Research Article

Scheduling and Routing of Dispatching Medical Staff to Homes Healthcare from Different Medical Centers with considering Fairness Policy

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Home healthcare, a novel type of health treatment provided at residents' homes for specific populations (elderly, disabled), is typically less expensive, more convenient, and efficient. The purpose of this article is to offer a paradigm for scheduling medical professionals from various medical institutes. With the need for home health care likely to expand significantly, future work is critical to lowering costs and ensuring service quality. The high expense of hiring nurses and doctors in this home health system (HHS) necessitates optimization approaches. To handle choice difficulties, we present a new algorithm that generates numerous scenarios, including current nurse schedules, the new demand under discussion, and future requests generated by the system. By analyzing several real-life factors and a new algorithm that produces numerous situations involving nurses' schedules to solve three problems, the model offered is integer number programming. The results indicate which center each nurse is dispatched from, and each nurse returns to the original routing point. Finally, average daily visits increase by roughly 20%, while daily travel times of each visit drop by 50%.

1. Introduction

Nowadays, different industries have increased the service capacity while saving costs by using different methods in solving routing and scheduling problems. One of the most suitable types of business in the service sector is related to home health systems (HSS). In the processes related to home health systems to send nurses or doctors to patients' homes to provide various medical services, time and cost planning is always involved. According to the report by the United States healthcare agency, more than 4.7 million patients used HHS services by 12,200 service providers. On the other hand, it should be noted that about 143,600 medical staff in this country are working full time in this field [1]. Numerous studies are pertinent to the concept of HHC services. The caregivers of HHC services are typically nurses, physicians, therapists, and nutritionists who

provide further data about these services. They can offer various services to help with the complete range of care. They are hired by a firm that oversees the patients' care. So far, much valuable research has been done in this field, which has improved the planning and allocation of medical staff to patients and improved the quality of services provided to patients at home. A case study conducted in 2016 by [2] shows that researchers have looked at this area from different perspectives, taking into account different goals and limitations. Among the plans that have been considered so far are minimizing travel time, travel costs, and the number of nurses employed, paying attention to patients' priorities, and observing justice. In addition, limitations such as uncertainty, time window, and required skills are considered. One of the less considered assumptions is the dispatch of medical staff from different departments or centers. In other words, in

previous research, the primary assumption is to be sent from one center and returned to the exact center after the operation.

The issue of vehicle routing in its initial state consists of several customers and a department (warehouse). The primary purpose of these issues was to minimize the cost or the total distance traveled from the origin and return to the same starting point. Fathollahi-Fard et al. [3] suggested HHC is an academic version of the classic Vehicle Routing Problem with Time Windows (VRPTW), with implementation to home care services that take into account working-time matching and care continuity. Because this is a more sophisticated improvement than a traditional VRPTW, which is NP-hard, an effective optimization solution technique to better execute HHC service planning is required.

In the real world, besides these VRP problems, we face more complex issues, such as multiwarehouse or multidepartmental routing problems (MDRP), which are a general form of vehicle routing problem (VRP) problems [4]. The problem of multivehicle vehicle routing was first proposed by Wang et al. [5]. However, other researchers such as Ueda and Fujii [6] and Deng et al. [7] had previously proposed this problem. They proposed innovative solutions without presenting a mathematical model for the problem. Shiri et al. [8] studied the routing problem by extending the Multidepot Vehicle Routing Problem (MDVRP).

It should be mentioned that multiwarehouse (departmental) routing problems are part of NP-hard problems. There is no specific algorithm for their optimal solution, so many researchers have tried to provide innovative and efficient solutions to these problems. The method of solving multiwarehouse routing problems in small dimensions was developed by Nucamendi-Guillén [9]. However, there has been an essential assumption in most vehicle routing issues so far. The initial department or warehouse is the same as the final warehouse (after service). The vehicle is returned to the same department after the service is completed. This assumption, or rather this limitation, was first dispelled by Sadati [10] with the publication of a study entitled "Flexible Allocation." According to this research, each device can be reloaded in another department, and the end department in each route can be different from the initial base. Our main contributions are the following:

(1) A scheduling algorithm for the flexible HHC routing and scheduling problem presented that considers future demand considerations and can manage numerous nurses with various competence levels

(2) Realistic evidence on effectively arranging practitioner routing and scheduling without limiting them to specific districts

(3) Algorithm efficiency under various scenarios, including multiple service areas, variable service hours, and diverse service objectives

This is the central assumption we need to make before (sending medical staff from one of the existing centers without any restrictions on returning to the sending center). Accordingly, in Section 2, related works will be reviewed; the

hypotheses and how to formulate the research problem will be presented in Section 3. In Section 4, the results of coding the model in GAMS software are presented. In Section 5, there are the results and summaries, future research horizons, and suggestions for expanding the topic to other discussions for the benefit of research enthusiasts in this field.

2. Related Works

During the first time in this research topic, 1 provided one of the first multiobjective approaches to minimize the entire cost of traveling distance for caregivers and the inconvenience of patients. A VNS and dynamic programming-based solution algorithm was created. Their primary discovery was that Pareto-based options might be used to balance total expense and patient annoyance.

This section explores appointment scheduling methods that address variable appointment intervals and heterogeneous no-shows. We begin with models that consider different appointment intervals. Our next step is to study models with heterogeneous no-show probabilities. Lastly, we will present the contributions of our proposal. Note that the appointment interval is different from the service time. The former is the scheduled duration during an appointment, while the latter is the patient's time. In the research conducted by Ruiz-Hernández et al. [11], it is assumed that service time is deterministic but unknown in work modeling different appointment intervals. According to Cayirli [12], they simulate different appointment and sequence rules by varying service times for new and previous patients and changing the presence of homogeneous absences. In order to converge with optimum appointment lengths for each class, Huang and Verduzco [13] reclassify patients into different types of visits and analyze performance measures, such as patient waiting time and physician downtime. Data mining has been used by Bentayeb et al. [14] to develop a time-of-service model for scheduling appointments using an appointment scheduler. With 84% accuracy, they predict service times using classification trees and regression trees. Simulations are then run to determine the best sequence of patients based on different scheduling rules. To our knowledge, no research articles are addressing variable appointment intervals that use an optimization approach to determine optimal patient assignments. Another recent research offered a set of VNS changes for a multidepot HHC that took into account doctor working-time balancing. The development of these adjustments was their key originality, and they demonstrated that their performance is quite competitive. Finally, to formulate a supply chain HHC with the option of request outsourcing, Ratcliffe et al. [15] presented a bilevel programming technique. Three hybrid optimization techniques have been developed to address this model.

Tirkolaee et al. [16] developed a new mixed-integer linear programming (MILP) model for the sustainable periodic capacitated arc routing issue (PCARP) in MSW management. The goals are to reduce overall cost total

environmental emissions, maximize citizen pleasure, and reduce workload variance simultaneously. Systems that consider heterogeneous no-show probabilities, on the other hand, rely primarily on stochastic programming approaches in terms of arrivals and service times. The service time is assumed to follow a particular probability distribution regardless of the appointment interval (fixed or variable). Due to the computational complexity of these models, appointments are typically split based on no-show probabilities rather than using the possibilities directly. By controlling two classes of patients with varying rhythms of showtimes, Yan et al. [17] apply a dynamic stochastic scheduler to maximize profits. In order to develop partially optimal scheduling rules, they create analytical bounds and approximations. Savelsbergh and Smilowitz [18] include multiple patient no-show probabilities and exponential service times in a sequential scheduling model, yet the appointment interval remains constant. Using different class probabilities and appointment intervals to schedule a full day, Ding et al. [19] investigate the analytical properties. For example, they suggest scheduling patients according to the rule of the shortest processing time (SPT) in the presence of homogeneous probabilities and variable appointment times. Habibnejad-Ledari et al. [20] develop a model for sequential appointment scheduling that considers both patient choice and service fairness at the same time. In stochastic programming, no-show probabilities are assigned to different patients with homogeneous appointment intervals. Mirjalili et al. [21] considered WOA and NSGA with various hypotheses to meet the analysis and different factors related to patients in the hospital. In the last part of the model, this paper has analyzed NSGA and WOA with three cases. Fairness policy first come, first serve (FCFS) considers the most priority factor to obtain from figure to strategies optimized solution for best satisfaction results. In 2018, Khodabandeh [23] used a Lagrangian relaxation-based method to solve a standard HHC model with the goal of minimizing total cost as a version of the VRPTW. They also took into account the travel balancing hypothesis. Their discovery was the performance of the lower limit in comparison to the precise solution. Derceel et al. [22] developed a linked optimization model that incorporated the nurse-scheduling problem with VRPTW at the same time. They compared the results of their hybrid algorithm to those of individuals. As a result, the scheduling system can be improved using modern predictive techniques applied to EHRs, which estimate the likelihood of patient no-shows. In research conducted by Tirkolaee et al. [24], the location-routing problem (LRP) is proposed to be expressed using stochastic demands and journey time. The second step modeled the inventory control problem using a queuing system based on the specified locations and routes. Two small and big illustrative cases and several problem scenarios are used to test the applicability of the proposed technique. Liu et al. [25] considered, for the cross capacitated arc routing problem, a chance-constrained programming model based on fuzzy credibility theory is proposed to deal with the uncertainties of the waste amount produced in metropolitan centers with the goal of total cost minimization and a Taguchi method development methodology to modify the parameters' values optimally.

3. Problem Status

The consideration constraint is the routing and scheduling of multiple nursing staff in a dynamic situation. Reference [25] has presented a definition but expanded it to enable various nurses. Furthermore, over the scheduling optimization, patients' multitimes are exponentially distributed with defined features.

$$K^n = \{b + i : i = 0, 1, \ldots, k\},$$
$$K_i^n + sd_i + h(l_i, l_j) \le K_j^n, \tag{1}$$

where b is the newest appointment time and $\varnothing$ is the period between appointments; h in minutes reflects the travel time between patients i and j, where N denotes the position of patient i. sd_i is the service during previsit by doctor for patient i.

(1) A visit, constituting a duty at a patient's home, must be performed as frequently as determined

(2) Every patient can choose their monthly visit days

(3) If approved, patients must be treated on the same days, at the exact times, by the same doctors per week during the specified service range

(4) Nurses begin tours from their residences and return home within the shift's time frame

4. Proposed Model

Before presenting the mathematical model, the essential hypotheses for this research will be stated, followed by the indices, variables, and parameters and, finally, the formulated model.
Assumptions:

(1) Each patient will be visited only once by each nurse

(2) The number of nurses is predetermined

(3) There is a fixed and uniform cost for each nurse to use (nurses' skills are assumed to be the same)

(4) The number and location of patients' residency are predetermined

(5) Department of referral and destinations are not necessarily the same for nurses (depending on the situation)

4.1. Model Index

(i) *i:* index intended for patients

(ii) *j:* index for patients

(iii) *k:* index related to nurses

(iv) *d:* Department Index (Medical Centers)

4.2. Parameters

N: number of patients

V: number of nurses

D: number of departments (medical centers)

G: number of patients and nurses (total nodes)

M: a huge positive number

F: fixed fee for hiring each nurse

R: working hours available

L_i: time of patient's visit

P_{ij}: the time taken for the nurse to leave the patient I to j

C_{id}: time for routing between patient I and department d ($C_{id} = C_{di}$)

X_{ijk}: variable zero and one: if nurse k travels to patient j's home immediately after patient's visit, it takes one, and otherwise zero

Y_{dik}: Variable zero and one: if nurse k travels from the medical center d to the patient's house, I will get the value of one and otherwise zero

Z_{idk}: variable zero and one: if nurse k returns from the patient I's home to treatment center d, she will get a value of one, otherwise zero

W_k: variable zero and one: if nurse k is used, it takes the value of one and otherwise zero

U_{lk}: auxiliary variable for use in subroutine deletion restriction

T_{ik}: the time nurse k arrives at the patient's home i

The objective function of the model is calculated as follows:

$$\text{Min } Z = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} \sum_{k=1}^{V} P_{ij} X_{ijk} + \sum_{i=1}^{N} \sum_{d=1}^{D} \sum_{k=1}^{V} C_{i\,d} Y_{dik}$$

$$+ \sum_{i=1}^{N} \sum_{d=1}^{D} \sum_{k=1}^{V} C_{i\,d} Z_{i\,dk} + \sum_{k=1}^{v} F * W_k. \tag{2}$$

Equation (1) shows the model's objective function, which is to minimize the total time and costs. It should be noted that three-time parameters and a cost index are considered: nurses' departure time from one of the departments (medical centers) to patients' homes, travel time between patients' homes, return time from patients' homes to one of the departments, and also fixed cost of using nurses.

And the constraints of the model are as follows:

$$\sum_{d=1}^{D} \sum_{k=1}^{V} Y_{\text{dik}} + \sum_{\substack{j=1 \\ j \neq i}}^{N} \sum_{k=1}^{V} X_{jik} = 1, \quad \forall i \in N, \tag{3}$$

$$\sum_{\substack{j=1 \\ j \neq i}}^{N} \sum X_{ijk} \sum_{d=1}^{D} \sum_{k=1}^{V} Z_{i\,dk} = 1, \; \forall i \in N. \tag{4}$$

Equations (3) and (4) indicate a concept, and that is that each patient is visited only once. Of course, the intended path in this constraint is different. Equation (3) indicates the

beginning of the route and movement from one department to the patient and between two patients, and (4) shows the journey between two patients and the end of the route.

$$\sum_{d=1}^{D} \sum_{i=1}^{N} \text{dik} - \sum_{j=1}^{N} \sum_{d=1}^{D} Z_{jdk} = 0, \quad \forall k \in V. \tag{5}$$

Equation (5) states that every nurse begins their journey from one medical center to another.

$$\sum_{d=1}^{D} Y_{di\,k} + \sum_{\substack{j=1 \\ j \neq i}}^{N} X_{jik} - \sum_{\substack{j=1 \\ j \neq i}}^{N} X_{ijk} - \sum_{d=1}^{D} Z_{idk} = 0, \quad \forall i, k. \tag{6}$$

Applying (6) makes the input and output equal for each visit. In other words, each patient is connected to the nurse only through one route.

$$U_{ik} - U_{jk} + GX_{ijk} \leq G - 1 \forall i, \quad j \in N, k \in V. \tag{7}$$

Equation (7) is known as subroutine deletion restriction.

$$t_{jk} + P_{ij} + L_j - t_{ik} \leq M(1 - X_{jik}) \forall i, j \in N, k \in V. \tag{8}$$

Equation (8) for calculating the time of arrival of a nurse at the home of a patient (here patient j) is according to the priority and latency and if it is possible to route between two patients of i and j.

$$C_{di} - t_{ik} \leq M(1 - Y_{\text{dik}}) \forall d \in D, k \in V, i \in N. \tag{9}$$

Equation (9) is used to calculate the time of arrival of the nurse to the patient's home in case of departure from the medical center. In other words, when the nurse arrives if the patient is at the beginning of the route:

$$\sum_{d}^{D} \sum_{i}^{N} Y_{\text{dik}} = W_k \forall k \in V. \tag{10}$$

Equation (10) states that if a nurse is sent from a medical center, it must first be assigned to the route and the patients.

$$\sum_{d}^{D} \sum_{i}^{N} Y_{\text{dik}} \leq 1 \forall k \in V. \tag{11}$$

From (11), it is understood that not every nurse either starts a route or only starts from a medical center.

$$\sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} (P_{ij} + L_i + L_j) X_{ijk} + \sum_{i=1}^{N} \sum_{d=1}^{D} C_{i\,d} Y_{\text{dik}}$$

$$+ \sum_{i=1}^{N} \sum_{d=1}^{N} C_{di} Z_{i\,dk} \leq R \forall k \in V. \tag{12}$$

Due to (12), the total time of the visit per day will not be available for each nurse more than the time.

$$X_{ijk} \in \{0, 1\} \forall i \in N, k \in V i \neq j, \tag{13}$$

$$Y_{\text{dik}} \in \{0, 1\} \forall i \in N, k \in V, d \in D, \tag{14}$$

$$Z_{i\,dk} \in \{0, 1\} \forall i \in N, \quad k \in V, d \in D, \tag{15}$$

$$W_k \in \{0, 1\} \forall k \in V, \tag{16}$$

$$U_{ik} \geq 0 \forall i \in N, k \in V, \tag{17}$$

$$t_{ik} \geq 0 \forall i \in N, k \in V. \tag{18}$$

Equations (12)–17) indicate the type and values allowed for the variables used in the model.

Moreover, in this research, a fairness policy for improving the performance of the proposed model is considered. No one would disagree that the working conditions of the staff in the health services have an essential effect on the patients' health. So, improving these conditions can increase the success of the treatment process and get the patient's satisfaction. In addition to this, it is known that efficient utilization of staffing has always been a critical concern in any organization and one of the most important means to achieve productivity gain. For this reason, staff and patient scheduling are an area that has become increasingly important in some hospital services with high demand but with limited staff [26]. As the request for healthcare increases, the appointment scheduling of outpatients significantly impairs the utilization rate of medical resources and the quality of service. However, hospital appointment scheduling is restrained by factors like the lack of slots, number of beds, the category of outpatients, timetable of surgeries, and room scheduling. As these factors make appointment scheduling complex, the traditional first come, first serve (FCFS) fairness strategy cannot guarantee effectiveness. Besides, the two significant purposes of healthcare services, i.e., enhancing the utilization rate of medicinal resources and maintaining fairness, usually confront each other. Thus, an adequate and fair strategy is demanded appointment scheduling of outpatients. As mentioned above, high demand for this service requires proper patient and personnel scheduling that ensures the maximum number of patients benefiting from this service via high utilization of staffing. Moreover, maximizing the number of patients benefiting from this service, it is essential to balance the workload of medical staff and make a fair schedule because of the working conditions mentioned above. The case study is conducted in the physiotherapy department service of a general hospital in Shanghai. Some problems that patients and staff encounter and some inappropriate applications in this service can be explained as follows [26]:

(1) Selection of patients for physiotherapy is made according to their application time for an appointment. That means the "the first come is first served" rule is accepted.

(2) The assignment of patients to the physiotherapist is made randomly, and fairness among them is not considered. Moreover, due to this unfair assignment policy, some physiotherapists may sometimes have an overcapacity workload while others have a lower-capacity workload.

(3) Later, the accepted patients are assigned a day for the therapy. In this system, the patients are not scheduled at any time interval in a day. In other words, people come to the service early in the morning on their treatment day and then take a sequence number. Because of this system, the patients have to wait long in the hospital.

A scheduling approach is proposed, which consists of three hierarchical mathematical models to select the maximum number of patients, achieve a fair distribution of patients among physiotherapists, and decrease patients' waiting time.

The first step of the process is to determine the maximum number of patients serving from this service concerning predetermined staff capacity. Patients must be selected before scheduling optimization because of the extremely high demand for this service. Hence, the selection of patients for treatment among the total patients is made according to doctors' priority, which means we provide FSFC policy in this stage. In the second step, it is aimed to assign patients among physiotherapists taking fairness into account. For that reason, the other important goal of the study is to provide a balanced schedule for every physiotherapist. Lastly, the selected patients are scheduled throughout a working day to minimize their waiting time [26].

5. Experimental Results

After modeling the research problem, coding was done to test the model's accuracy in GAMS software, which is a problem, for example. In this case, two nurses must visit six patients. The number of medical centers (departments) is assumed to be 3 cases. Other preliminary data for this issue are as Table 1, Table 2, and Table 3.

It is worth noting that the available time of nine hours is considered as a work shift. Also, the amount of fixed cost for each nurse is ten monetary units.

Finally, the solution to the problem, which is the same route and time for each nurse, as well as the total cost, is as follows:

(i) For the first nurse (K1)

(ii) Starting point: Medical Center (Department) No. 2 (d2)

(iii) Arranging patient visits: patient number three (3), then patient number one (1)

(iv) Return point: Medical Center (Department) No. 3 (d3)

(v) For the second nurse (k2)

(vi) Starting point: Medical Center (Department) Number One (d1)

(vii) The sequence of patients' visits: patient number six (6), then patient number four (4), then patient number five (5), and finally patient number two (2)

(viii) Return point: Medical Center (Department) No. 2 (d2)

(ix) The value of the objective function was 27.7

TABLE 1: Time required for each patient visit.

Patient	1	2	3	4	5	6
Time	1	0.5	1	2	1	0.5

TABLE 2: Time elapsed for dispatching nurses from departments to patients.

Patient	Department		
	D1	D2	D3
1	2	1	0.5
2	1.5	1	1
3	2	0.7	1
4	0.5	1	3
5	1	2	1.5
6	0.5	1	1

TABLE 3: Travel time between two patients.

	1	2	3	4	5	6
1	0	2	1	1	3	1
2	2	0	2	3	2	2
3	1	2	0	2	3	3
4	1	3	2	0	1	1
5	3	2	3	1	0	3
6	1	2	3	1	3	0

The time for nurses to arrive at patients' homes will be as follows (Table 4); based on the data collected this arrival time is solved with the mathematic solver, which is shown as follows.

Moreover, in Figures 1 and 2, the performance of this method is compared with the method based on a genetic algorithm, which shows the better performance results of the proposed method.

The results presented in Figure 1 show that, in all cases, the performance of the proposed method was better than the genetic algorithm. The most significant difference between these two methods is seen in Case 2. Moreover, Figure 2 shows that the CPU time of the proposed method has always been less than the genetic algorithm. Therefore, it is concluded that the proposed method to solve the problem, both in terms of quality and speed of action, has the necessary efficiency.

6. Discussion

Whereas it is ideal for nurses to be near the core of their service areas, this is not always practicable. The model depicts a scenario in which nurses are not near the center of their service areas. This model depicts the daily average appointments and transit times for each visit for every patient. Although improving the model and evolutionary algorithm increases average daily visits in each scenario, the increments are more significant than those shown in Table 4. Furthermore, adjusting the locations of nurses has a more powerful impact on results when it comes to routing healthcare than it does when it comes to scheduling healthcare. For instance, evaluating scenarios reduces typical

TABLE 4: The time for nurses to arrive at patients' homes.

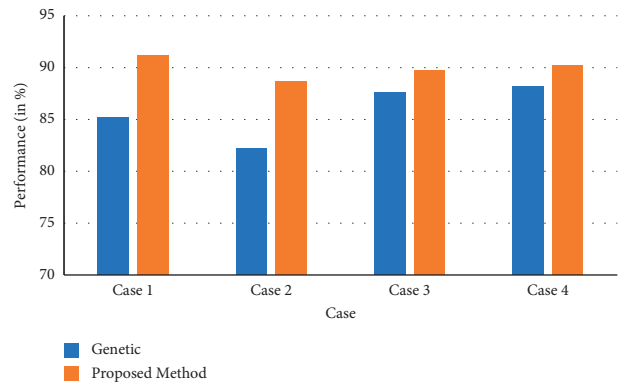| Patient	Nurse	
	1	2
1	2.7	—
2	—	8
3	0.7	—
4	—	2
5	—	5
6	—	0.5

FIGURE 1: Comparison of the proposed method and genetic algorithm based on performance indicator.
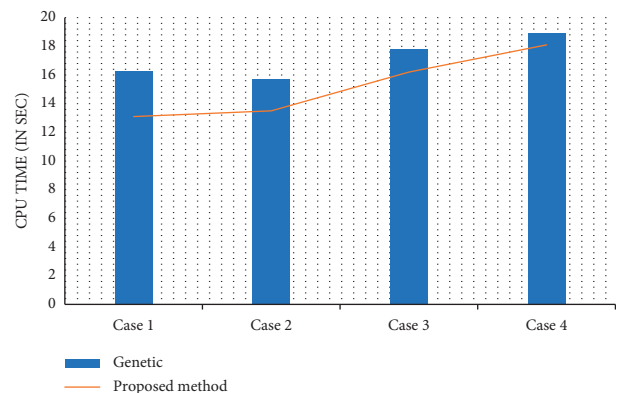

FIGURE 2: Comparison of the proposed method and genetic algorithm based on CPU time indicator.

daily nurse visits by roughly 10%, while routing home healthcare reduces consultations by only 2%.

On the other hand, the heuristic method displays the same behavior across a wide range of patient scenarios. If two nurses are on staff and demand is high; appointing nurses to districts boosts average daily visits and reduces per-visit travel time. Generally, the results suggest that when routing and scheduling, taking into account the entire service area, demand across the entire service area and all nurses at the same time produces better outcomes in terms of average everyday calls in each scenario. Furthermore, the basic scenario of routine home nursing appears to be more resilient to changes in nurse positions and predicted

demands. Idealized prerequisites for a district line problem include equal-sized regions, demand, and central nursing placements. As a result, average daily visits with per-transit times are near optimal.

7. Conclusion

This study was conducted on one of the branches of health systems in which medical staff refers to patients' homes to provide medical services. One of the innovations made in this article is the use of multiple departmental routing problems (MDRP) with the assumption of flexibility in choosing the source and destination for ensuring the accuracy of the modeling and the assumptions considered in the research and sample questions were coded in GAMS software. The solutions indicated the efficiency of the proposed model, one of these issues presented in the computational results section.

One of the important management aspects of this research is to reduce the decision time to serve patients at home. This issue has a great impact on the quality of service. Using the proposed mathematical model and the solution method can greatly help managers and decision makers in this field.

However, suggestions for future studies and development of this issue can be made, such as increasing the variable cost of overtime or differences in costs according to nurses' skills or the use of time window concepts. Metaphorical algorithms such as particle swarm or genetics can also be used to prove the performance of the proposed model on a larger scale.

Data Availability

The Author have declare based on this manuscript the Data available on request.

Conflicts of Interest

The authors declare there are no conflicts of interest.

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