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Routing and Scheduling for A Home Health Care Problem Considering Health Workers' Skills

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Abstract

In Home Health Care (HHC) operations, one of the major aims of HHC centers is to timely meet patients' demands. According to the feedback from HHC centers, their decision-makers deal with some complexity in scheduling and routing of their health workers. Inspired by this point, the present research introduces a new HHC routing and scheduling problem considering different skill levels of health workers and different levels of patients' needs. So, in such a condition, a highly qualified health worker can visit those patients who need lower-skilled demands while a low-qualified health worker cannot visit those who request higher skills. In this way, the total cost of the system will be lower compared to the situation in which the patients' needs exactly match the health workers' skills. Moreover, we consider that the maximum number of homes each health worker is tasked to visit during the day is specified and if more patients than this specified limit are assigned to each health worker, an additional cost will be imposed on the center in proportion to the excess number of patients. Since patient satisfaction, which is obtained with timely visits, is important for each HHC center, a hard time window is considered for each patient. The presented model is solved using the GAMS software with the CPLEX solver. Along with the MIP approach, a metaheuristic algorithm based on a Simulated Annealing (SA) algorithm is adopted to solve the problem. The results give the managers insight into this method of cost management in comparison with manual and traditional traditional planning. This study may help the decision-makers of HHC centers make more accurate decisions, which in turn result in timelier service provision, increase the patients' satisfaction level, and improve the overall efficiency of HHC centers.

Keywords: Home health care, Routing and scheduling, Health worker, Metaheuristic algorithm.

1 | Introduction

In any society, health care centers are directly involved in the health of individuals in that society, and provision of easy access to health services is of great importance. The term Home Health Care (HHC) refers to a service where a set of health workers serve the patients in their homes. In the HHC system, the schedule and routing of health workers are devised in such a way as to carry out several different services for patients in the comfort of their homes. To plan this system, patients requiring services are assigned to health workers with suitable skills and optimal routes are mapped for the health workers [1].

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HHC centers provide a wide range of care services such as medical tests, wound care, injections, psychological counseling, and visits. Providing care in patients' homes is generally less expensive, more convenient for patients, than and often as effective as the care provided in hospitals [2].

Importantly, HHC centers perform medical and other types of service for senior citizens and patients struggling with chronic discomforts. According to 2019 projections of World Health Organization (WHO), the world population aged at least 60 might increase from 962 million to an estimated 1.4 billion by the year 2030 and to over 2.1 billion by the year 2050 [3]. Thus, the number of senior citizens and, as a result, the number of people requiring various types of care is expected to increase in the coming years, intensifying the need for more HHC services.

In HHC problems, the procedure of providing services for patients is often classified as follows. Firstly, the HHC center collects the required information from their patients. Next, the decision-makers at the HHC center develop a suitable schedule considering the collected data and their available resources. Lastly, the health workers are dispatched to patients' homes with a list of the tasks they are expected to perform [4].

Routing and scheduling of human resources are the most important issues in HHC planning. HHC scheduling and routing problems often require the integration of several factors and it is a very complex one due to the significant and various constraints such as routing, skill requirement, assignment, and time windows involved in this subject [5].

According to HHC centers, two of the most significant challenges faced by the centers are related to operational costs and delayed service for patients. A key objective at HHC centers is to meet the needs of patients in a timely manner [5]. It should be noted that delayed service may not only have a negative impact on the quality of treatment, it may also incur tardiness penalty costs and result in patient dissatisfaction [6].

The problem investigated in the present study is a young but growing research area because of its importance for today's society. Given the wide variety of treatments, investments in human resources, required equipment, and the prevalence of different diseases, it is necessary to support HHC providers with the latest scientific knowledge.

In a HHC problem, different patients have different levels of demands and thereby need different levels of skills and qualifications in their health workers. As a result, skill requirement constraints represent a critical aspect of HHC problems. Another important factor is the workload of health workers. The maximum number of homes each health worker visits during the day should be specified and if more patients are assigned to each health worker than the specified limit, they should be paid for their additional daily visits proportionally. This extra cost, however, may be lower than the cost of hiring additional health workers.

This study contributes to the HHC routing and scheduling problem by dealing with the following aspects: 1) we consider patients with different types of demand who, as a result, require different types of medical skills and qualifications. In this regard, we define a system which classifies the health workers according to their qualifications and skills and assigns a specific skill level to each health worker. Notably, health workers with high-level skills can perform services for patients who require simple services; however, health workers with low-level skills are not permitted to serve patients requiring specialized services. 2) To balance the workload of the health workers, the maximum number of homes each health worker should visit during each working day is specified. If a health worker ends up visiting more patients than the specified limit, they will receive an additional fee per each extra patient they visit. 3) We use a Simulated Annealing (SA) algorithm to solve the instances of the problem.

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This paper is organized as follows. Section 2 presents the recent works on HHC routing and scheduling problems. The mixed integer linear formulation is presented in Section 3. Section 4 illustrates the solution approach for the proposed problem. Then, numerical instances for the problem are investigated and analyzed in Section 5. Finally, the last section concludes the paper.

2 | Literature Review

Given the importance of the HHC routing and scheduling problem, in recent years, researchers have focused more on this issue and published various HHC optimization problems. The problem studied in the present research is commonly introduced as an HHC routing and scheduling problem in the literature. To the best of our knowledge, the earliest study on the HHC routing and scheduling problem was carried out by Begur et al. [7], who has presented a sequential savings algorithm to handle an HHC problem in the USA. Afterward, Cheng and Rich [8] have presented a two- and a three-index formulation for the HHC problem and their solution method has been based on heuristic methods. Different review papers on this topic have been published so far. For more information, readers may refer to them [1], [5], [6], [9].

The most fundamental differences among the previous works in the field of HHC routing and scheduling are the considered objectives, constraints, and solution methods. Thus, the following is a small overview of previous studies with a focus on objectives, constraints, and solution methods.

The majority of works have considered the travel distance or the routing costs in the objective function (see [10]-[14]). However, some papers have taken into account several aims such as various costs and the satisfaction of nurses and patients in a weighted objective function [6]. Other terms considered in the objective function have included health worker salaries and the costs related to deviations from preferred visit times. Due to the high costs associated with nurse overtime, the reduction of overtime is often considered as a goal for HHC centers when the work time is longer than the contract. In other words, considering appropriate working hours for each cure staff member is essential in routing and scheduling problems. Trautsamwieser and Hirsch [13] have introduced a model formulation for planning and scheduling nurses in Austria with the objective of satisfaction of clients and nurses. Li et al. [15] have considered the travel costs, the waiting penalties of out-patients, and the benefit of patients' preference satisfaction in an objective function.

In HHC problems, planning and routing often need to integrate several constraints related to the management of nurses' work regulations, patient satisfaction, nurses' preferences, and matching of health workers' skills and patients' requirements. HHC problems also consider the measurement of the workload balance of nurses. These constraints have been differently implemented in recent works. Thus, combining these constraints often makes the modelling and solution of this problem difficult. In various studies, the time window constraint has been considered because treatments were often time-sensitive. For some patients, drugs should be better prescribed at a specific time, so, in this condition, a hard time window is considered. In some cases, both soft and hard time windows have been considered for visiting patients, and penalties have been imposed on the objective function if the service occurred outside the time window [6]. Eveborn et al. [12] have developed a decision support system for Swedish HHC centers including urban areas, and because of the high density of clients, all trips have been done on foot. Their other study on this topic has been found in [16]. Fikar and Hirsch [17] have considered the possibility of going to clients' homes by walking, time windows, interdependencies, assignment constraints, break regulations, and mandatory working time in their problem.

En-nahli et al. [18] have optimized the goals of HHC centers, therapists, and patients. The goals of the centers included long-term services for patients with appropriate therapists and reduced travel and waiting costs. The therapists wanted to ensure that their workload was fair and the goal of the patients was to visit the preferred therapist within a specified time window. Liu et al. [19] have introduced two mixed integer programming models for a special vehicle routing to deliver drugs and medical devices to patients at their homes and collect bio samples and unused drugs from patients' homes simultaneously. As demonstrated

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in [11], [20], [21], the interdependent services have been considered with synchronization and temporal precedence between services. Elbenani et al. [22] have focused on the resolution of an HHC problem by taking into account that nurses should collect blood samples from some patients at their homes and deliver them to the clinic before a specific time window. Wirnitzer et al. [23] have focused on the number of nurses who are changed by the HHC center mid-treatment. The aim has been to let nurses stay with their respective patients throughout the entire treatment course and to send as few different nurses to each patient as possible. Fikar and Hirsch [17] have developed a model where a transport service transferred health workers to clients' homes and picked them up after they have completed their services. In recent years, HHC centers have been provided more complex care, such as end-of-life care, chemotherapy, and rehabilitation. In fact, HHC centers decide on the outsourcing of some of their activities. So, the decision is made on whether to manage all activities by the home care center itself or to outsource some activities. Rodriguez-Verjan et al. [24] have designed a home care network with the aim of locating HHC centers in an area considering medical demands, cost of resources, and facilities. They have optimized the management of HHC activities by making outsourcing decisions to treat patients. Two mixed-integer linear programs have been proposed to solve the problems and some decisions have been proposed at both strategic and tactical levels. Li et al. [15] proposed a HHC routing and scheduling problem which also considers outpatient services. The authors formulated the problem as a mixed-integer nonlinear and convex programming model in which the physicians are arranged for either door-to-door or outpatient services. Cinar et al. [25] studied a real-world problem wherein the nurses are tasked with checking upon patients either by visiting their homes or by making telephone calls. In this problem, patients are each assigned a priority. Furthermore, if some of the patients cannot be visited in their home within the planning horizon, they are checked upon through phone calls.

In the field of HHC routing and scheduling problems, solution methods are divided into two groups: exact solution methods and heuristic /metaheuristic methods. In the group of exact solution methods, the Branch-and-Price (B&P) approach is commonly used to solve the HHC problem (see [11], [26], [27]). It should be noted that in this field, the sub-problem includes a vehicle routing problem. Since the vehicle routing problem is an NP-hard problem, the HHC routing and scheduling problem is an NP-hard problem, too. Therefore, exact methods need more time to solve large-size problems. That's why the majority of works have implemented heuristic/ metaheuristic to solve large-size instances (see [10], [14], [15], [17], [28]-[30]). More recently, Decerle et al. [31] developed an approach based on matheuristic algorithm where different strategies were employed to assign visits and health professionals to the respective HHC business in order to solve the problem.

In the present study, an HHC routing and scheduling problem is studied to propose an efficient routing and scheduling strategy for the HHC problem. In the practice of HHC, different patients have different types of demands, which seek different types of skills and qualifications of health workers. The problem is modeled considering the skill requirements of patients. Thus, patients' demands are classified into several types according to the required skills. Different levels are defined for classifying health workers according to their skill. A highly qualified health worker can serve patients who need lower-skilled demands while a low-qualified health worker cannot visit patients who request higher skills. Specifically, in this paper, health workers are divided into three common categories: 1) some health workers provide specialized services (level-3), 2) Some provide general services (level 2), and 3) The third category provides low-level services (level-1). To balance the workload of health workers, the maximum number of visits is specified and if the number of patients assigned to a health worker exceeds this limit, more costs will be imposed on the center in proportion to the excess number of patients.

Table 1. Constraints of the HHC routing and scheduling problem in the literature.

References	Planning Horizon		Time Window	Skill Requirement	Working Regulation
	Short	Long			
Eveborn et al. [16]	*		*	*	
Akjiratikarl et al. [10]	*		*		
Dohn et al. [26]	*		*	*	
Trautsamwieser and Hirsch [13]	*		*	*	*
Rasmussen et al. [11]	*		*		
Mankowska et al. [20]	*		*	*	
Bard et al. [29]		*	*		*
Fikar and Hirsch [17]	*		*	*	*
Hiermann et al. [14]	*		*	*	
Yuan et al. [27]	*		*	*	*
Redjem and Marcon [32]	*		*		
Wirnitzer et al. [23]		*		*	*
Braekers et al. [33]	*		*	*	*
Macron et al. [34]	*		*		
Zhan et al. [35]		*	*		*
Shi et al. [4]	*		*		
Martin et al. [30]		*	*		
Fathollahi-Fard et al. [36]		*	*		
Frifta and Masmoudi [21]	*		*		
Decerle et al. [31]	*		*		
Cinar et al. [25]		*	*		
This work	*		*	*	*

The contributions of this paper are listed as follows:

I. We introduce and model a new HHC routing and scheduling problem which incorporates various types of demand and different levels of health worker skills and qualifications. Thus, patients' demands are classified into several types according to the required service and, correspondingly, the health workers are also classified according to their skill levels. In this system, highly qualified health workers are permitted to serve patients who need relatively lower-skilled services. However, the opposite is not true and health workers with low-level skills cannot serve patients who require specialized services. In addition, to balance the workload of health workers, the maximum number of visits for each health worker is specified. If more patients are assigned to a health worker than the predefined limit, more costs will be imposed on the center in proportion with the number of extra patients. In other words, if a health worker ends up vising more patients than the allowable limit on a working day, an additional fee is paid to the health worker for each extra visit.

II. We developed a metaheuristic algorithm based on SA to identify near-optimal solutions for the presented problem.

III. We investigate the accuracy and efficiency of the model by performing a sensitivity analysis on the problem's parameters. The computational evaluations indicate that the proposed algorithm can obtain good solutions for different instances.

3 | Problem Description and Formulation

This paper presents a model for solving an HHC problem. A simultaneous routing and scheduling problem is considered. This paper aims to find routes for nurses to visit all patients. The skill requirements of patients spread over different levels, and require different kinds of medical skills and qualifications. Thus, the demands of patients are classified into several levels according to the required skills. Health workers are also divided into different levels based on their own skills. In such a condition, a highly qualified health worker can serve patients who need lower skilled demands while a low-qualified health worker cannot visit patients who request higher skills. Specifically, in this paper, health workers are divided into three common categories: 1) some health workers provide specialized services, 2) some provide general services, and 3) the third category provides lower-level services. In this model, a time window for each patient is also considered. To balance the workload of health workers, the maximum number of visits is specified, and if the number of patients assigned to a health worker exceeds this limit, more costs will be imposed on the center in proportion to the excess number of patients.

The model is defined on a complete directed graph G = (V, E). The set of node V consists of the nodes of HHC center (0) and patients (J) (V = {0}∪J) and E is the set of arcs, E= {(i,j): i,j ∈V, i ≠j}. The set K includes the set of health workers. The model minimizes multiple costs such as travel costs, fixed costs of health workers, and additional visits the health workers may perform. The model determines the optimum number of health workers with different qualifications at the HHC center. The assumptions of the problem are listed as below:

- *Each health worker leaves the HHC center, visits assigned patients, and finally returns to the HHC center.*
- *The HHC center defines different levels to classify health workers according to their skills.*
- *Each health worker is tasked to perform a maximum number of patients and if the number of visits exceeds this number, more costs will be imposed on the center in proportion with the number of extra visits.*

The sets and parameters are defined as below:

Sets.

J: set of patients.

V: set of nodes that include a HHC center and patient nodes.

K: set of health workers.

Parameters.

L_j: the level of service for the jth patient's demand.

$[a_j, b_j]$: time window for patient j∈J.

C_1: travel cost.

C_{2k}: fixed cost for the kth health worker.

C_{3k}: cost of assigning additional patient to the kth health worker.

Le_k: level of skills for the kth health worker.

N: maximum number of visits specified for each health worker.

t_{ij}: travel time between nodes i and j.

C_{ij}: distance between nodes i and j.

Decision variables.

x_{ijk}: a binary variable: if a health worker directly travels from node i to node j, it will be one, otherwise 0.

y_k: a binary variable; if the kth health worker is dispatched, it will be one, otherwise 0.

st_i: time the visit starts for patient i∈J.

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E_k: number of additional patients assigned to the kth health worker.

The mixed integer linear formulation for this problem is defined:

$$TC = C_1 \sum_{i\in V} \sum_{j\in V} \sum_{k\in K} c_{ij} \cdot x_{ijk} + \sum_{k=1}^{n} C_{2k} y_k + \sum_{k=1}^{n} C_{3k} E_K, \tag{1}$$

$$\sum_{i\in V} \sum_{k\in K} x_{ijk} = 1, \quad j \in J \tag{2}$$

$$\sum_{j\in V} x_{ijk} - \sum_{j\in V} x_{jik} = 0, \quad \forall i \in J, K \in K \tag{3}$$

$$\sum_{j\in J} x_{0jk} \le 1, \quad \forall k \in K \tag{4}$$

$$\sum_{i\in J} x_{i0k} \le 1, \quad \forall k \in K \tag{5}$$

$$\sum_{i\in V} \sum_{j\in J} x_{ijk} \le N + E_k, \quad \forall k \in K \tag{6}$$

$$L_j \sum_{i\in V} x_{ijk} \le Le_k, \quad \forall j \in J, k \in K \tag{7}$$

$$st_j \ge st_i + t_{ij} + u_i - (1 - x_{ijk}).M, \quad \forall i \in V, \forall j \in J, k \in K \tag{8}$$

$$a_j \le st_j \le b_j, \quad \forall j \in J \tag{9}$$

$$\sum_{j\in J} x_{0jk} \le M.y_k, \quad \forall k \in K \tag{10}$$

$$x_{ijk}, y_k \in \{0,1\}. \quad \forall i \in V, \forall j \in J, k \in K \tag{11}$$

The *Objective Function (1)* minimizes the total travel cost, the fixed cost of health workers, and additional visits the health workers may perform. *Constraint (2)* specifies that each patient is visited only once. *Constraint (3)* indicates that a home health worker leaves the patients' homes after visiting the patients. *Constraints (4)* and *(5)* indicate that each health worker starts from the HHC center, visits several patients, and returns to the HHC center ultimately. *Constraint (6)* indicates that the total number of patients visited by a health worker cannot exceed the given constant and if it exceeds, the cost of it will be added to the objective function. *Constraint (7)* describes the skill requirements to assign health workers to patients according to their levels. *Constraint (8)* denotes the arrival time of each health worker to start visits at patients' homes. *Constraint (9)* indicates that the service should be performed within the patients' time windows. *Constraint (10)* indicates which health worker is dispatched. *Constraint (11)* indicates the domains of the variables.

4 | Solution Methodology

In this section, the accuracy and efficiency of the proposed model were investigated on a series of instances. To ensure the accuracy and validity of the proposed model, some small-sized instances were solved and analyzed using the CPLEX solver. Since HHC routing and scheduling problem is an extended VRP problem, it is NP-Hard, and the CPLEX solver can find optimal solutions only for instances of very small size. In addition, we deal with problems with higher number of visits, and it is impossible to obtain the optimal solution with a commercial solver in a proper time. Thus, we decided to propose a SA algorithm to address the problem. Moreover, the results of the CPLEX solver and the SA algorithm were compared on small instances. The model was tested on randomly generated instances. In this study, the total number of requests and the travel time between patients, the level of request of each patient, the level of each health worker, the service time of each patient and the desirable time window for each patient were randomly generated.

4.1 | Simulated Annealing (SA)

SA is a probabilistic technique for solving optimization problems. Specifically, it is a powerful stochastic search algorithm to approximate global optimization in a large search space. In this paper, a SA algorithm is adapted according to the characteristics of this problem to achieve optimal performance. The appropriate representation structure of the solution is significant to the development of the algorithm. We employ a widely-used structure to show the routes, where the points greater than the number of patients indicate the breaking point. The other integers represent the numbers assigned to the patients.

3	4	6	7	2	5	1

Fig. 1. Solution representation for the problem.

For example, in *Fig. 1*, the number of points is 6, the number of health workers is 2, and "7" indicates the breaking point. As such, the first health worker goes to points 3, 4, and 6, while the second health worker goes to points 2, 5, and 1.

In the proposed algorithm, the initial solution is generated randomly by considering the constraints. During the search process, the algorithm attempts to transform the current solution into one of its neighbors. Therefore, a set of operators (including inverse, insert, and swap) are used to generate neighbor solutions. Thus, the SA algorithm moves to a new solution through one of the operators. The proposed algorithm uses parameters including maxIt, subIt, T_0, and α_0. The parameter maxIt denotes the number of algorithm's main iterations. The parameter subIt indicates the number of times each internal iteration (i.e. inside the main loop) occurs. T_0 represents the initial temperature. The temperature decreases during the process and α_0 is the coefficient that controls the cooling schedule. The structure of the SA algorithm is shown in *Algorithm 1*.

Algorithm 1. The proposed SA algorithm.

Generate initial solution S
T=T_0
for i=1 to max_ iteration
    for j=1: max_ sub_iteration
    S': pick neighborhood S
    If (cost (S')<cost (S))
    S: = S'
    else
      r= random (0,1)
     if r<$e^{(cost(S)-cost(S'))/T}$
     S: = S'
     end
     end
T=$T_0 . \alpha_0$
end.

4.2 | Adjusting SA Parameters

In this research, the Taguchi method is used to determine the best values for the SA parameters. In minimization problems, the Signal-to-Noise (S/N) ratio is calculated by *Eq. (12)* in which y_i is the response variable and n is the number of experiments [37].

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right). \tag{12}$$

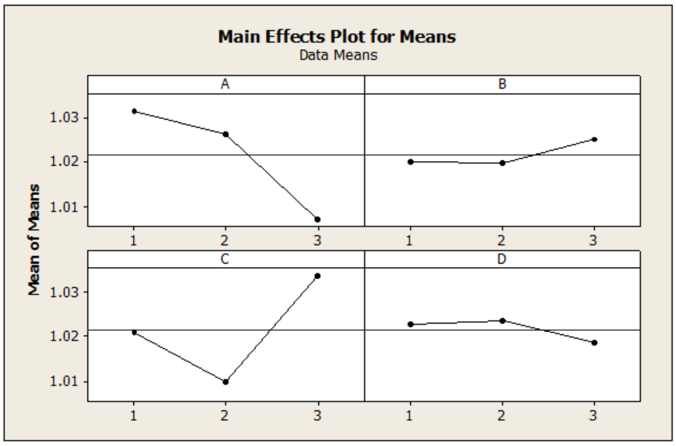
We employ the Taguchi method to find the values of the parameters which affect the performance of the proposed algorithm. Therefore, a problem with average size i.e. composed of 30 patients is chosen to adjust the SA parameters. We consider four main factors (max_Iteration, sub_Iteration, T0, and α0) at three levels for each factor. *Table 2* shows the four parameters of SA and their values.

Table 2. The different factors and levels of the of the SA parameters.

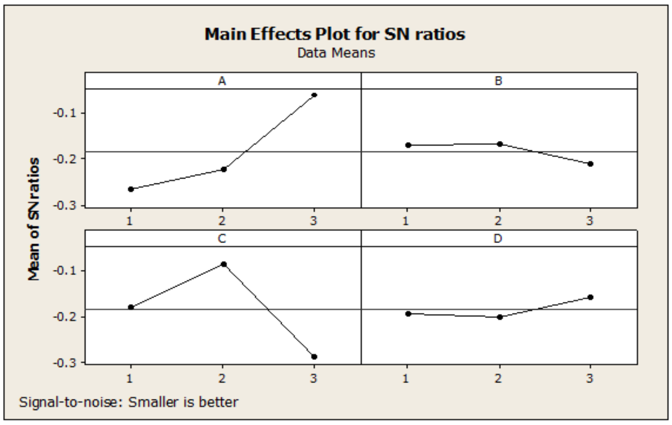
Factors/Levels	Level 1	Level 2	Level 3
Max Iteration	100	200	300
Sub Iteration	50	100	150
T_0	30	40	50
α_0	0.9	0.95	0.99

We evaluate the influences of four factors, over mean of response and the S/N ratio. *Fig. 2* shows different levels of the SA parameters, the mean of response, and the mean S/N ratio calculated for each level. The smallest value of mean and largest value of the S/N ratio is selected for each factor. In the end, the following values are chosen for the parameters:

Max iteration= 300; Sub iteration= 100; $T_0 = 40$; $\alpha_0 = 0.99$.



a.



b.

Fig. 2. Mean values and mean S/N ratio values.

4.3 | Numerical Instances

To evaluate the sensitivity of our model, we generated several random problem instances with different sizes. Our solution procedure is tested on these instances. First, some small-sized instances were solved and analyzed using the CPLEX solver. Moreover, the results obtained from the CPLEX solver and the SA algorithm were compared at small scales.

Example 1. In this example, 10 patients with different levels of needs and 4 health workers with different skill levels are considered (*Tables 3* and *4*). The proposed model determines how to dispatch the health workers and the routes passed by the health workers for visiting, as shown in *Table 5*. As seen in this example, health workers can only visit those patients whose needs are at a lower level than the health workers' skill levels.

Table 3. The level of service for the patient demands.

j	1	2	3	4	5	6	7	8	9	10
Le(j)	2	1	3	1	2	1	3	2	3	1

Table 4. Level of skills for health workers.

k	Le(k)
1	2
2	1
3	2
4	3

Table 5. Routes of health workers with 10 patients.

K	Routes
3	2-1-4-6-8
4	9-7-3-5-10

The maximum number of homes that each health worker is tasked with visiting during the day is specified. If more patients are assigned to a health worker than the specified limit, the health worker will be paid an additional fee in proportion to the extra patients. In *Table 6*, the effect of the maximum number of visits each health worker can perform is investigated. This table includes the columns of problem size, and the maximum number of visits specified for health workers. The model determines the number of dispatched health workers and additional patients assigned to each health worker.

Moreover, the "TC" column reports the total cost. This table shows that if the maximum number of visits made by each health worker is reduced, the number of health workers dispatched on visits or the additional patients assigned to each health worker increase, leading to a rise in the total cost.

Table 6. Sensitivity analysis on the specified maximum number of visits for each health worker.

$\lvert J \rvert$	N	Number of Dispatched Health Workers	E_K	TC
8	8	1	0	173
8	6	1	2	293
8	4	2	0,0	329
8	3	2	0,2	449
12	8	2	0,0	408
12	6	2	0,0	408
12	4	3	0,0,0	595
12	3	3	3,0,0	770
15	8	2	0,0	426
15	6	3	0,0	594
15	4	3	0,0,3	778
15	3	4	0,0,2,1	970
20	8	3	0,0,0	688
20	6	3	0,0,2	808
20	4	5	0,0,0,0,0	1044
20	3	5	0,2, 2,1,0	1345

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Table 7 indicates the sensitivity analysis of various costs of assigning additional patients to the health workers. This table reports the columns of problem size, the maximum number of visits specified for health workers, and various costs of assigning additional patients to each health worker. The model determines the number of dispatched health workers, the number of additional patients for each health worker, and the total cost. As this table shows, if the cost of assigning additional patients to the health worker decreases, even more extra visits are assigned to the available health workers than the usual quota.

Table 7. Sensitivity analysis on the cost of assigning additional patients to each health worker.

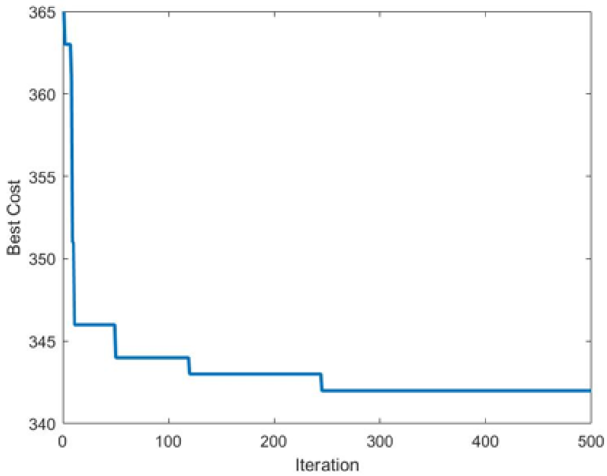
$\lvert J \rvert$	N	C_3	Number of Dispatched Health Workers	E_K	TC
8	5	60	2	0,0	329
8	5	50	1	3	325
8	5	40	1	3	295
14	5	60	3	0,0,0	608
14	5	50	3	0,0,0	608
14	5	40	2	4,0	580
18	5	60	4	0,0,0,0	828
18	5	50	3	1,1,1	823
18	5	40	3	1,1,1	793

In *Table 8*, to examine the presented metaheuristic algorithm, several small-sized problems solved by the CPLEX solver were compared with the SA algorithm. For small-sized problems, the metaheuristic algorithm provides an optimal or near-optimal solution. The average time the SA algorithm uses to solve the problem is far less than the exact method. As the dimensions of the problem get bigger, the runtime of the exact method increases in an accelerated manner while the effect of the problem size on the computational time of the SA algorithm is not as notable as the exact method and in large-sized problems, it will be not possible to get the optimal solution with the CPLEX solver in a reasonable time. Therefore, for large-sized instances, it will be much more efficient to use the SA algorithm. The results obtained from the exact method and the SA algorithm were compared at small scales. Moreover, *Table 8* presents the results of different instances for a large-size problem (i.e. 30, 40, and 50 patients). In this table, the results of the SA algorithm indicate a maximum gap of 2% for all tested instances, demonstrating the ability of the SA algorithm to find proper solutions.

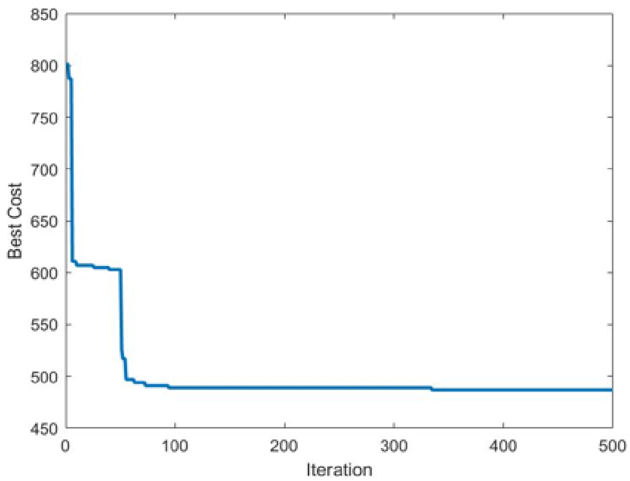
Table 8. Comparison of the results of the SA algorithm and CPLEX solver.

		"CPLEX Solver"		" SA "		
NO.	$\lvert J \rvert$	**TC**	**Run Time(s)**	**TC. Best**	**TC. Average**	**Run Time(s)**
1	10	342	21	342	342	10
2	12	487	118	487	487	11
3	15	626	3600	626	628	11
4	20	861	3600	863	868	12
5	30	_	_	1206	1222.6	16
6	40	_	_	1890	1910	20
7	50	_	_	2220	2266.5	26

The best results of the SA algorithm for 10, 12, 15, and 20 patients are represented in *Figs. 3* and *4*.

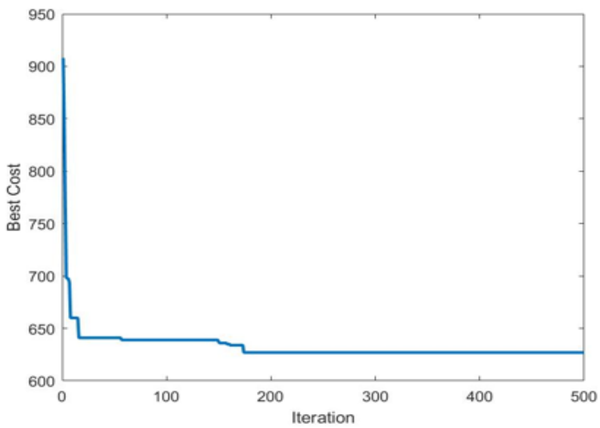


a.



b.

Fig. 3. The results of the SA algorithm for 10 and 12 patients.



a.

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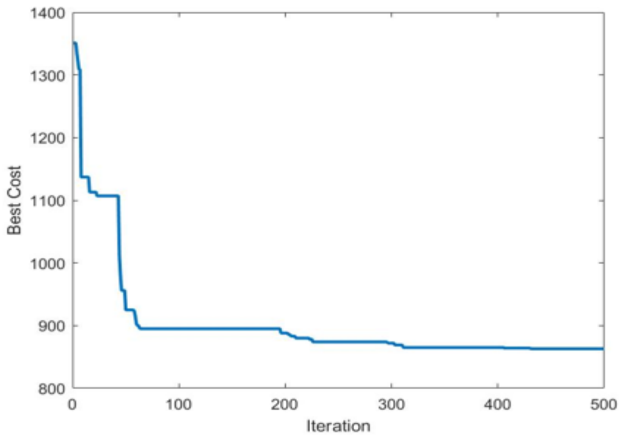

b.

Fig. 4. The results of the SA algorithm for 15 and 20 patients.

This research can be a scientific guide for the decision-makers of HHC centers to make proper decisions on the scheduling and routing of their health workers considering the preferences of patients and health workers. In this study, highly qualified health workers can visit patients who need simple services; however, health workers with low-level skills cannot visit patients who need specialized services. This way, the total cost of the system will be lower compared to the situation in which the patients' needs exactly match the health workers' skills. This study is expected to help the decision-makers at HHC centers devise appropriate routing strategies for different types of patients with specific needs.

In this research, the maximum number of homes each health worker should visit each day is clearly specified and if more patients are assigned to a health worker than the specified limit, additional costs are imposed on the center based on the number of extra patients. In some cases, it is perhaps more economical to have the existing health workers visit additional patients instead of hiring new health workers.

The results give the managers insight into this method of cost management in comparison with manual and traditional planning. This study may help the decision-makers of HHC centers make more accurate decisions which, in turn, result in timelier service provision, increase the patients' satisfaction level, dispatching health workers tailored to the patients' disease levels and improve the overall efficiency of HHC centers.

5 | Conclusions

This paper introduces a new HHC routing and scheduling problem which deals with different skill levels of health workrs. In this system, each patient demands a set of services, which must be provided at his/her home, and a desirable time window is established for the visits. The patients' needs spread over different levels. In such a condition, a highly qualified health worker can visit patients who have lower skill demands while a low-qualified health worker cannot visit patients who request higher skills. Moreover, the maximum number of homes that each health work is tasked to visit during the day is specified and if more patients than this specified number are assigned to each heath worker, an additional cost will be imposed on the center in proportion to the excess number of patients. The model aims to schedule the minimum number of health workers whilst balancing workloads and guaranteeing demand satisfaction. Over this problem, a mixed integer programming formulation is introduced. This model facilitates the optimization of the routing and scheduling problem whilst balancing workload. As part of the solution strategy, a mathematical programming problem is solved with the GAMS optimization software. For larger instances, a metaheuristic algorithm is used to find the proper solution. It is interesting to extend this work with the urgent demand of some patients or considering that some patients cancel the visit.

Declaration of Interest Statement

No financial interest or benefit has arisen from the direct applications of our research.

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