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An Integrated Model of Green IoT and Vehicle Routing for Physician Attendance Scheduling in Home Care

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ABSTRACT

With the advancement of technology, especially telemedicine and health care, information must meet the needs of people, especially people with low mobility, the elderly, and people who have difficulty accessing medical resources and services. These services must be accessed swiftly and dependably, prioritizing individual cases. One of the primary challenges in healthcare is routing and scheduling to cater to people's requirements. Various tools, including the Green Internet of Things, have the capability to gather information from patients and promptly transmit it to doctors and hospitals. Additionally, implementing green routing and reducing energy consumption through the Green Internet of Things can have environmental impacts. This article presents an integrated model of the Green Internet of Things and vehicle routing to schedule doctor visits in home healthcare. The objectives of this model are to minimize total costs and enhance customer satisfaction by utilizing information from the Green Internet of Things. Several factors are taken into account in this model, such as time windows, doctors' expertise, and the types of services requested by patients. The problem was addressed using MOGWO and NSGA II. The findings highlight that an increase in patient satisfaction leads to higher total costs for visits and vehicle routing. An analysis of 15 numerical examples across various scales demonstrated that the efficiency of MOGWO surpasses that of NSGA II and LP-Metric.

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1. Introduction

In the last 20 years, the number of beds in private hospitals and clinics has decreased. The aging population has contributed to an increase in the number of people with chronic diseases, leading to functional escalation. Patients undergoing treatment for advanced chronic diseases or palliative care require care that, for some reasons, must be in their home environment (Movahed et al., 2023). In recent years, the health system has been in jeopardy due to numerous economic and organizational challenges. This issue has prompted the substitution of home care services for traditional approaches. This system was established as an alternative to possibly reduce the costs of the health care system while ensuring satisfaction with the quality of services (Xiang et al., 2023). The development of these structures is accelerating significantly, while the method of organization followed is still industrial and heterogeneous. The services provided by them are not limited to the provision of care services, that is, the production and implementation of medical and paramedical procedures. In fact, the service provider also plays a crucial role in the management of operational aspects (organizational component). Receiving health care at home rather than in the hospital reduces the cost of the entire health system, and in many cases, is more convenient and effective than the care provided in a hospital, thereby mitigating resources scarcity caused by the limited number of hospital beds (Euchi, 2022). 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 increase in the population of elderly people (Nikzad et al., 2021). As a result, providing the necessary health care services for the elderly poses a challenge for health care systems in various countries. Many countries have invested in long-term care to improve the cost and quality of services. When these services are offered directly within individuals' residences, long-term care is commonly referred to as home health care (Zhou et al. 2020).

Today, the provision of services in the health and treatment sector, industry, service, production, etc. is not the same as in the past, and with the arrival of new technologies, including the Internet of Things, it has taken on a new form. The Internet of Things refers to the Internet connection between objects and equipment, which are located in the environment around us. These appliances or objects connected to the Internet can be controlled and managed using software in smartphones, tablets, computers, gadgets, smart watches, televisions, and any other object (Ghahremani-Nahr et al., 2022). To put it simply, the Internet of Things refer to the connection of sensors and devices with the Internet network. Through this connection and interaction between devices connected to the network and users with authorized access, it is possible to observe and control the devices connected to the network for users. These tools enable the provision of remote services, identify the type of services patients need, and find efficient ways to serve them, etc. (Aliahmadi et al., 2022). To enhance the benefits and mitigate the damage of the Internet of Things, there is a growing inclination towards the green Internet of Things. The green Internet of Things is environmentally friendly and will substitute for the Internet of Things in the future. These tools help patients receive the services they need from specialized doctors as soon as possible, without causing a negative impact on the environment (Alsharif et al. 2023).

In this paper, focusing on the two issues of Internet of Things and planning of doctors to provide health services at home, an integrated model of Internet of Things and vehicle routing is designed to schedule the presence of doctors in home care under conditions of uncertainty. The presented model aims to minimize the total costs and maximize the satisfaction of patients from receiving services along with the use of green Internet of Things. The important decisions made in this model include vehicle routing to schedule the presence of doctors, allocation of doctors with different levels of expertise to meet the needs of patients in uncertain conditions. Therefore, in order to address non-deterministic parameters, a pessimistic fuzzy programming method along with LP-Metric, NSGA II, and MOGWO have been used to resolve the problem.

The importance of this research lies in addressing a critical challenge in modern healthcare: optimizing physician attendance scheduling for home care while integrating green Internet of Things (IoT) technology to enhance efficiency and sustainability. As healthcare systems worldwide face increasing pressure due to aging populations, rising healthcare costs, and limited hospital capacities, home-based medical services have emerged as a viable solution to improve patient accessibility and reduce system burdens. However, ensuring timely and effective physician visits while considering environmental impacts remains a challenging issue that requires innovative solutions.

This study contributes to the field by proposing an integrated model that combines vehicle routing with green IoT technologies to improve scheduling efficiency, reduce costs, and enhance patient satisfaction. By leveraging real-time data collection from IoT-enabled medical devices, the model optimizes doctor assignments and travel routes, minimizing unnecessary fuel consumption and greenhouse gas emissions. Moreover, the study applies advanced metaheuristic algorithms to solve the scheduling problem, providing a robust approach to address the inherent uncertainties in healthcare service delivery.

The research question guiding this study is how to develop an optimized scheduling and routing framework that ensures efficient physician home visits while incorporating sustainability principles via green IoT. This question is significant as it addresses both operational challenges in healthcare logistics and broader concerns related to environmental sustainability.

The structure of the article is as follows. In the second part, literature review and research gaps are discussed. In the third part, the integrated model of Green Internet of Things and vehicle routing is presented for scheduling the presence of doctors in home care, and the pessimistic fuzzy programming method is used to address non-deterministic parameters. In the fourth part, problem-solving methods and parameter setting of algorithms are presented. In the fifth section, numerical examples are analyzed, and in the sixth section, conclusions and future research suggestions are discussed.

2. Literature Review

Nozari et al. (2023) presented a mathematical model for home health care routing and scheduling as well as scheduling of qualified physicians. In this model, limitations related to the time window, workload, and staff limitations are considered. Shi et al. (2017) presented a mathematical model for the home health care scheduling problem with fuzzy demand. They also proposed a hybrid genetic algorithm for model analysis. Experimental results for Solomon and Hamburger benchmark samples indicate that the proposed algorithm is efficient. Mirabnejad et al. (2019) presented a new model by considering the main characteristics of the nurse scheduling and routing problem, such as continuity of care and time dependencies. They used genetic algorithm to resolve the utilization problem, and designed an initial solution that included nurse and patient preferences, job opportunities, nurse qualification and waiting time. Shi et al. (2019) developed a model for the HHC routing and scheduling problem, considering uncertain travel and service times from a robust optimization perspective. They used different meta-heuristic algorithms, such as TS, SA and local search, to solve the problem. The comparison between the solutions obtained by the stochastic model and the robust optimization model also attest to the advantage of the robust model. Euchi et al. (2020) presented a new method for home health care routing and scheduling problem by leveraging artificial intelligence techniques. This methodology is proposed to optimize services provided in a distributed environment. The aforementioned method has demonstrated significant improvements in both time management and cost reduction. Ratta et al. (2021) scrutinized the utilization of blockchain and the Internet of Things within the realm of healthcare and medical systems. Their study delved into the obstacles faced in this area, as well as its potential prospects for the future.

Goodarzian et al. (2021) developed a bi-objective model to balance routing and personnel scheduling in home health service logistics. Considering two objective functions of service cost minimization and service time minimization, they developed an algorithm called SEO. By comparing their results with FA and BA algorithms, they revealed that the efficiency of their proposed algorithm is significantly higher. Szmelter-Jarosz et al. (2021) presented a distributed optimization method for home health service routing and physician attendance scheduling. Torres et al. (2021) presented an innovative method for the problem of routing and planning patient visits at home. The outcomes of their method indicated a significant decrease in the waiting time for medical assistance, dropping from 82 minutes to 24 minutes. Rest and Hirsch (2022) examined causal loop diagrams to visualize the effects of epidemics, blackouts, heat waves, and floods on the home health care system. These diagrams help in understanding system design, cascading effects and simplifying the process of identifying action points to mitigate the effects of disasters. Fu et al. (2022) modeled a stochastic home care scheduling and routing problem with skill requirements to minimize total operation time. Furthermore, a combined approach of genetic algorithms and simulation optimization was introduced, incorporating an approximate allocation rule to assess its efficiency. Ghiasvand Ghiasi et al. (2022)

presented a bi-objective mathematical model based on a mixed integer linear programming approach for the routing and scheduling problem of home health care to minimize the travel costs for nurses and the maximum working time differences between nurses. Moreover, due to the high complexity of the problem, two meta-heuristic methods of genetic algorithm of non-dominant sorting and multi-objective particle swarm optimization algorithm were employed to solve the problem in both medium and large dimensions. The statistical results indicate that the genetic algorithm for non-dominant sorting outperformed the multi-objective particle swarm optimization algorithm in medium and large problems, as evidenced by two key indicators: average distance from the ideal point and the number of Pareto solutions. In total, the results of the indicators indicate that the genetic algorithm of non-globe sorting performs efficiently and effectively in solving problems of different sizes. Bahadori-Chinibelagh et al. (2022) proposed a new multi-depot home healthcare routing model, assuming overall distance control. In this model, patient care routing decisions and the order of their visits were highly important to reduce costs. They also proposed two heuristic algorithms to solve their model and checked their efficiency in addressing it. In this model, the presented approach aims to determine an optimal path to provide services to patients at home. They also used four meta-heuristic algorithms to solve the problem. The results suggested that the use of the IoT system helps to maximize the overall vehicle occupancy and can effectively optimize the number of trips, thereby minimizing the 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 systems of service requests with the Internet of Things in real time. This conceptual framework focuses on utilizing simulation to replicate the organization, rules, and behavior of the system, while optimization is employed to search for the allocation of personnel and equipment in order to strive for optimization considering resource availability.

Sangeetha et al. (2023) designed a decision recommendation system that identifies the actual needs of HHCs and coordinates the pathways of a group of caregivers across a mixed fleet of services. They used discrete firefly algorithm in their proposed model. The results showed that the proposed algorithm has significantly reduced costs and time efficiency. Fallah et al. (2021) developed an extensive local search method for addressing the task of scheduling and routing physicians to provide home services within a Dutch organization. The results of their research suggested that by reducing the waiting time from 90 minutes to 30 minutes, 15% of the total costs will increase. Ma et al. (2023) proposed an optimization model with multiple objectives to achieve minimum service cost and minimum delay cost. They also proposed a brainstorming optimization method with specific multi-objective search (MOBSO) mechanisms to resolve the problem. Masmoudi et al. (2023) presented two meta-heuristic algorithms, named SA-ILS and ALNS, to optimize the routing and scheduling problem of physicians providing home care to patients. The results suggested that SA-ILS is a suitable algorithm for addressing the proposed mathematical model.

Based on the literature review, it can be observed that until now, the integrated model of green Internet of Things and vehicle routing has not been presented to schedule the presence of doctors for providing home care. Therefore, in this article, a model has been designed to schedule the presence of doctors in home care and vehicle routing, with data obtained based on Green Internet of Things. The integration of the presented model with the fuzzy programming method leads to the reduction of the calculation error. In this article, unlike previous research, patients' satisfaction with receiving services from doctors is also considered.

3. Definition of the Problem

The importance of Green Internet of Things in today's world, e.g., in providing medical services to patients and home care, has led to the presentation of a mathematical model based on the Green Internet of Things in this section. The purpose of this mathematical model is to integrate Green Internet of Things and vehicle routing to schedule the presence of doctors in home care. To achieve this goal, as indicated in Figure 1, there is a group of patients requiring various services from doctors possessing different levels of expertise. In this form, the required information about the type of services needed by patients, vehicles, low-traffic routes, etc., is provided to the hospital by Internet of Things tools. Subsequently, based on the type of services requested by each patient, a group of doctors moves towards the patients and delivers the required services. The integration of Green Internet of

Things and the presented model is aimed at determining the optimal path for the movement of doctors. This routing with the help of the Internet of Things tool leads to a reduction in traffic, a reduction in greenhouse gas emissions, and a reduction in fuel consumption.

In the presented mathematical model, the allocation of doctor types to patients and the optimal routing of each doctor's movements aim to minimize the costs of the entire system and maximize patient satisfaction from receiving services from various doctors. Each patient must receive services from doctors within a predetermined time window, and their satisfaction is directly linked to the expertise level of the doctor.

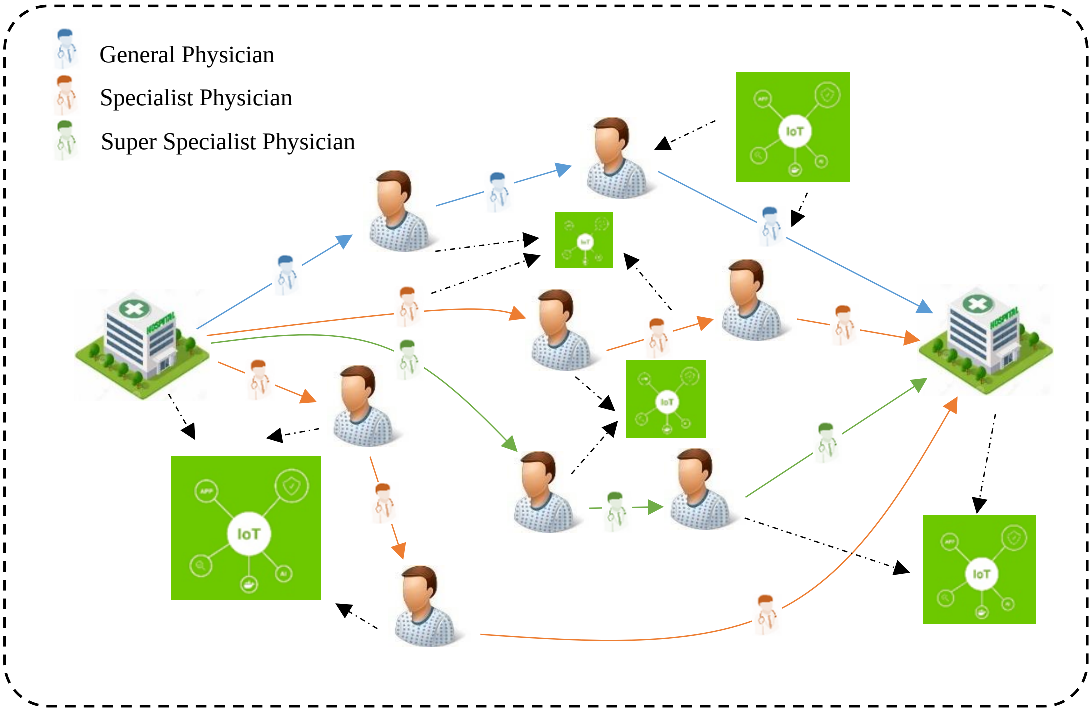
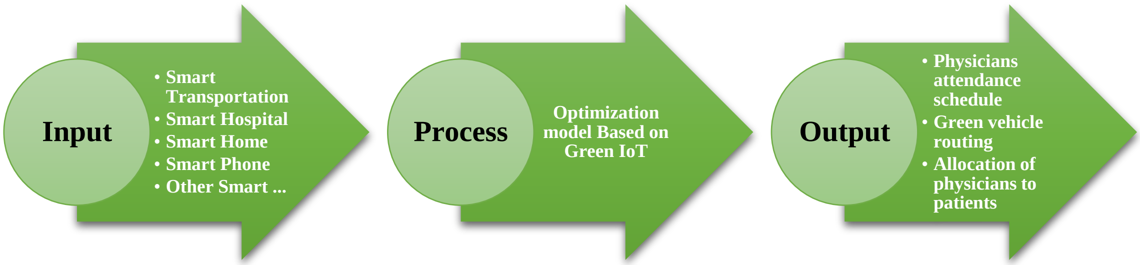


Fig. 1. Integrated model of green IoT and Vehicle Routing for Physician Attendance Scheduling



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

- The proposed model includes providing different services to patients in different periods.
- Each patient must receive all the requested services in each period of time.
- The origin and destination of the movement of doctors to provide services to patients is the hospital.
- The number of doctors in the entire considered period is limited.
- Doctors are considered at three levels: general practitioner, specialist doctor and super specialist doctor.
- Only one doctor with different levels of expertise is needed for each patient's visit.
- The duration of the visit of a specialist doctor is longer than that of a specialist and general doctor.
- The accuracy of a patient visit by a super-specialist doctor is more than that of a specialist and general doctor.

- The cost allocated to each level of doctor is different from each other.
- Vehicle cost and speed are non-deterministic parameters of the model.

Based on the above assumptions, there are P number of patients to receive S services by I doctor with L expertise level in T time period. The origin and destination of the movement of doctors to visit patients are two different hospitals with symbols O and D. Therefore, the total number of nodes in a studied graph, $G = (N_0, A)$, is equal to $N_0 = \{O, D, P\}$, where A represents the arcs of the graph. Other symbols used in modeling are described below.

Parameter

p_{islt}	1; If the doctor $i \in I$ with the level of expertise $l \in L$ is able to provide services $s \in S$ in the time period $t \in T$, and 0 otherwise.
q_{jst}	1; If patient $j \in P$ needs services $s \in S$ in time period $t \in T$ 0; otherwise.
t_{isl}	Duration of providing services $s \in S$ by doctor $i \in I$ with expertise level $l \in L$
d_{jk}	The distance between two nodes j and k ،$(j, k) \in A$
$\tilde{c}$	Travel cost per kilometer by vehicle $\sim(c^o, c^m, c^p)$
$\tilde{a}$	Average vehicle speed $\sim(a^o, a^m, a^p)$
h_{il}	The fixed cost of visiting a doctor $i \in I$ with a level of expertise $l \in L$
g_{isl}	Skill and precision of doctor $i \in I$ with level of expertise $l \in L$ in providing services s∈S to patients
$[e_j, f_j]$	The time window of providing services to patient $j \in P$
a_l	Total number of available doctors with expertise level $l \in L$
α	Uncertainty rate
M	A large positive number

Decision Variables

Y_{ijklt}	1; If the doctor $i \in I$ with the level of expertise $l \in L$ visits patient k in the time period $t \in T$ after the visit of patient j, and 0 otherwise.
Z_{ilt}	1; If the doctor $i \in I$ with the level of expertise $l \in L$ is employed for the visit in the time period $t \in T$, and 0 otherwise.
S_{ijt}	Start time of doctor $i \in I$ for visiting patient $j \in P$ in time period $t \in T$

The mixed integer linear programming model controlled by the pessimistic fuzzy programming method for the vehicle routing problem concerning home care physician attendance scheduling is as follows.

$$Min\,OBF_1 = \sum_{i \in I}\sum_{(j,k)\in A}\sum_{l \in L}\sum_{t \in T} \cdot \frac{d_{jk} \cdot \left(\dfrac{c^o, +2c^m + c^p}{4}\right)}{\left(\alpha\left(\dfrac{a^o + a^m}{2}\right) + (1-\alpha)\left(\dfrac{a^m + a^p}{2}\right)\right)} Y_{ijklt} + \sum_{i \in I}\sum_{l \in L}\sum_{t \in T} h_{il} . Z_{ilt} \tag{1}$$

$$Max\,OBF_2 = \sum_{i \in I}\sum_{s \in S}\sum_{(j,k)\in A}\sum_{l \in L}\sum_{t \in T} g_{isl} . p_{islt} . q_{jst} Y_{ijklt} \tag{2}$$

$s.t.$:

$$\sum_{i \in I}\sum_{(j,k)\in A} Y_{ijklt} \le 1, \quad \forall j \in P, l \in L, t \in T \tag{3}$$

$$\sum_{(O,k)\in A} Y_{iOklt} = \sum_{(j,D)\in A} Y_{ijDlt} = Z_{ilt}, \quad \forall i \in I, l \in L, t \in T \tag{4}$$

$$\sum_{(j,h)\in A} Y_{ijhlt} = \sum_{(h,k)\in A} Y_{ihklt}, \quad \forall h \in P, i \in I, l \in L, t \in T \tag{5}$$

$$S_{ijt}+\left(t_{isl}.q_{jst}+\frac{d_{jk}}{\left(\alpha\left(\frac{a^{o}+a^{m}}{2}\right)+\left(1-\alpha\right)\left(\frac{a^{m}+a^{p}}{2}\right)\right)}\right)Y_{ijklt}\le S_{ikt}+M.\left(1-Y_{ijklt}\right), \tag{6}$$
$$\forall i\in I,\left(j,k\right)\in A,s\in S,l\in L,t\in T$$

$$\sum_{s\in S}\sum_{(j,k)\in A}t_{isl}.q_{jst}Y_{ijklt}\le M.Z_{ilt},\quad \forall i\in I,l\in L,t\in T \tag{7}$$

$$p_{islt}.S_{ijt}\ge e_{j}.\sum_{(j,k)\in A}q_{jst}Y_{ijklt},\quad \forall j\in P,i\in I,s\in S,l\in L,t\in T \tag{8}$$

$$p_{islt}.S_{ijt}\le f_{j}.\sum_{(j,k)\in A}q_{jst}Y_{ijklt},\quad \forall j\in P,i\in I,s\in S,l\in L,t\in T \tag{9}$$

$$\sum_{i\in I}\sum_{t\in T}Z_{ilt}=a_{l}.\quad \forall l\in L \tag{10}$$

$$Y_{ijklt},Z_{ilt}\in\{0,1\}\ \&S_{ijt}\ge 0 \tag{11}$$

Equation (1) minimizes the visitation cost of doctors with different expertise levels, as well as the cost of vehicle routing to schedule the presence of doctors. Equation (2) maximizes patients' satisfaction from receiving services by doctors with different levels of expertise. Equation (3) guarantees that each doctor with a certain level of expertise provides services to at most one patient. Equation (4) indicate that the origin and destination of doctors' movement to visit patients is the hospital. Equation (5) suggest that every doctor visits another patient after visiting one patient. Equation (6) shows that the starting time of the doctor's visit for each patient should be greater than the time of the previous patient's visit plus the travel time. Equation (7) specifies the types of doctors with different levels of expertise in each time period for visiting patients. Equations (8) and (9) specify the time limit of the doctor's presence to visit the patients. Equation (10) suggests that the total number of doctors is limited in all time periods. Equation (11) shows decision-making variables.

4. Solution Methods

Providing an integrated model of Green Internet of Things and vehicle routing for scheduling the presence of doctors in home care has led to the formation of two objective functions: minimizing the total cost and maximizing patient satisfaction. On the other hand, vehicle routing models are considered an NP-hard problem, and meta-heuristic algorithms should be used to solve such problems since the time to solve NP-Hard problems increases exponentially with increasing problem size. In this article, LP-Metric method is used to validate the mathematical model and problem sensitivity analysis, and MOGWO and NSGA II are used to solve the model in larger sizes. In the next section, problem-solving methods and the initial solution of the problem are presented.

4-1. LP-Metric

In the LP-Metric method, it is necessary to obtain the best value of each objective function by the individual optimization method. That is, the value of each objective function should be obtained first without considering the other objective function to use it in calculations. Equation (12) shows the method of achieving efficient solutions in random weights w_i.

$$L_{p}=w_{1}\left[\frac{\left(OBF_{1}-OBF_{1}^{*}\right)}{\left(OBF_{1}^{*}\right)}\right]+w_{2}\left[\frac{\left(OBF_{2}^{*}-OBF_{2}\right)}{\left(OBF_{2}^{*}\right)}\right] \tag{12}$$

Random weights in this method are obtained through Monte Carlo simulation in 50 consecutive iterations.

4-2. NSGA II

NSGA II starts by generating a random population of chromosomes. Chromosomes are strings of proposed values for the problem's decision variables, each representing a potential answer to the problem. During each generation, these chromosomes are evaluated according to the optimization goals, and the chromosomes that are considered to provide a better answer to the problem in question have a greater chance to reproduce the problem solutions. Based on the obtained values of the objective functions in the population of strings, a fitness number is assigned to each string. This fitness number will determine the selection probability for each field. Based on this selection probability, a set of fields is first selected. To produce the next generation, new chromosomes, called children, are created by combining two chromosomes from the current generation using the combination operator or by modifying the chromosome using the mutation operator. Therefore, the new strings replace strings from the initial population so that the number of strings population is constant in different calculation iterations. The random mechanisms that act on the selection and removal of strands are such that the strands with more fitness have a higher probability to combine and produce new strands and are more resistant to the replacement stage than other strands. Figure 2 represents the flowchart of NSGA II.

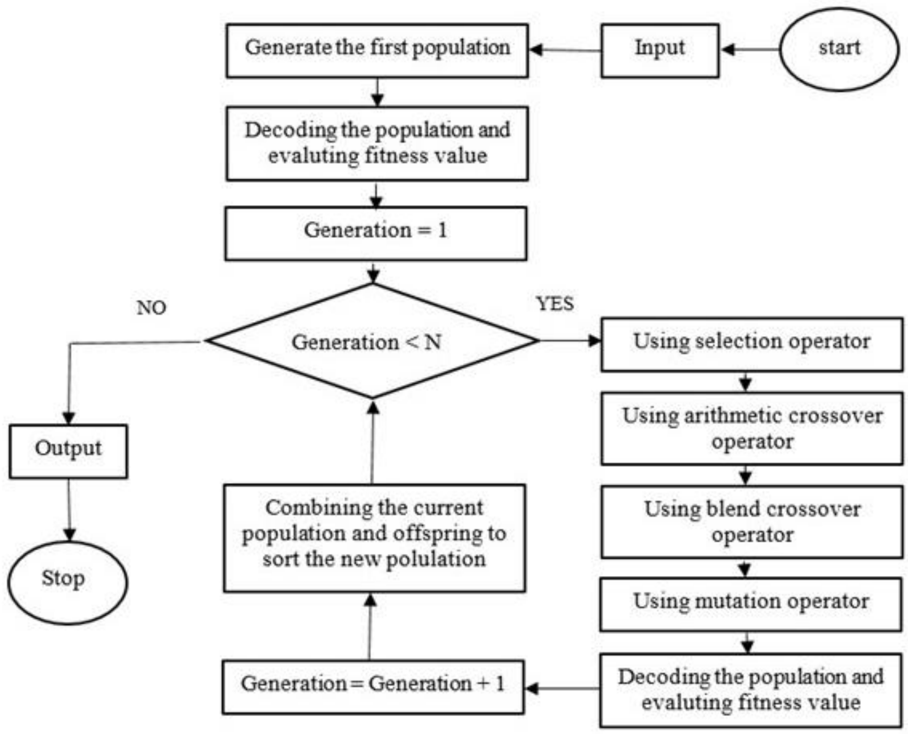


Fig. 2. Flowchart of NSGA II

4-3. MOGWO

Gray wolves live in groups. The leaders consist of one male and one female, who are called Alpha. Alpha is primarily responsible for making decisions about hunting, where to sleep, when to wake up, etc. Alpha's decisions are communicated to the group. However, some democratic behavior has also been observed where an Alpha obeys the other wolves in the pack. In congregations, the entire herd acknowledges the Alpha by laying low. The Alpha wolf is also the dominant wolf because his orders must be followed by the group. Alpha wolves are only allowed to mate in packs. It is worth noting that the Alpha is not necessarily the strongest member of the herd, but the best member in terms of management in the herd. The second level in the Gray Wolves hierarchy is Beta. Betas are subordinate wolves who assist the Alpha in making decisions or other pack decisions. A Beta wolf can be either male or female, and they are the best replacement for the Alpha if Alpha dies or grows old. Beta executes Alpha's commands throughout the herd and gives feedback to Alpha. The Omega Wolf is the lowest rank in the Gray Wolf hierarchy. Omega wolf plays the role of a victim. Usually, Omega Wolves must obey all high-level and dominant Wolves. They are the last wolves allowed to eat. If the wolf is not an Alpha or an Omega, it is called a Delta. Delta wolves must be subordinate to Alpha and Beta. However, they dominate Omega.

In the mathematical modeling of social hierarchy of wolves, (α) Alpha is considered as the most suitable solution. Subsequently, (β) Beta and (δ) Delta are the second and third most suitable solutions, respectively. The remaining candidate solutions are assumed to be Omega (X). To hunt, gray wolves must find and surround their prey. Therefore, the following equations update the positions of the wolves around the prey.

$$\vec{D} = |\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)| \tag{13}$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A}.\vec{D} \tag{14}$$

In the above equation, $\vec{C}$and $\vec{A}$ are coefficient vectors. $\overrightarrow{X_p}$is the position vector of prey and $\vec{X}$ is the position vector of gray wolves. It is a balancing act between siege and hunting. Therefore, the search radius must be optimized during the process. For this purpose, the equations related to the two coefficients used in the above relationships are as follows.

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{15}$$

$$\vec{C} = 2\overrightarrow{r_2} \tag{16}$$

The above equations enable gray wolves to update their position around the prey. As a result, the following equations are used for hunting.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_1.\vec{X}_\delta - \vec{X}\right| \tag{17}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta \tag{18}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{19}$$

Figure 3 presents the flow chart of MOGWO.

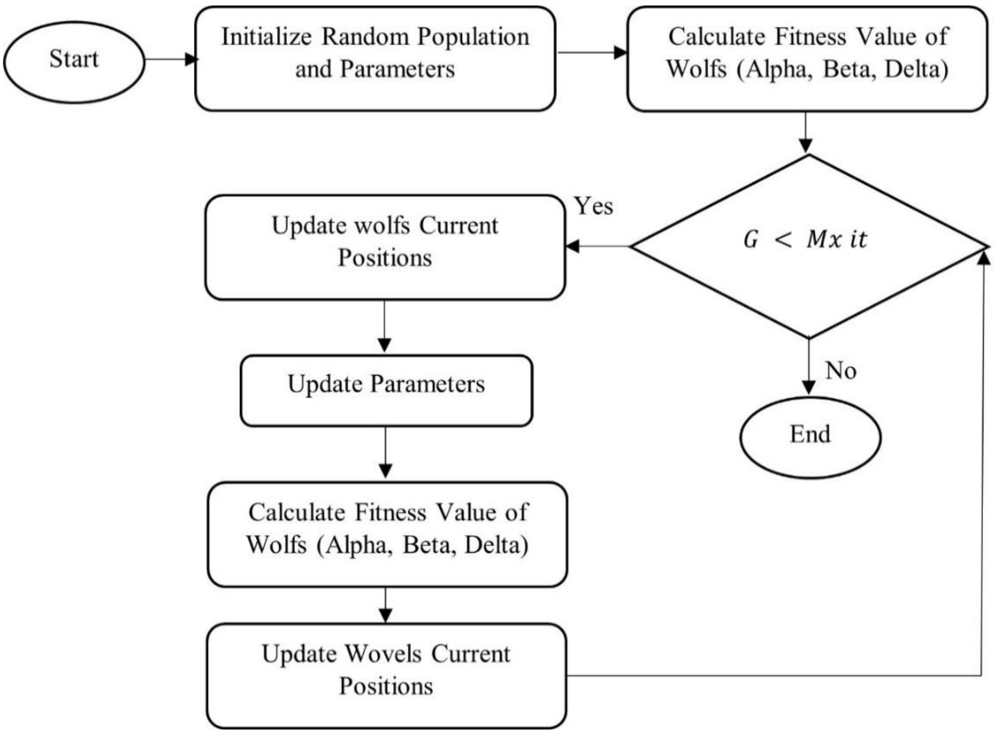


Fig. 3. Flowchart of MOGWO

4-4. The Initial Solution

The most important part of any algorithm is the design of the initial solution to the problem. There are different ways to design the initial solution, such as using arrays and matrices. In this section, by presenting a hypothetical example, the design of the initial solution of the proposed model is discussed, considering two doctors and five patients over a specified period of time. Figure 4 presents the initial solution of the problem in a matrix.

Patients	1	2	3	4	5
Physician's visit sequence	2	5	1	3	4
Priority visit	0.54	0.37	0.37	0.40	0.67

Figure 4. The Initial Solution of the Problem

Some important assumptions are required to understand figure 4. For example, it is assumed that doctor 1 provides type 1 services and doctor 2 provides type 2 services. In Table 1, each patient's need for the type of service is presented.

Table 1. Each Patient's Need for Various Services

Patients	***Physician services***	***Service Level***
1	1	*General Physician*
2	2	*Specialist Physician*
3	1	*General Physician*
4	2	*Specialist Physician*
5	1	*General Physician*

To decode Figure 4, the following steps must be taken:

Step 1- First, the patients assigned to each doctor are determined based on the type of service requested and the level of expertise.

- 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

Step 2- The optimal routing of the doctor's movements towards the patients is determined based on the first line of the initial solution. In this manner, patients are visited in order according to the sequence of nodes. Patient visits occur from lower sequence values to higher sequence values. After the doctor visits the first patient, a random number between 0 and 1 is generated to decide whether to visit the next patient. If the generated random number is less than 0.5, the patient will be visited along the same current path; if the random number is greater than 0.5, the patient will be visited by another doctor.

- Visiting patients by doctor 1 as O → 3 → 1 → 5 → D
- Visiting patients by doctor 2 as O → 4 → 2 → 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 for exceeding the doctor's visit time for patients from the Time window.

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 near-optimal solution.

4-5. Parameter Setting

Setting the initial parameters of meta-heuristic algorithms is performed to enhance the search for solutions aimed at achieving near-optimal solutions. In this method, a set of different levels is defined for each parameter, and an initial parameter value is proposed for each row. Subsequently, based on Taguchi's tests consisting of the number of parameters and defined levels, the mathematical model of the solution and RPD value are obtained based on the equations (20) and (21) (Taguchi & Konishi, 1987). The best value of each parameter level is calculated based on the results obtained from the average graph of the S/N ratio.

$$Fitness_i = \frac{|NPF + MSI + SM + CPUTime|}{4} \tag{20}$$

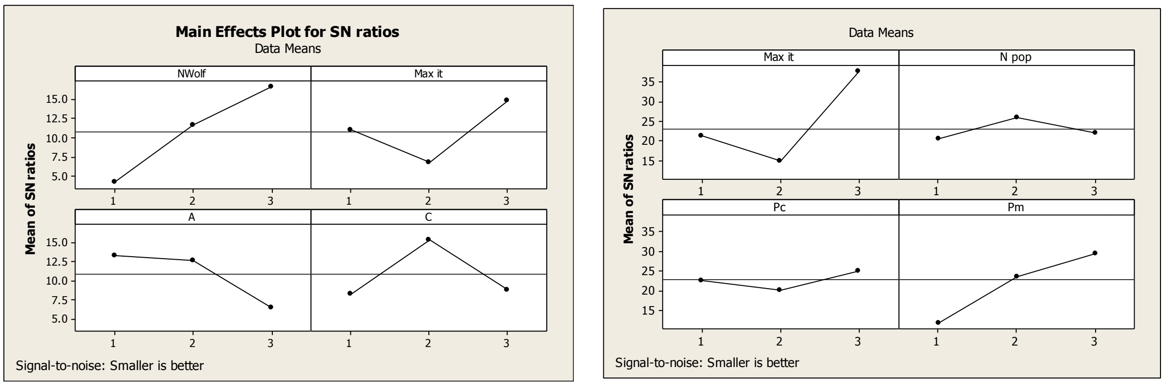
$$RPD_i = \frac{Fitness_i - Best\ Fitness}{Best\ Fitness} \tag{21}$$

In the above equations, $Fitness_i$ is the test solution obtained from the integration of four indicators: NPF, MSI, SM, and $Best\ Fitness$. Moreover, Best Fitness is defined as the best value of all tests obtained. The indicators, used to compare and achieve the results of each experiment, are presented in Table 2 (Ghahremani Nahr et al., 2023).

Figure 5 depicts the average graphs of S/N ratio within NSGA II and MOGWO parameter setting.

Table 2. Comparison Indices of Algorithms in Parameter Setting

Index	Equation	Effective
Number of Pareto front (NPF)	-	A higher value is better
Maximum Spread Index (MSI)	$\sqrt{\sum_{m=1}^{M}\left(max_{i=1:\lvert Q\rvert} f_m^i - max_{i=1:\lvert Q\rvert} f_m^j\right)^2}$	A higher value is better
Space Metric (SM)	$\sqrt{\frac{1}{\lvert Q\rvert}\sum_{i=1}^{\lvert Q\rvert}\left(min_{k\in Q\cap k\neq i}\sum_{m=1}^{M}\lvert f_m^i - f_m^k\rvert - \sum_{i=1}^{\lvert Q\rvert}\frac{min_{k\in Q\cap k\neq i}\sum_{m=1}^{M}\lvert f_m^i - f_m^k\rvert}{\lvert Q\rvert}\right)^2}$	A lower value is better
$CPU - time$		A lower value is better



MOGWO *NSGA II*

Figure 5. Average Diagram of S/N Ratio in Meta-Heuristic Algorithms

According to Figure 5, it can be argued that the highest point in the average graph of the S/N ratio is the selection of the desired level for setting the meta-heuristic algorithm parameter. Therefore, in order to increase the efficiency of NSGA II, the N_{pop} parameter is 200, the Max it parameter is 200, and the P_c and P_m parameters are 0.08 and 0.9, respectively. In MOGWO, the N Wolf parameter is set to 300, the Max it parameter is set to 200, and the A and C parameters are assigned values of 1 and 2, respectively. Table 3 presents the summary of the results of setting the parameters of the algorithms.

Table 3. Summary of MOGWO and NSGA II Parameter Setting Results

Algorithm	Parameter	Level 1	Level 2	Level 3	Best Value
NSGA II	$N\ pop$	100	150	200	**200**
	$Max\ it$	150	200	300	**200**
	P_c	0.03	0.05	0.08	**0.08**
	P_m	0.7	0.8	0.9	**0.9**
MOGWO	$N\ wolf$	100	150	200	**300**
	$Max\ it$	150	200	300	**200**
	A	1	2	3	**1**
	C	1	2	3	**2**

5. Analysis of Numerical Results

5-1. Validation and Analysis of the Mathematical Model

LP-Metric has been used to validate the two-objective mathematical model and sensitivity analysis. In this method, in addition to obtaining the best value of the objective function individually, the set of efficient solutions is obtained by changing the weight of each objective function (Equation 12). For this purpose, Monte Carlo simulation was employed to create random weights. The numerical example, considered for validation and sensitivity analysis, includes five patients, two types of medical services, three types of expertise levels, four doctors for two consecutive days. The values of the parameters of the problem are randomly generated in Table 4. Furthermore, the level of expertise of each doctor and the type of service provided by them are presented in Table 5. The type of demand needed by each patient every day has been collected by Green Internet of Things tools and provided to the hospital.

Table 4. Values of Deterministic and Non-Deterministic Parameters of the Problem

Parameter	Range	Parameter	Range
x_j, y_j	$\sim U(0,25)$	f_j	$\sim U(1,540)$
d_{jk}	$\sqrt{(x_j - x_k)^2 + (y_j - y_k)^2}$	t_{isl}	$\sim U(50,60)$
$\tilde{a}$	$[50,70,85]$	$\tilde{c}$	$[\sim U(4,5), \sim U(5,6), \sim U(6,7)]$
e_j	$\min\{1, \lvert f_j - U(120,240)\rvert\}$	h_{il}	$\sim U(500,700)$
α	0.5	g_{isl}	$\sim U(60,100)$

Table 5. The Level of Expertise of Doctors and the Type of Their Services

Patients	Type of requested service		Physician	Physician services	Service Level
	Period 1	Period 2		Each period	
1	1	2	1	1	General
2	2	2	2	1-2	Specialist
3	1	1	3	1	General
4	2	2	4	2	Specialist Super
5	1	1			

The two-objective mathematical model was solved by $LP - Metric$ in GAMS 23.4.2 software with the Cplex solver and the set of effective solutions in 50 consecutive iterations of Monte Carlo simulation, as shown in Table 6.

Table 6. Set of Efficient Solutions with LP-Metric

Efficiencies Solution	OBF1	OBF2	Efficiencies Solution	OBF1	OBF2
1	2529.82	5703.44	7	2700.14	6999.97
2	2535.27	5815.20	8	2751.35	7272.78
3	2553.73	6057.90	9	3016.09	7443.44
4	2600.16	6426.09	10	3029.46	7563.81
5	2625.45	6736.68	11	3058.37	7608.11
6	2669.31	6956.13	**Best Value***	**2432.69**	**8114.36**

The results presented in Table 6 suggest that employing doctors with a higher level of expertise during patient visits increases overall patient satisfaction, while also leading to higher visit costs. According to the limitations of the problem, the maximum patient satisfaction is 8114.36. Therefore, the lowest average satisfaction observed in the analysis is 70.28%, while the highest average satisfaction is 93.76%. The scheduling of doctors' presence in home care and vehicle routing obtained for the first efficient solution are illustrated in Figure 6.

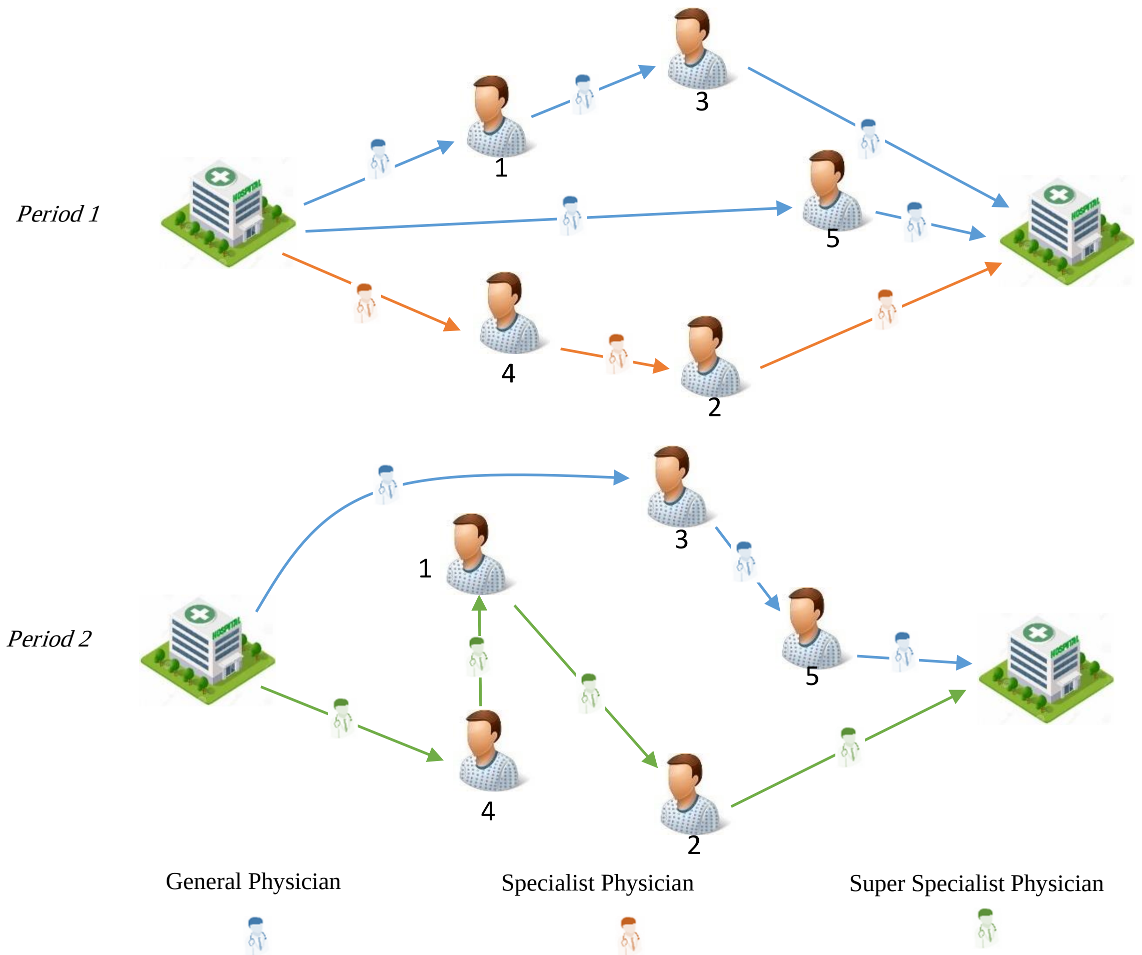


Figure 6. Physician Attendance Scheduling in Home Care and Vehicle Routing With LP-Metric

The results of model implementation and output variables analysis indicate that the designed model moves in the direction of equal optimization of two objective functions. For more detailed analysis, Table 7 represents the changes of the objective functions of efficient solution No. (1) in different rates of uncertainty.

Table 7. Set of Efficient Solutions with LP-Metric

Uncertainty Rate	OBF1	OBF2	Average patient satisfaction
0.1	2385.67	6000.78	% 73.95
0.2	2415.90	5974.12	% 73.62
0.3	2445.74	5974.12	% 73.62
0.4	2503.62	5703.44	% 70.29
0.5	2529.82	5703.44	% 70.29
0.6	2589.64	5703.44	% 70.29
0.7	2670.28	5528.67	% 68.13
0.8	2710.55	5528.67	% 68.13
0.9	2784.67	5323.22	% 65.60

The results presented in Table 7 indicate that as the uncertainty rate increases, the speed of vehicles decreases, total costs rise, and the average patient satisfaction declines. Specifically, with a 40% increase in the uncertainty rate, the level of satisfaction decreases by 4.69%.

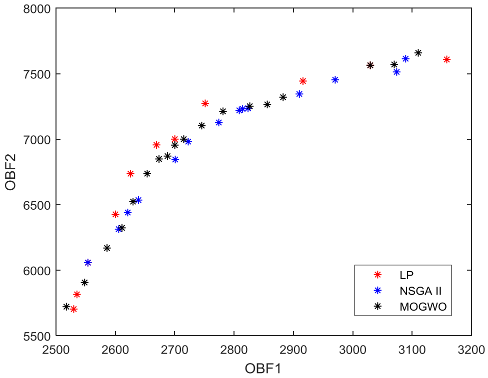
5-2. Analysis of Different Numerical Examples

The NP-hard nature of the mathematical model has facilitated its application in this paper to address problems with larger sample sizes compared to NSGA II and MOGWO. Consequently, Table 8 presents the sizes of the sample problems in larger dimensions. The size of the first sample problem is equivalent to the numerical example analyzed in the previous section.

Table 8. Size of Numerical Examples in Different Sizes

Sample Problem	|P|	|I|	|T|	|S|	Sample Problem	|P|	|I|	|T|	|S|
1	5	4	2	2	9	60	16	15	4
2	10	4	2	2	10	70	16	15	5
3	15	6	4	2	11	80	20	15	5
4	20	6	4	3	12	90	20	20	5
5	25	8	6	3	13	100	24	20	6
6	30	8	6	3	14	120	24	25	6
7	40	12	8	4	15	150	28	30	6
8	50	12	8	4					

After designing the numerical examples, the Pareto front obtained from the first numerical example with LP-Metric, MOGWO, and NSGA II is illustrated in Figure 7. The data used in this analysis are presented in Table 4.



Index	LP	NSGA II	MOGWO
NPF	11	14	18
MSI	230.60	286.47	265.94
SM	0.348	0.560	0.412
CPU-Time	223.81	28.49	26.33

Fig. 7. Pareto Front Obtained from the Solution of the Numerical Example of Small Size

According to Figure 7, it can be argued that an increase in the total patient satisfaction correlates with an increase in the total costs associated with the problem. In this sample problem, LP-Metric obtained 11 efficient solutions, NSGA II achieved 14 efficient solutions, and MOGWO achieved 18 efficient solutions. Moreover, the results indicate that the problem-solving time with NSGA II and MOGWO is significantly less than that for LP-Metrics. Notably, MOGWO has obtained the lowest computation time with the highest number of efficient solutions, demonstrating the high efficiency of this method in solving the vehicle routing problem for scheduling the presence of doctors in home care. Table 9 indicates the indices obtained from different solution methods.

Table 9. Comparison Indices of Efficient Solutions in Different Numerical Examples

Sample	MOGWO				NSGA II			
Problem	NPF	MSI	SM	CPU-Time	NPF	MSI	SM	CPU-Time
1	18	265.94	0.412	28.49	14	286.47	0.560	26.33
2	21	319.41	0.588	38.63	18	286.24	0.364	36.89
3	21	333.39	0.476	48.26	20	237.65	0.297	46.10
4	28	248.93	0.429	57.60	28	356.30	0.356	55.02
5	22	364.21	0.316	68.28	30	277.79	0.407	65.22
6	18	358.73	0.470	82.48	24	284.07	0.510	78.78
7	25	286.56	0.342	97.21	20	283.39	0.391	92.86
8	16	269.43	0.386	117.71	18	356.64	0.448	112.44
9	27	380.41	0.631	143.88	18	256.54	0.314	137.43
10	30	261.13	0.298	176.60	24	247.41	0.457	168.69
11	25	254.60	0.532	210.81	20	248.82	0.295	201.38
12	27	303.89	0.465	257.71	28	248.90	0.578	246.17
13	16	248.74	0.552	316.67	16	320.93	0.583	302.50
14	22	259.56	0.386	380.37	23	308.67	0.462	363.34
15	29	248.83	0.417	441.50	27	238.50	0.546	421.74

Based on the average indicators presented in Table 9, MOGWO has managed to obtain 23 efficient solutions during 164.41 seconds with a spread of 293.58 and a uniformity of 0.446. However, NSGA II has obtained 21.86 effective solutions in 156.99 seconds with a spread of 282.55 and a uniformity of 0.437. These results indicate that the efficiency of MOGWO is higher than that of NSGA II in terms of searching the problem space, while the efficiency of NSGA II is higher than that of MOGWO in terms of execution speed. The similar results of the two algorithms have led to the investigation of the significant difference between the two solution methods using the T-Test test at the 95% confidence level. Figure 8 presents the results of the T-Test statistical test to check the significant difference of the indicators.

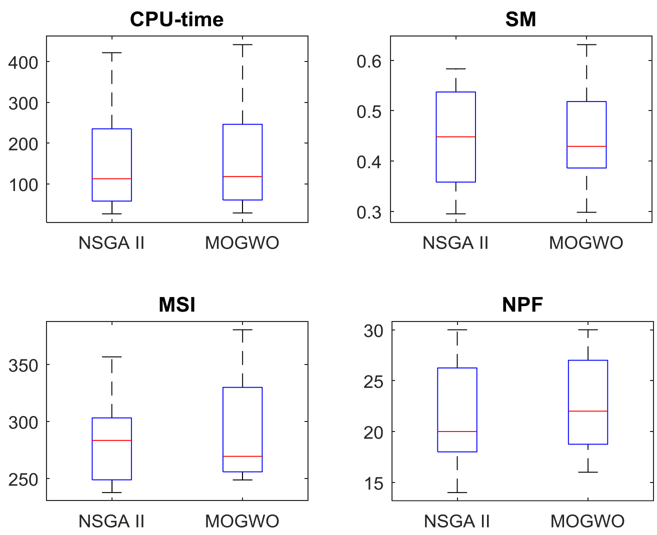


Fig. 8. Box Plot and T-Test Statistical Test Results

Index	NPF	MSI	SM	CPU-time
T-Value	0.65	0.70	0.24	0.16
P-Value	0.521	0.487	0.881	0.875

Based on the results, there is no significant difference between the average of all comparison indices, as indicated by P-Value > 0.05. The ranking of the solution methods in these cases is conducted using TOPSIS, with equal weights assigned to the comparison indicators. In this context, MOGWO has obtained the top rank with a desirability weight of 0.558.

6. Conclusions and Suggestions

In this article, an integrated model of Internet of Things (IoT) and vehicle routing was presented for scheduling the presence of doctors in home care. The importance of treating patients with respect to sustainability aspects led to the minimization of total costs and maximization of patients' satisfaction from receiving services based on Green Internet of Things in the presented model. Due to uncertainty in the real environment, pessimistic fuzzy programming method was used to control non-deterministic parameters. The results indicated that employing doctors with a higher level of expertise to visit patient will lead to an increase of total patient satisfaction and total costs. The analysis revealed that the lowest average patient satisfaction is 70.28%, while the highest average patient satisfaction is 93.76%.

By examining the effect of the uncertainty rate on the values of objective functions of the model, it was also observed that, with the increase of uncertainty rate, the speed of the vehicles declines, the total costs rise, and the patient satisfaction decreases. So that with a 40% increase in the uncertainty rate, the level of satisfaction decreases by 4.69%. On the other hand, due to the NP-hard nature of the problem, MOGWO and NSGA II were employed to solve it. The analysis of 15 sample problems revealed that MOGWO achieved 23 effective solutions in 164.41 seconds, with an extent of 293.58

and a uniformity of 0.446. In contrast, NSGA II obtained 21.86 effective solutions in 156.99 seconds, with a spread of 282.55 and a uniformity of 0.437. These results indicate that the efficiency of MOGWO is higher than NSGA II in terms of searching the problem space, while the efficiency of NSGA II is higher than MOGWO in terms of execution speed. Furthermore, there was no significant difference between the average indices. Therefore, by using TOPSIS, MOGWO obtained a higher desirability weight than NSGA II.

A critical aspect of this study is comparing its findings with previous research to highlight the contributions and improvements introduced by the proposed model. While various studies have addressed physician scheduling and vehicle routing in home healthcare, they have often focused on either optimizing travel routes or improving service allocation, disregarding sustainability aspects. Some have employed heuristic and metaheuristic algorithms, yet they have been primarily focused on minimizing operational costs rather than integrating environmental concerns.

The results of this study imply that incorporating Green IoT not only enhances the efficiency of physician scheduling but also significantly reduces fuel consumption and greenhouse gas emissions, which is deemed a valuable advancement compared to previous models. Unlike earlier research that relied on static scheduling, the proposed approach dynamically adjusts routes based on real-time patient data, leading to higher patient satisfaction and improved resource utilization. Furthermore, the application of MOGWO in this study demonstrates superior performance in finding efficient solutions compared to traditional optimization techniques, reinforcing the robustness of the proposed methodology.

The various limitations identified in this article, such as the lack of consideration for laboratory services, have prompted the design of a hybrid model for providing health services in conjunction with laboratory services. Additionally, the objective function of minimizing harmful environmental effects is suggested for further research. The development of combined solution methods to achieve better results is also proposed as a future direction.

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