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RESEARCH PAPER

Home Health Care Scheduling and Routing with Temporal Dependencies and Continuity of Care

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Abstract

Due to facing an acute shortage of beds in hospitals, the danger of getting involved in hospital infections and high-cost hospitals care, the Home Health Care industry has encountered high demands in recent years. Different stakeholders with various interests are involved in home health care that makes the process of planning and scheduling of nurses, who offered services, challenging. This paper, therefore, focuses on scheduling and routing nurses traveled to the patient's home by considering the main features of the problem such as Continuity of Care and temporal dependencies. A new formulation for adjusting time distance between two consecutive jobs performed by a nurse is presented. A feasible solution has to consider nurse and patient's preferences, time windows for jobs, nurse's qualification and waiting time. A genetic algorithm is proposed to solve the problem. The computational results show the efficiency of the proposed algorithm especially for large size instances. Finally, the effect of nurse's dispatching policy on the objective function, waiting and travelling times is examined.

Keywords:
Continuity of Care;
Genetic Algorithm;
Home Health Care;
Mathematical Programming;
Temporal Interdependency

Introduction

In recent years, Home Health Care (HHC) services have encountered high demands and the reason behind this is the appearance of new diseases, lack of nurses in hospitals, and an increase in the aging population. In addition, family members often live far from each other in modern life and there is no possibility to take care of the individuals needful to care by the other family's members [1]. The population share of people older than 65 years was five percent in 1960 while it has been increased to nine percent in 2018 and is expected to increase to sixteen percent in 2050. Demographic transition in birth and death rates in recent years will lead to an older age. The annual birth rate was 2 percent around the 1960s. It is around 1.09 percent in 2018 and is expected to reach 0.05 percent by 2050. This trend leads to less care for older parents from their children.

The most advantages of keeping patients at home can be summarized as the decrease in therapeutic costs, preventing the lack of admission or delay in the admission of patients in hospitals, the possibility of keeping the patient's social relations, the decrease of patients stay in hospitals, the decrease of the danger of getting involved in hospital infections and fewer costs rather than hospital services. As well, services related to sending nurses are including a variety of activities such as medical services, therapeutic services, social and pharmaceutical services,

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preparing the patients’ food, taking baths, and home cleaning. These services are given to patients, old individuals, children, and people who suffer from physical and mental disabilities.

Determining shifts and finding routes for nurses were previously done manually. In light of this evidence, scheduling manually has a wide range of challenges. First, scheduling might be not optimized. Second, solving problems with high dimensions is a time-consuming process. Thus, it is vital to implement efficient and effective procedures to tackle these problems. Solving such problems has been under attention in recent years by utilizing mathematical models. A comprehensive review and recent advances in HHC optimization can be found in Fikar et al. and Cissé et al. [2,3]. Bertels et al. [4] show that the HHC problem without considering the time interdependencies conditions is an NP-Hard problem; therefore, the problem cannot be solved effectively in polynomial time. The NP-hardness of the problem is the reason to use metaheuristic algorithms or other methods to solve the problem in a reasonable time, especially in large-size samples. In this paper, the nurse scheduling is done in a single period (day). This problem is, in fact, a combination of the VRP problem and scheduling. However, some features of this problem differentiate it from classic VRP problems. Some of these features are as follows: i) in HHC problem some patients must be visited more than one time, ii) different qualification levels are considered for nurses, and iii) there are time dependencies between some jobs. In other words, one of the features that make the HHC problem more complicated, compared to VRP is temporal dependencies, in this case, there must be a time distance between two jobs done for one patient.

The main contribution of this paper is developing a new mathematical model for HHC by considering temporal dependencies, continuity of care, and adjusting time distance between two consecutive jobs performed by a nurse. For this purpose, a new formulation is developed for adjusting the time distance between two consecutive jobs performed by a nurse. A metaheuristic solution based on a genetic algorithm is also developed to overcome computational time issues.

The structure of the paper is as follows: First, the related works in HHC are reviewed. Problem definition and some main features of HCC are presented in Section 3. The proposed solution method will be discussed in Section 4. Numerical results and sensitivity analysis on some main parameters will be presented in Section 5.

Literature Review

This section presents some related studies, mainly categorized as single period and multi-period problems.

Regarding single period problems, Eveborn et al. [5] have formulated the HHC problem based on set partitioning and use a repeated matching algorithm to solve it. They considered different traveling times based on the type of vehicles. Trautsamwieser et al. [6] considered the effect of flood disasters on HHC scheduling problems. They exploited the Variable Neighborhood Search (VNS) approach to solve the problem for real instances. The nurse’s qualification to do the jobs, the nurses' and patients’ preferences, and breaking time for nurses have been considered as assumptions in this research work. Rasmussen et al. [7] had modeled the problem as a set portioning problem and to solve the problem a Branch and Price (B&P) approach was used. Five kinds of temporal dependencies had been introduced, and these temporal dependencies were modeled as general precedence conditions. Koeleman et al. [8] have modeled HHC as a Markov decision process. The optimal scheduling policies have been considered for two with and without waiting rooms. Rodriguez et al. [9] used three sources of information to estimate demand and applied a two-stage stochastic programming approach to formulating the problem. Braekers et al. [10] is the first paper in the HHC problems that forms a bi-objective mathematical model. The first objective function minimizes cost included travel and overtime costs, while the second considers an inconvenience score for each job concerning time windows. To solve the problems in real dimensions a metaheuristic algorithm was presented. Liu et al. [11] formulated an HHC problem with consideration of lunch breaks for workers. A B&P algorithm was applied to exactly solve the problem. Some clients were left uncovered. Hiermann et al. [12] considered the HHC problem minding the mode of transportation for nurses. The constraints of the problem were divided into two soft and hard categories. Nurses, patient's preferences, and the nurses' qualifications to do jobs were considered in that. In addition, four metaheuristics were proposed to solve the problem. Decerle et al. [13] formulated the HHC problem for assigning nurses to jobs on a given day while considering synchronization constraints, nurses' qualification, and time windows for nurses and jobs. The synchronization visits could be violated by considering penalty in the objective function. In Fikar et al. [14], a solution procedure for daily planning of HHC problems was provided. Nurses of different qualification levels were delivered to the patients' homes by a transport service and the possibility of walking was considered too. In Mankowska et al. [15], which is more closely to the current study, patients were divided into two groups: the patients that need one service and the patients that need two services with precedence. To solve the problem, a variable neighborhood search with a new matrix solution representation has been used. In the recent case, between the starting time and ending time of jobs, there should be a maximum and minimum time distance. Decerle et al. [16] applied an ant colony algorithm to solve a single period HHC problem by emphasizing the workload balancing among nurses. Recently, Euchi et al. [17] applied artificial intelligence techniques to optimize the offered services in an HHC problem.

Regarding multi-period HHC problems, Bard et al. [18] has minded the scheduling periods weekly. The therapists were also divided into two groups. Licensed therapists must-visit patients who were visited for the first time. In the objective function, they were trying to minimize the costs of visits and traveling of patients. To solve the problem a greedy randomized adaptive search procedure was developed. Lanzarone et al. [19] were seeking to minimize the maximum overtime among nurses. Each patient was assigned to a nurse and this assignment would not change until the end of the patient's therapy period. They considered uncertainty in new patient's demands.

One of the main features of the HHC problem is continuity of care. This kind of restriction ensures that each patient is assigned to a small group of nurses. To consider continuity of care, Cappanera et al. [20] limited the number of nurses that can visit patients during the time horizon. Duque et al. [21] presented a bi-objective mathematical model based on set portioning. The patient-nurse preference and the time preference were considered. The problem instances were provided by a local organization in Belgian. To consider continuity of care, patients were divided into two groups based on the number of visits per week: patients requiring less than three visits per week and patients requiring more than three visits. In the study done by Carello et al. [22] nurses were assigned to patients based on territory and skills. Patients with uncertain demand were divided into five groups based on continuity of care. For soft continuity of care, a reassignment cost was associated. In Carello et al. [23], three stakeholders, who are involved in HHC, were considered. As well, overtime cost, workload balance, and the reassignment of jobs were considered in the objective function. Continuity of care, nurses' compatibly with patients, and nurses' availability were regarded too. Moreover, a fairness metric was given to distribute works evenly among nurses. Patient demands were considered in both deterministic and uncertain cases. Besides, due to the uncertainty inherited in treatment duration, the authors presented a robust cardinality-constrained formulation. Recently, Grenouilleau et al. [24] developed a new decomposition method for the HHC problem with Predefined Visits.

Table 1 shows an illustrative sample of some recent studies on the HHC by mathematical programming approach. While this is by no means a representative sample of all existing research in the literature, it is sufficient to illustrate the gaps in the current research.

Table 1. A brief literature reviews on developed mathematical models in HCC

Author	X-period	Number of terms	Overtime	breaks	Continuity of Care (COC)	Waiting time	Part-time work	Synchronization	Soft Constraints	Nurses Qualifications	Time window for Nurses	Time window for Jobs	Staff Satisfaction	Customer Satisfaction	Time adjustment
Bachouch et al. [33]	Multi	1	✓	✓	✓			✓		✓	✓	✓			
Bertels et al. [6]	Single	5							✓	✓	✓	✓	✓		
Eveborn et al. [5]	Single	1			✓				✓	✓		✓		✓	
Hertz et al. [34]	Multi	2											✓		
Trautsamwieser et al. [35]	Single	7	✓	✓					✓	✓	✓	✓	✓	✓	
Trautsamwieser et al. [36]	Single	7	✓	✓		✓			✓	✓	✓	✓	✓	✓	
Rasmussen et al. [7]	Single	3						✓		✓	✓	✓			
Nickel et al. [38]	Multi	4	✓		✓				✓	✓		✓			
Cappanera et al. [39]	Multi	1								✓					
Mankowska et al. [15]	Single	3						✓		✓		✓			
Lanzarone et al. [19]	Multi	1	✓		✓										
Trautsamwieser et al. [37]	Multi	1		✓		✓				✓	✓	✓	✓	✓	
Bard et al. [18]	Multi	2	✓	✓			✓			✓	✓	✓			
Carello et al. [22]	Multi	2	✓		✓					✓					
Hiermann et al. [12]	Single	13	✓						✓	✓	✓	✓	✓	✓	
Fikar et al. [14]	Single	3	✓	✓		✓				✓		✓	✓		
Duque et al. [21]	Multi	2			✓					✓	✓	✓	✓	✓	
Braekers et al. [10]	Single	4	✓			✓			✓	✓	✓	✓		✓	
Rest et al. [40]	Single	4	✓	✓		✓				✓	✓	✓	✓		
Guericke et al. [41]	Multi	3	✓	✓			✓		✓	✓		✓	✓		
Cappanera et al. [20]	Multi	5			✓					✓					
Decerle et al. [13]	Single	3						✓		✓	✓	✓			
Liu et al. [42]	Single	2								✓		✓			
Shi et al. [43]	Single	2										✓			
Du et al. [44]	Multi	3										✓			
Decerle et al. [16]	Single	3				✓			✓	✓	✓	✓		✓	
Grenouilleau et al. [45]	Multi	1							✓	✓	✓	✓	✓	✓	
Euchi et al. [17]	Single	4	✓	✓					✓	✓	✓	✓			
This Study	Single	1			✓	✓		✓		✓		✓	✓	✓	✓

From Table 1 it can be concluded that very few studies take into account main subjects such as continuity of care, temporal dependencies, job synchronization, nurse's qualifications, the time window for both nurses and jobs, staff satisfaction as well as customer satisfaction simultaneously. In this paper, a new mathematical model is developed to consider the aforementioned real-world assumptions simultaneously. For this purpose, a new formulation for adjusting the time distance between two consecutive jobs performed by a nurse is presented. Since the problem studied here is NP-hard, an evolutionary algorithm is also proposed to solve large size cases in a reasonable time.

Problem definition

Consider a set of nurses and a set of jobs. All jobs must be done and no job is left uncovered. There is no time window for nurses and nurses are available all day long. Jobs must be done in a hard time window. It means the beginning and ending time for each job must be in the related time window and doing the jobs out of the related time window is not authorized. The nurses must begin the jobs at one starting point and finish them at the ending point. With respect to the formulation of this problem in the present paper, we can consider the beginning and ending points of jobs at any other point. For example, the beginning point can be an office. In other words, each nurses' home is considered as a virtual job with zero time. It is possible that two or more jobs are related to one patient, and there may not be any special relation among these jobs, like bathing assistance in the morning and preparing food at noon. There may also be some special relation among the jobs, like taking medicine before or after having food. The patients' preferences about nurses and also nurses' preferences about patients are considered. For example, a female nurse may not prefer to be sent to male patients. In addition, each nurse can do some special jobs. For instance, a nurse may have the ability to do daily jobs like preparing food, taking bath, and doing some easy medical affairs, however, may not have the ability to do professional medical affairs.

The temporal dependencies are considered and one kind of it is synchronization. For example, when two nurses for a patient with special physical conditions (like overweight or physical disability) are needed to take a bath. In this situation, if one nurse arrives sooner at the patients' home, he/she must wait for the other one. In Drexl [25], a complete description of the synchronization in VRP problems is presented. The other case is when there must be a time distance between two jobs done for one patient. For example, a patient takes his/her medicine at a set time after having food and there must be a maximum (d_{ij}^{max}) and a minimum (d_{ij}^{min}) time distance between the beginning time of doing these two jobs. As well, the situation in which there is no relation between two jobs related to a patient is considered as two distinct jobs.

One of the most important features in healthcare is the Continuity of Care (COC). There are different definitions for COC. Haggerty et al. [26] identified three types of COC. In this paper, relational COC is considered. It implies that each patient faces a low number of nurses as possible. The decrease of nurses sent to take care of patients on the one-hand increases the sense of responsibility of nurses as well as nurses' efficiency and on the other hand, decreases the therapy period that leads to the improvement of patients' satisfaction. COC is very important especially for patients that need mental health. However, specializing one nurse to one patient and not changing him/her is impossible because of the nursing shortage and a high number of patients. Despite its importance, considering COC increases the complexity of the problem. Therefore, this feature of the HHC problems attracts a little attention to the optimization problems. Carello et al. [22] present complete definitions of various kinds of relational COC. In the present paper, the jobs are divided into three categories based on COC: 1) The jobs that need hard COC. It implies that the specialized nurse does not change until the end of the therapy period, 2) The jobs that need soft COC. In this case, changing a nurse specialized in a job will result in a penalty in the objective function. The penalty is calculated based on the assignment of nurses to the jobs in the previous days, iii) the jobs do not require COC. Sets, parameters, and variables are defined in Table 2.

Table 2. Sets, parameters and variables.

Sets	
J	Set of Jobs
O_1	Set of the starting location of nurses
O_2	Set of the ending location of nurses
J^s	Set of all soft jobs
J^h	Set of all hard jobs
N	Set of nurses
J^d	Set of jobs with temporal dependencies
S	Set of jobs with synchronization
Parameters	
q_{in}	Equal one if nurse n is qualified to do job i
p_j^n	Penalty for soft job j if perform by nurse n
$\Gamma(\mathrm{j,n})$	Equal one if hard job j is performed by nurse n
μ_{ij}	Equal one if job j must be performed after job i
d_{ij}^{min}	Minimum time between start time of jobs i and j when $\mu_{ij} = 1$
d_{ij}^{max}	Maximum time between start time of jobs i and j $when$ $\mu_{ij} = 1$
w_n	Maximum waiting time between two consecutive jobs performed by nurse n
W_n	Minimum time distance between two consecutive jobs performed by nurse n
$[a_i, b_i]$	Time window for job i
t_{ij}	Travelling time from job i to job j
d_i	Duration of job i
γ_j	is equal to 0 or 1.
M	A big number
Decision variables	
x_{ijn}	A binary variable, one if nurse n moves from job i to job j
s_j^n	Nurse's arrival time at job j
t_j^n	Nurse's starting time at job j

$$Min \sum_{j \in J^s, i \in J \cup O_1} p_j^n \, x_{ijn} \tag{1}$$

The objective function minimizes the penalties for jobs that need soft COC. In Eq. 1, penalties are calculated based on historical data.

$$\sum_{n \in N, i \in J \cup O_1} x_{ijn} = 1 \qquad \forall j \tag{2}$$

$$\sum_{j\in J, i\in O_1} x_{ijn} \leq 1 \qquad \forall n \tag{3}$$

$$\sum_{i\in J, j\in O_2} x_{ijn} \leq 1 \qquad \forall n \tag{4}$$

The second constraint ensures that all the jobs are done and there is no job left uncovered. The third and fourth constraints guarantee that the nurses must start and finish their jobs at starting and ending points respectively.

$$\sum_{i\in J\cup O_1} x_{ijn} = \sum_{k\in J\cup O_2} x_{jkn} \qquad \forall n,j \tag{5}$$

Constraint (5) is the flow conservation constraint and implies that each nurse that goes to the one job to do his/her duty must exit it.

$$\sum_{i\in J\cup O_1} x_{ijn} \geq \Gamma(\mathrm{j},\mathrm{n}) \qquad \forall n,j \tag{6}$$

Constraint (6) ensures that the same previous nurse must do hard jobs.

$$\mu_{ij}\left(t_j^n - t_i^m\right) + \mu_{ji}\left(t_i^m - t_j^n\right) \geq d_{ij}^{min} - M_1\left(2 - \sum_{k\in J, j\in O_2} x_{kin} - \sum_{k\in J, j\in O_1} x_{kjn}\right) \forall\, n,m \in N, \forall i,j \in J^d \tag{7}$$

$$\mu_{ij}\left(t_j^n - t_i^m\right) + \mu_{ji}\left(t_i^m - t_j^n\right) \leq d_{ij}^{max} + M_2\left(2 - \sum_{k\in J, j\in O_2} x_{kin} - \sum_{k\in J, j\in O_1} x_{kjn}\right) \quad \forall\, n,m \in N, \forall i,j \in J^d \tag{8}$$

Constraints (7) and (8) ensure the minimum and maximum time distance between jobs with temporal interdependencies. These constraints force the latter job (j) to be started at least d_{ij}^{min}after the first job and not later than d_{ij}^{max}. In the case that d_{ij}^{min}=$d_{ij}^{max} = 0$, there is synchronization between jobs.

$$t_i^n + \left(d_i + t_{ij}\right)x_{ijn} \leq s_j^n + b_i\left(1 - x_{ijn}\right) \qquad \forall n,i,j \tag{9}$$

$$t_i^n + \left(d_i + t_{ij}\right)x_{ijn} \geq s_j^n - b_j\left(1 - x_{ijn}\right) \qquad \forall n,i,j \tag{10}$$

Constraints (9) and (10) show the relation between the starting time of the first job and its duration and the arrival time of the second job, minding the time distance between two jobs.

$$a_i \sum_{i\in J\cup O_1} x_{ijn} \leq t_i^n \quad \forall n,j \tag{11}$$

$$b_i \sum_{i\in J\cup O_1} x_{ijn} \geq t_i^n \quad \forall n,j \tag{12}$$

$$t_i^n + d_i \leq b_i \quad \forall n,i \tag{13}$$

Constraints (11), (12) and (13) ensure that the starting and finishing time of each job must be in its time window.

$$a_j - t_{ij} - d_i - t_i^n \leq w_n x_{ijn} + M_3\left(1 - x_{ijn}\right) + M\gamma_j \qquad \forall n,i,j \tag{14}$$

$$a_j - t_{ij} - d_i - t_i^n \geq W_n x_{ijn} + M_4\left(1 - x_{ijn}\right) - M\left(1 - \gamma_j\right) \qquad \forall n,i,j \tag{15}$$

Constraints (14) and (15) ensure that the waiting time must be less than a certain number. In other words, there should be a distance between the ending time of a job and its successor's time window/the starting time. Indeed, constraint (14) forces that waiting time must be less than a specified number w_n. Otherwise, constraint (15) is activated which implies that there must be a specified time distance between doing two consecutive jobs by one nurse. These constraints take into account nurses' preferences.

$$t_i^n - s_i^n \leq M\delta_{i1} \quad \forall n, i \tag{16}$$

$$t_i^n - a_i \leq M\delta_{i2} \quad \forall n, i \tag{17}$$

$$\delta_{i1} + \delta_{i2} \leq 1 \qquad \forall i \tag{18}$$

Constraints (16) to (18) show the relation between the arrival time and the job starting time, with respect to the lower bound of the time window.

$$x_{ijn} \leq \max(q_{in}, q_{jn}) \ \forall n, i, j \tag{19}$$

Constraint (19) ensures that jobs can be visited by nurses who are qualified to do them.

$$s_i^n \leq t_i^n \quad \forall n, i \tag{20}$$

$$s_i^n \geq 0 \quad \forall n, i \tag{21}$$

$$x_{ijn} \in \{0,1\} \quad \forall n, i, j \tag{22}$$

$$\delta_{i1}, \delta_{i2} \in \{0,1\} \ \forall i \tag{23}$$

$$\gamma_j \in \{0,1\} \ \forall j \tag{24}$$

$$q_{in} \in \{0,1\} \ \forall n, i \tag{25}$$

$$\mu_{ij} \in \{0,1\} \ \forall i, j \tag{26}$$

Constraints (20) to (26) define possible domains of the variables.

Solution approach: Genetic Algorithm (GA)

Without considering COC and time window for nurses, Mankowska et al. [15] worked on a simpler version of the problem studied here and concluded that the computation time of the HHC scheduling problem is heavily dependent on the dimensions of the problem. In other words, the HHC problem without considering COC and time window for nurses belongs to NP-hard problems and there is no exact algorithm with polynomial order to solve it. Thus, our proposed HHC problem can be categorized as an NP-hard problem too. This way, heuristics and metaheuristics approaches are appropriate to find near optimum solutions for large problems in a reasonable time. A popular population-based metaheuristics Genetic Algorithm (GA) is, therefore, applied to solve the proposed HHC model. The effectiveness of the Genetic algorithm to find near-optimal solutions in a rational time for routing and scheduling problems has been shown in previous studies e.g. Shi et al. [27], Liu et al. [28], Algethami et al. [29], and Algethami et al. [30].

The genetic algorithm, proposed by Holland in 1967 for the first time, is a metaheuristic population-based algorithm that has a lot of applications in solving combinatorial problems. This algorithm begins its work with an initial population that each of them is equivalent to one point of the solution space called a chromosome. In each iteration, several chromosomes are chosen and new chromosomes (children) are made using crossover and mutation operators [31]. Fig.1 shows the general framework of the proposed GA to solve the HCC problem modeled in the previous section.

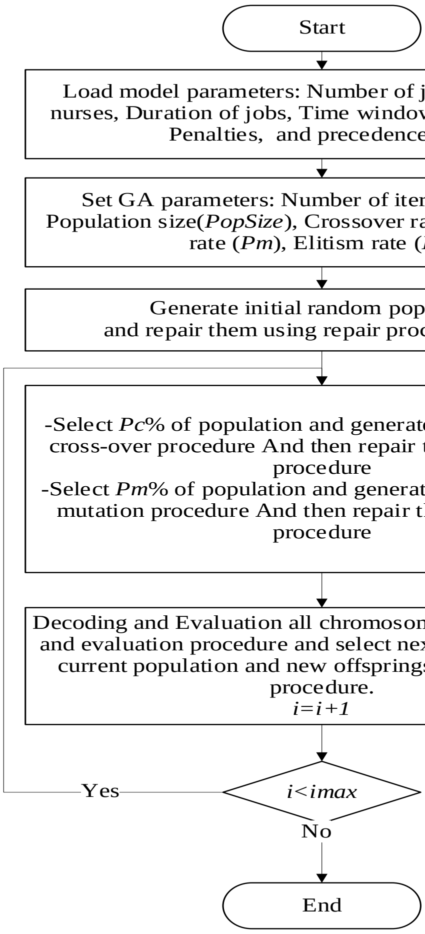

Fig. 1. Framework of the proposed solution algorithm

Solution representation and decoding of chromosomes

Based on the GA, a chromosome is equivalent to a point of the solution space. The solution representation is the most important part of the algorithm that has a remarkable effect on its efficiency. Since this algorithm is population-based, the solution representation should have two features: first, in addition to simplicity, it does not occupy the memory of the computer; second, each chromosome must be equivalent to only one point of solution space. The chromosome given in this algorithm has N_j gene, which N_j is equal to the number of jobs. Each gene is therefore equivalent to one job. Fig. 2 shows a sample chromosome of a problem with 10 jobs and 5 nurses.

Job 1	Job 2	Job 3	Job 4	Job 5	Job 6	Job 7	Job 8	Job 9	Job 10
1	3	3	5	2	1	2	2	5	3

Fig. 2. solution representation

The important topic about solution representation is the way of encoding and decoding chromosomes. In the considered problem, each point of solution space includes assignment nurses to jobs, the sequence of services, and nurses scheduling with respect to the assumptions and the constraints. About assignment of nurses to jobs and based on Fig. 2, nurse 1 is assigned to jobs 1 and 6, nurse 2 is assigned to jobs 5, 7 and 8, nurse 3 is assigned to jobs 2, 3, and 10, and nurse 5 is assigned to jobs 4 and 9. Besides, nurse 4 is idle in this chromosome. The sequence of services of nurses is determined based on the lower bound of the time window. This way, if in the chromosome given in Fig .2, the lower bound of the time windows is as $a_j = [20,10,50,30,40,80,90,70,60,100]$; the route of nurse 2 is as 5, 8, and 7. About scheduling of nurses, there are many assumptions and constraints including the minimum/maximum time distance between the starting times of two successive jobs, time windows, and so on. The chromosomes and the decoding process are designed in such a way that the jobs are done with respect to the lower bound of time windows and the minimum time distance between two jobs. Other constraints are considered using the penalty and repair mechanism that is described below.

In the following, the chromosome decoding is presented briefly.

- Step 1: sort all jobs according to their lower bound of time windows (a_j)
- Step 2: in the sorted array, for each job=1 $to\ N_j$ repeat step 3 (to calculate arrival time of nurse *n* to job *j*, s_j^n) and step four (to calculate start time of job *j* doing by the nurse n, t_j^n).
- Step 3:

$$s_j^n = \begin{cases} Max\left(a_j, t_j^n\right) & if\ job\ j\ is\ the\ first\ job\ of\ nurse\ n \\ t_j^n + d_j + t_{ij} & else \end{cases} \tag{27}$$

- Step 4:

$$t_j^n = \begin{cases} Max\left(a_j, s_j^n\right) & if\ job\ j\ does\ not\ have\ a\ prequiste \\ Max\left(a_j, s_j^n, \sum_{n=1}^{N_n} t_i^n + d_{ij}^{min}\right) & else(if\ job\ i\ is\ prequiste\ of\ job\ j) \end{cases} \tag{28}$$

The significant issue in designing the metaheuristic algorithms is the way of encountering infeasible chromosomes made during reproduction. There are many approaches to face infeasible chromosomes, such as applying the penalty function in evaluating the infeasible chromosomes and the repair mechanism that is described in the following section.

Initial population generation and repair mechanisms

As mentioned earlier, in the proposed algorithm the initial population is made randomly. In each chromosome, each gene is equivalent to one job; it starts from the first gene and assigns one nurse to each gene randomly. There are two basic assumptions in assigning nurses to jobs. First, some jobs called hard jobs must only be done by a fixed nurse. Besides, about the other jobs and depending on the quality of nurses each job can be done by a group of nurses. For this reason, some chromosomes, which are created in the reproduction process or by GA operators, may not fulfill these assumptions. To face this challenge each infeasible chromosome is amended by a repair mechanism. The proposed repair procedure is used in three situations: after creating the initial population, after generating children by the mutation, and after the crossover operator.

- Step 1: for all jobs=*1*:N_j , if job *j* is a hard job, go to step 2, else go to step 3.
- Step 2: If the assigned nurse to job *j* is not qualified, change him\her with a qualified nurse.
- Step 3: If the assigned nurse to job *j* is not qualified, choose one of the qualified nurses randomly and assign him\her to job *j*.

Fitness evaluation and the penalty function

One of the common approaches in facing infeasible solutions is using the penalty function. In this case, the infeasible chromosomes are not eliminated, but by using a penalty function and depending on their derivation from constraints, their value of objective function gets worse. Therefore, their chance to stay in the next generations will be decreased. The reason for not eliminating these chromosomes is that an infeasible chromosome may become a chromosome with a very well fitness by a small change through crossover and mutation operators.

Based on Eq. 1 the Objective Function Value (OFV) of each chromosome is equal to the sum of penalties for soft jobs (P_0). However, as far as there is the possibility of generating the infeasible solutions, the OFV of infeasible chromosomes is increased using Eq. 29 in which *P* is the penalty coefficient and it can take every number to itself with respect to the problem data.

$$OFV = P_0 + P * (P_1 + P_2 + P_3 + P_4) \tag{29}$$

As is mentioned earlier respect to the chromosome designing and decoding process some constraints are always satisfied and some others may be satisfied by the repair mechanism. However, in four cases, as described below, a chromosome may become infeasible which results in penalties from P_1 to P_4. Consider a chromosome: in the case, that nurse *n* finishes job j in $t_j^n + d_j$, the penalty pen_1^{jn} depending on deviation from b_j, will be calculated as Eq. 30 in which N_n is the number of nurses:

$$pen_1^{jn} = Max\left(0, t_j^n + d_j - b_j\right) \Longrightarrow p_1 = \sum_{j=1}^{N_j}\sum_{n=1}^{N_n} pen_1^{jn} \tag{30}$$

If the job *i* is the prerequisite of job *j* the time distance between the starting times of these two jobs must be placed in the interval $[d_{ij}^{min}, d_{ij}^{max}]$. Since d_{ij}^{min} always is satisfied in the decoding process, the penalty pen_2^{jn} is calculated by Eq. 31, regarding d_{ij}^{max}:

$$pen_2^{jn} = Max\left(0, \sum_n t_j^n - \sum_n t_j^n - d_{ij}^{max}\right) \Longrightarrow p_2 = \sum_{i=1}^{N_j}\sum_{j=1}^{N_j} pen_2^{ij} \tag{31}$$

The waiting time of nurse *n* for doing the job j (E_{jn}) must be less than $r_1$or more than r_2. Otherwise, the penalty pen_3^{jn} will be calculated by Eq. 32:

$$pen_3^{jn} = Min\left(E_{jn} - r_1\ , r_2 - E_{jn}\right) \Longrightarrow p_3 = \sum_{i=1}^{N_j}\sum_{j=1}^{N_n} pen_3^{jn} \tag{32}$$

Each nurse must have finished his/her job before a specified time (b_n). If this is violated, the penalty pen_4^{jn} will be calculated as below:

$$pen_4^{jn} = Max\left(0, t_j^n + d_j + t_{ij} - b_n\right) \Longrightarrow p_4 = \sum_{j=1}^{N_j} \sum_{n=1}^{N_n} pen_4^{jn} \tag{33}$$

In Eq. 33, the job j is the last job of a nurse.

The Crossover and Mutation operators

The crossover operator is used to generate children by the combination of two parents. In this algorithm, the one-cut-point and two-cut-point crossovers are used to generate two children by two parents. The Crossover procedure can be summarized as follows:

Step 1: select randomly two chromosomes $p_1 = (p_1^1, \ldots \ldots .., p_n^1)$ and $p_2 = (p_1^1, \ldots \ldots .., p_n^1)$ as parents.

Step 2: generate a random number r, between 0 and 1. If $r < 0.5$ go to step 3 (one-cut-point), else go to step four (two-cut-point)

Step 3: a position i between 1 to $N_j - 1$ be randomly chosen and two offspring $O_1$and O_2 are generated:

$$O_1 = (p_1^1, \ldots \ldots .., p_i^1, p_{i+1}^2 ..., p_n^1), O_2 = (p_1^2, \ldots \ldots .., p_i^3, p_{i+1}^1 ..., p_n^1)$$

Step 4: two positions i and j between 1 to $N_j - 1$ be randomly chosen $(i < j)$ and two offspring O_1 and O_2 are generated as below:

$$O_1 = (p_1^1, \ldots \ldots .., p_i^1, p_{i+1}^2 .., , p_j^2, p_{ij+1}^1, ., p_n^1) \text{ , } O_2 = (p_1^2, \ldots \ldots .., p_i^2, p_{i+1}^1 .., , p_j^1, p_{ij+1}^2, ., p_n^2)$$

If P_1 and P_2 are two chosen parents and O_1 and O_2 are two generated children an example of one-cut-point crossover and two-cut-point crossover are shown in Fig. 3.

Selected parents

P_1:	1	3	3	5	2	1	2	2	5	3
P_2:	2	5	3	4	4	1	3	2	2	3

(a)

O_1:	1	3	3	5	4	1	3	2	2	3
O_2:	2	5	3	4	2	1	2	2	5	3

(b)

O_1:	1	3	3	4	4	1	2	2	5	3
O_2:	2	5	3	5	2	1	3	2	2	3

Fig. 3. Crossover operators: (a) one-cut-point crossover with i=4; (b) two-cut-point crossover with i=3 and j=6

The mutation operator is used to make a new solution by making random changes in a selected parent. Here three different mutation operators are used (Swap, Uniform, Inversion). Based on the Swap operator two genes are randomly chosen from a chromosome and their values are replaced with each other. This way, the created chromosome is a new point of the solution space. It is clear that this operator makes minor changes in selected chromosomes. regarding the inversion operator, one part of a chromosome is randomly chosen and their genes values are arranged diversely. Finally, the uniform operator selects the P_u percent of genes and replaces their values with random values between 1 to n (number of nurses). For example, in Fig. 4 if P shows the selected parent, O_1, O_2 and O_3 are offspring that may be created via each of the aforementioned mutation operators. As it is observed each of these operators can make different changes in the parent chromosome and make a high capability to search the whole solution space without falling into the local optimum trap.

Selected parent

P:	1	3	3	5	2	1	2	2	5	3

(a)

O1:	1	3	1	5	2	3	2	2	5	3

(b)

O2:	1	3	3	5	5	2	2	1	2	3

(c)

O3:	1	4	3	5	2	4	2	2	5	1

Fig. 4. Mutation operators: (a) swap; (b) inversion; (c) uniform.

The selection strategy to form new generation

After generating children using the crossover and mutation operators, the next generation is selected from the current population and the created children. To do this, two approaches are used simultaneously: Elitism and Roulette wheel selection. First, all chromosomes are arranged based on their fitness and N_{elite} number of their best are chosen to attend in the next generation *(*N_{elite} *=PopSize*ElitismRate).* The remainder of the members of the next generation is chosen randomly by the Roulette wheel selection procedure in which a selection probability is assigned to each chromosome according to its fitness. Naturally, the more fitness value of one chromosome results in its higher chance to be in the next generation.

The computational results

In this section, the mathematical model and the proposed genetic algorithm are evaluated by solving several examples. In addition, sensitivity analysis is performed to evaluate the behavior of the problem under different conditions. Thus, the managerial guidelines will be presented. The genetic algorithm is encoded using MATLAB software. CPLEX solver is used to solving the proposed mathematical model through GAMS 24.7.3. The experiments are done on a Windows 10, 64-bit laptop with Intel 1.80 GHz and 6-GB RAM.

Parameter setting

The values of the input parameters of the genetic algorithm have a prominent role in the performance of the algorithm. To set the best values of the selected parameters, The Taguchi method is used. Five main parameters in the genetic algorithm in three different levels are considered, as it is shown in Table 3. To find the proper value of parameters, the L^{27} orthogonal array is used. For more detailed information, interested readers are referred to Sazvar et al. [31] and Navazi et al. [32]. In brief, Fig. 5 shows the results of the Taguchi method as: Mutation rate=0.1, Crossover rate=0.5, Uniform mutation rate=0.4, Elitism rate=0.8 and population size = N_j.

Table 3. Different level of parameters

	Level 1	Level 2	Level3
Mutation rate (Pm)	0.05	0.07	0.1
Crossover rate (Pc)	0.5	0.7	0.9
Population size (npop)	Nj	3Nj	5Nj
Uniform mutation rate (Pu)	0.2	0.4	0.6
Elitism rate (Er)	0.05	0.08	0.1

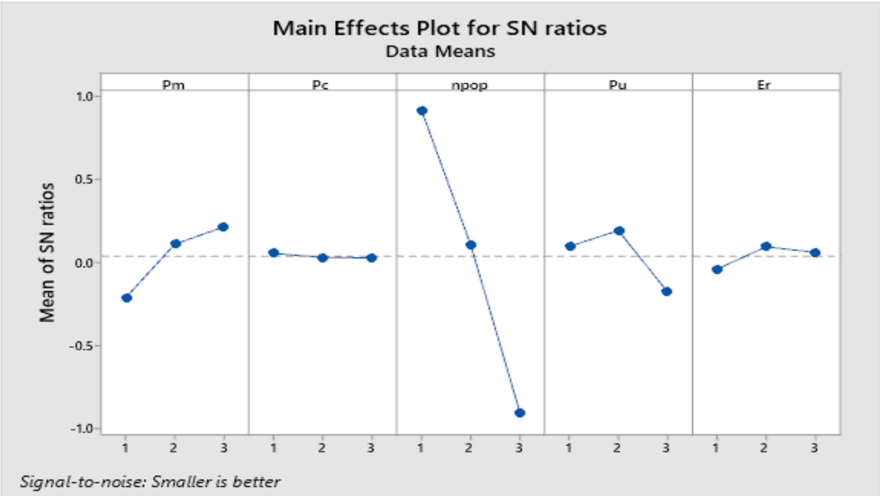

Fig. 5. The results of Taguchi method

Evaluation of the proposed GA

To evaluate the performance of the proposed genetic algorithm, 14 problems are generated in different dimensions reported in Table 4.

Table 4. Characteristics of the generated examples

Instance	$\|J\|$	$\|J^h\|$	$\|J^s\|$	$\|N\|$	$\|S\|$	$\|J^d\|$
1	18	3	6	8	0	4
2	18	3	6	8	4	4
3	18	3	6	8	2	4
4	41	5	11	15	2	6
5	41	5	11	15	4	6
6	58	11	41	50	0	6
7	81	6	61	50	0	4
8	12	5	5	100	0	2
9	14	5	5	100	0	4
10	18	5	5	100	0	8
11	55	4	47	89	0	4
12	55	4	47	89	0	4
13	59	4	51	90	0	4
14	18	5	5	100	0	8

In Table 5, a comparison is given between the results of solving the examples with the proposed genetic algorithm and the GAMS software. HHC is an NP-hard problem, there is only the possibility of solving the small and medium examples by the GAMS software. As it is shown in Table 5, in some cases GAMS could not find optimal solutions, and '-' indicates that the PC comes out of memory.

Table 5. Performance of developed GA

		CPLEX		GA			
	Lower Bound	Objective function	CPU time(s)	Best objective function	CPU time(s)	Average	Worst
1	12	12	2	13	3	15.4	17
2	12	12	2	13	5	14	15
3	26	26	2	30	1	30	30
4	150	150	9	175	9	179.8	188
5	111	111	38	120	24	125	135
6	2860	2860	299	2876	282	2889.2	2897
7	4605	4605	1761	4628	1500	4629.2	4631
8	955	955	465	955	24	955	955
9	955	955	485	955	17	955	955
10	955	-	-	955	10	955	955
11	2896	2896	687	2902	607	2907	2913
12	2894	-	-	2903	604	2911.6	2925
13	9148	-	-	9161	659	9168.2	9173
14	955	-	-	955	50	955.8	957

Regarding Table 5, the average of the gap between the best of GA and optimum values is violated between 0 to 16.6% (test problem no.4). The minimum and maximum gaps between the average solution obtained by GA and optimum values are equal to 0 and 28% (test problem no.1) respectively. Table 5 shows the running time of the proposed GA versus that of CPLEX too. We see that the running time of CPLEX is exponential regarding problem size. Though GA's running time is almost linear.

Sensitivity analysis

The impact of the number of jobs with precedence

It should be noted that the complexity and computational time of each instance depend on the number of jobs, the number of jobs with precedence, the number of jobs with synchronization, and the nurses' quality matrix. The computational experiments on generated instances confirm this.

For example, the impact of the number of jobs with precedence on the solution time is investigated. This is done by keeping the total number of jobs fixed and increasing the number of jobs with precedence. An instance with 100 nurses and 20 jobs is considered. Five jobs are hard and five jobs are soft. The number of jobs with precedence was increased from 2 to 10. CPLEX solver could not find an optimal solution (except for the first instance). The GA algorithm is used to solve the instances. In all cases, the proposed algorithm solved the problem in a reasonable time. The results also show the advantages of the proposed algorithm, in particular in the case of jobs with precedence. Fig. 6 shows the effect of the number of jobs with precedence on running time. As this figure shows by increasing the number of jobs with precedence from 2 to 10, the running time goes up dramatically and increases 2.8 times. Consequently, based on the numerical results, the number of jobs with precedence, which is one of the main differences between the HHC problem and VRP, is one of the influential factors in solving time.

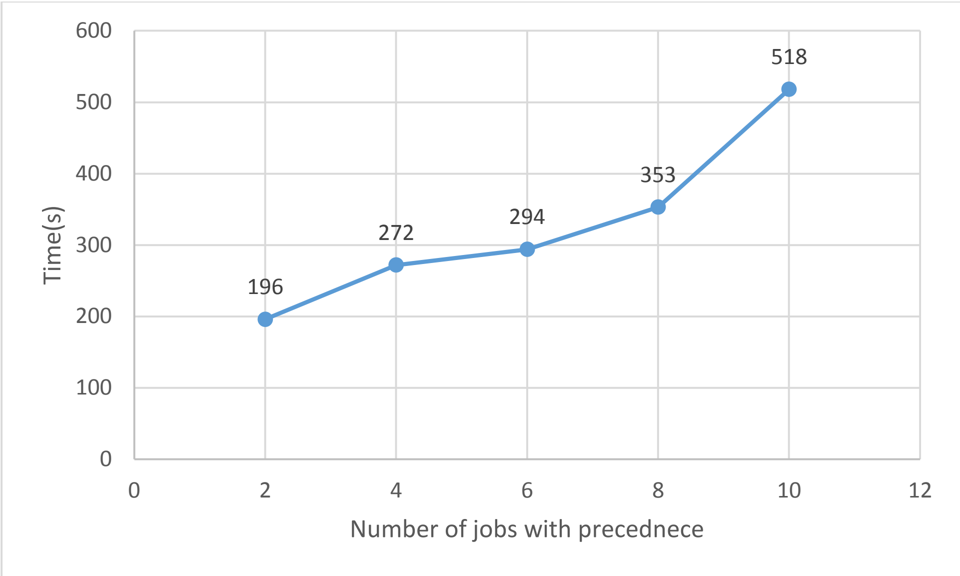

Fig. 6. Impact of jobs with precedence

Dispatching policy

In this part, different policies of dispatching nurses are compared. Nurses can start/end their jobs at home or office, this depends on the HHC agency's policy or contractual agreement. To compare the effect of each policy on the solution, different examples are considered and for each one, the starting and ending point of nurses is changed. The objective function, the sum of waiting time of all nurses and total traveling time is calculated. The result is shown in Table 6. As it is shown in Table 6, in all cases, the objective function does not change. This shows that changing the nurses dispatching policy generally has not effect on the objective function. Hence, the HHC office without worrying about the impact of the nurse dispatching policy on the objective function can choose one of the policies according to the condition. Also as it is shown in the last column of Table 6, it can be seen that the effect of changing the policy of sending nurses on total traveling time is negligible. However, the nurses' dispatching policies have a meaningful effect on the waiting times.

To compare the effect of each dispatching policy on the total waiting time, the obtained results are illustrated in Fig. 7. The results show that by using different strategies of dispatching nurses, the total waiting time of nurses is changed. As well, in some cases, changing the policy of sending nurses may lead to a failure to solve the problem by GAMS (In one case, the applied PC comes out of memory).

Table 6. Different policies of dispatching nurses

	Instance	Objective function	Sum of waiting time	Total travelling time
office to home	1	172	252	962
home to office	1	172	335	969
home to home	1	172	252	967
office to office	1	172	252	954
office to home	2	961	0	315

	Instance	Objective function	Sum of waiting time	Total travelling time
home to office	2	961	40	351
home to home	2	961	27	305
office to office	2	961	0	305
office to home	3	81	101	949
home to office	3	81	74	942
home to home	3	infeasible	infeasible	infeasible
office to office	3	81	201	944
office to home	4	170	319	979
home to office	4	170	257	961
home to home	4	170	243	989
office to office	4	170	318	930

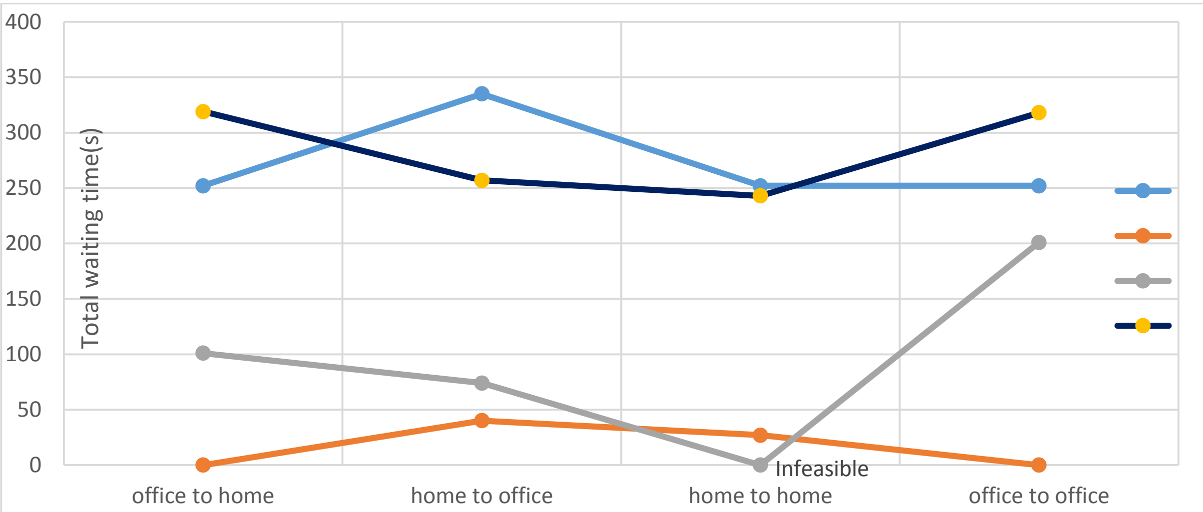

Fig. 7. Comparing the sum waiting time

Conclusion and future research

In this study, a mathematical model for the daily planning of HHC was formulated. In the developed model all jobs must be done. Real-world constraints such as continuity of care and temporal dependencies were considered as two main aspects of the problem. Besides, a new formulation for adjusting the time distance between two consecutive jobs performed by a nurse was presented. The solution obtained by the proposed GA algorithm was compared with the exact ones. The result showed the efficiency of the proposed algorithm. As well, the numerical results demonstrate that changing the nurses dispatching policy generally does not affect the objective function ie. total penalties for jobs need soft COC. However, the dispatching policy can change the total waiting time meaningfully. For example, in problem instance 2, the total waiting time was zero when office to home/office to office policy was implemented. While it was increased to 40 and 27 by applying home to office and home to home policies respectively. For future study and regarding Table 1, various aspects such as overtime, breaks, and part-time nurses can be considered. The different cases of disasters that cause new conditions and need rescheduling can be under attention too. As it was shown, besides the dimension of the problem, the quality matrix has a crucial impact on the complexity and computational time of the problem. Deeper analysis to evaluate the effect of the quality matrix can be under attention, which is marginally addressed. As well, developing other solution algorithms with the help of hybrids or other types of metaheuristics and comparing them with the developed GA, in terms of performance criteria, can be a fruitful direction to do further researches. or Also, a more comprehensive analysis of the nurse dispatching policy and the impact of different aspects of it can be considered.

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