due to the problem being NP-hard, NSGA-II, MOPSO, and MOICA were used. The comparative results of a numerical example show the high efficiency of the algorithms in terms of comparison indices of effective solutions compared to the epsilon method. Also, the analysis of numerical examples of larger sizes showed that the MOICA is the most efficient in terms of solving problems in large sizes. After that, NSGA-II and MOPSO are the next priority, and the MOICA is high efficient than other algorithms in solving the model with a 0.6534 desirability weight. As future suggestions, it is possible to propose the use of a robust method in controlling uncertain parameters. Also, due to the variety of services requested by patients, it is suggested to consider more levels such as laboratories in the problem.

Table 13- Comparison between MOPSO, MOICA, and NSGA-II method

Scale	**Problem no**	**Number of vehicles**	**Number of services**	**Number of doctors**	**Exact**	**MOICA**	**MOPSO**	**NSGA-II**	**GAP 1 (%)**	**GAP 2 (%)**	**GAP 3 (%)**
Small	PR1	1	1	1	37,200	37,550	42,235	45,547	0.009	0.135	**0.224**
	PR2	2	1	1	85,250	85,892	88,325	89,478	0.007	0.049	**0.049**
	PR3	3	2	2	131,150	131,590	142,458	152,678	0.003	0.086	**0.164**
	PR4	4	2	2	300,325	325,658	345,748	401,642	0.08	0.151	**0.337**
	PR5	5	3	3	480,625	506,857	578,642	605,147	0.08	0.203	**0.259**
Medium	PR6	10	4	5	-	725,648	782,356	825,356	-	-	**-**
	PR7	15	5	5	-	900,367	989,347	990,441	-	-	-
	PR8	15	6	5	-	925,457	1,025,369	1,253,369	-	-	-
	PR9	15	6	4	-	956,369	1,500,346	1,300,258	-	-	-
	PR10	20	6	5	-	987,589	1,550247	1,478,369	-	-	-
Large	PR11	20	5	5	-	989,347	1,600,369	1,500,369	-	-	-
	PR12	20	5	4	-	1,025,369	1,147,259	1,600,369	-	-	-
	PR13	25	6	5	-	1,500,346	1,253,369	1,650,479	-	-	-
	PR14	25	5	5	-	1,550247	1,300,258	1,700,897	-	-	-
	PR15	25	5	4	-	1,600,369	1,478,369	1,750,369	-	-	-
Average									0.0358	0.1248	**0.2066**

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