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Home Care Services Planning With Time Windows and Periodic Demands Under Continuity of Care

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***Abstract*—Because of improving in healthcare systems, we have witnessed an increasing trend in the life expectancy leading to a larger proportion of the people who need more care. On the other hand, due to the life styles, taking care of elderly people by relatives has been reduced. As a result, demand for home care services is growing fast and providers of such services have confronted with over demand and need to employ planning methods in order to reduce the operational costs. In this paper, we introduce a problem arising when providing supportive care for people in the home. Essentially, we are given a set of customers whose demand have to be provided over a given time horizon. Our proposed model accounts for general skill levels of the nurses and care continuity. Also patient time windows and scenarios should be respected. We develop a mixed integer linear programming model to solve the problem. Since the developed model includes scheduling, routing and assignment problems, exact methods are not suitable solution approaches for such problem. Thus, we have developed a Simulated Annealing metaheuristic algorithm that incorporates heuristic and math-based local searches. Computational tests on a set of randomly generated instances indicate the effectiveness of the developed algorithm.**

Keywords— Home care services; care continuity; time window; scheduling; vehicle routing problem

I. Introduction

Home Care Services is an alternative to conventional clinical treatments and includes serving medical, paramedical and social services to patients at their own home. The home care industry has grown significantly during last decade. This growth has several reasons such as: population aging, social changes, an increase in the number of patients that suffer from chronic illnesses, development of new medical technologies and services, and governmental pressure [1].

It is expected that demand for home care services would be twice until 2030. This fact is because home care services are going more popular since it is more desirable and less-stressing for patients [2]. American Medical Association predicted there would be yet an over demand by 20% gap at 2030 [3].

The main resources for providing home care services are: Nurses, transportation vehicles, medical equipment and instruments, administrative buildings, and administrative staff. High operational costs and low payments causes near-zero profit margin for home care providers and it is even negative in rural areas [4].

Home care studies pursue some criteria which are expressed as constraints and objective function in mathematical programming.

Nurses’ skills and patients’ needs matching is a quality of service (QoS) criterion which is considered as a hard constraint in the most of researches. Some of the patients need special cares that only some of the nurses can provide it suitably. Nurses’ skills structure mostly is considered hierarchically. In some cases, general structure is considered and nurses’ skills cannot compensate each other. This structure especially happens in institutions that serve more services than medical services. Skill Matching also is considered as soft constraints too. Any deviation from soft constraint’s target should be accounted by a penalty function.

Care Continuity which is noticed considerably in previous papers, is also related to QoS. This criterion states that several visits of a patient should have done by one constant nurse or a limited number of nurses. Many reasons are given for this policy which most important are: patient preference, reducing information loss and improving treatments quality. This criterion is considered as hard or soft constraints.

Generally, home care optimization problems consist of three sub problems, namely 1-assignment of patients and nurses, 2-scheduling appointments, and 3-daily routing for nurses. In some papers, only one of these problems has taken into account while some others considered all three sub problems when introducing problem. Those who considered all three problems had two approaches for it. First approach is based on decomposition methodology. In this approach, the prime problem is decomposed into two major problems (assignment problem & scheduling and routing problem). Second approach is integrated solving to all three problems. As the problem is NP-Hard, the first approach is attracted more attentions. In the decomposition approach, the assignment problem is solved and then schedules and routes are determined. However in integrated approach, a comprehensive model is proposed and solves all three problems.

Trautsamwisr and Hirsch [5] introduced a daily home care services planning problem. In this paper, authors do not consider care continuity in their proposed model, however, soft and hard time windows, skill matching and nurses mandatory break times are considered. Nickel et al. [6] addressed short-term and long-term home care planning problems. In proposed model, skill matching and time windows are incorporated as hard constraints while care continuity is considered as a soft constraint. The objective function is to minimize the total costs including lost demands, care continuity deviations, over time, and travel costs. Rasmussen et al. [7] proposed a model for home care staff scheduling. In addition to medical cares, the authors considered general needs such as cleaning, home services when modeling problem. In addition, temporal dependency constraints have taken into account. These constraints regulate dependency between jobs including synchronization, overlap, minimum time difference between two jobs, and maximum time difference between two jobs. Time windows, skill matching, and patient-nurse preferences are considered to model the problem. The authors investigated a multi-objective function which includes minimizing total costs, travelled distances, preferences deviations, and lost demands. Yalcindag et al. [8] investigated a human resource planning problem in health home care. They only considered care continuity and over time for modeling. The authors solved the problem by a two-stage approach.

Cappanera and Scutella [9] investigated all three sub problems of home care in an integrated way. Their proposed model includes skill matching and partial care continuity. Their goal is to balancing the utilization factor of nurses. In the model developed by Maya Duque et al. [10], the authors consider a concept opposite of care continuity which states that each costumer should be served by at least two nurses in order to reduce the costs occurring by the absence of a given nurse. They used a bi-objective model maximizing patient-nurses preferences and minimizing traveled distances in a lexicographic order.

In this paper, time windows, skill matching, care continuity, and full demand covering are considered simultaneously which have not been studied in the previous research works. Furthermore, care continuity standard for every patient is considered based upon type of disease. In other words, in the necessary case, all needed appointments should be done by just one constant nurse. But it is possible to assign more than one constant nurse to some other patients. Moreover, it is supposed that skills' structure is general. In this structure, skills have same values and cannot compensate each other and every nurse can have one or more skills.

Mostly time horizon is considered daily in home care literature. Daily planning is not useful for home care services providers since every day planning and imparting to nurses, results in time wasting and loss of nurses' and institute's resources. In this paper a longer time horizon is adapted to solve such problems.

Another point which is ignored in previous researches is periodic demands and service selection by patients. Periodic demands may have two reasons: 1-different appointments of some treatments like hormone injections should be done by a regular time gap for example every two day or every three days, 2-patient prefers to determine a regular plan for his/her treatment. Our proposed model considers periodic demands in which only time gap is crucial in periodic demands and it is not important when first appointment starts.

II. Problem Definition

A. Problem Description

In this paper, all three sub problems related to home care are considered. It is supposed that all demands should be served completely while respecting constraints. Each patient can demand one or more appointments during the time horizon. It is considered that time horizon is a 6-days period. As time horizon is not long, random changes are not noticeable; hence the problem is considered deterministic.

Demands in our proposed model are of periodic demand type which is ignored in previous papers. Periodic demands state different appointments of a patient how should be served based on some scenarios. It can be every day, every other day or every two days in between during the time horizon. Each nurse is paying based on a constant working time during time horizon. Even if nurse is not utilized all of his/her working time, complete working time should be paid. For the sake of demand covering, over time is allowed too. Each nurse's residence is considered as the start point and end point of the routes since any nurse's roster is imparted earlier the week and it is no longer needed to going more to office.

A common constraint in literature is time windows. Our proposed model addressed hard time windows. Time windows are considered in two equal shifts: morning and evening. Each patient declares one of this shifts as his/her preferred visit time to institute. Also, skill matching is addressed in this paper. A nurse-patient assignment is allowed only if the nurse has specific qualification that patient needs. Furthermore, the care continuity is considered for each patient. Some patients should have complete care continuity while others need partial care continuity.

Our objective function minimizes cost including nurses overtime costs and total travel costs.

B. ILP Model

In this section, the problem is modeled as a mixed integer linear programming model. The parameters are defined in table I. In this table is noticeable that: 1 nodes are considered in mathematical model which nodes number 0 and $|p|+1$ showing nurses' residences. These two points are same and just for better readability of model are considered separately. $t^n_{p,p'}$ and $c^n_{p,p'}$ are equal for all nurses between demand nodes and only are different in two parts: 1-travel time and travel cost between route start point and first visit point ($t^n_{0,p}$.$c^n_{0,p}$). 2-travel time and travel cost between last visit and route end point ($t^n_{p,|p|+1}$.$c^n_{p,|p|+1}$). Moreover, $t^n_{0,|p|+1}$ and $c^n_{0,|p|+1}$ are equal to zero.

TABLE I. NOTIONS DEFINIATION

Parameter	Definition
$N = \{1,\dots,\|N\|\}$	Set of nurses
$P = \{1,\dots,\|P\|\}$	Set of demands
$T = \{1,\dots,\|T\|\}$	Set of time horizon days
$S = \{1,\dots,\|S\|\}$	Set of scenarios
Q_n	Set of skills of nurse
A_p	Set of allowable nurses for patient p
S_p	Set of preferred scenarios by patient p
α	Overtime cost per time unit
τ	Day duration
h_n	Working time of nurse n
η_p	Needed skill by patient p
r_p	Care continuity threshold of patient p
v_p	Number of appointment needed by patient p
d_p	Service time for patient p
$[a_p, b_p]$	Time window for patient p
$t^n_{p,p'}$	Travel time between patient p and p' by nurse n
$c^n_{p,p'}$	Travel cost between patient p and p' by nurse n
a_{sd}	A binary parameter. If it equals to 1 it a visit can be done on day d in scenario s.

As travel time and travel cost in the forward and backward path between two nodes are identical, the problem graph is a symmetrical graph. The set of allowable nurses for patient p is determined by term (1).

$$A_p = \{n \mid \eta_p \in Q_n\} \tag{1}$$

In order to model the problem, we used following variables:

$X^{nd}_{p,p'} = \begin{cases} 1 & \text{if nurse } n \text{ travels along } (p,p') \text{ on day} \\ 0 & \text{otherewise,} \end{cases}$ $\forall n \in N, \forall d \in T, \forall p \in P \cup \{0\}, \forall p' \in P \cup \{|P|+1\}$

$R^n_p = \begin{cases} 1 & \text{if nurse } n \text{ is assigned to patient } p, \\ 0 & \text{otherwise,} \end{cases}$ $\forall p \in P, \forall n \in N$

$Y_{ps} = \begin{cases} 1 & \text{if scenario } s \text{ is assigned to patient } p, \\ 0 & \text{otherwise,} \end{cases}$ $\forall s \in S, \forall p \in P$

O_n : Over time of nurse n $\forall n \in N$

U^{nd}_p: Patient p visit time by nurse n on day d $\forall p \in P \cup \{0, |P|+1\}, \forall n \in N, \forall d \in T$

The problem can be formulated as follows:
Objective function (2) minimizes the total cost which is composed of nurses' over time costs and total travel costs. Constraint (3) guarantees that all the demands will be satisfied. Also this constraint assures only nurses with adequate skill can visit patient p. Constraint (4) computes nurses over time during the time horizon. Three factors increase nurse's workload: service time, travel time, and waiting time. Waiting time happens when a nurse arrive at a patient's home earlier than the determined time window. If total workload of a nurse during the week exceeds its working time, O_n will be forced to have a values which is equal with nurses over time. Constraints (5) and (6) ensure that each nurse leaves his/her residence and also return to it every day. If the nurse does not visit any patient, variable $X^{nd}_{0,|p|+1}$ will be equal to 1 which means nurse does not travel any paths and visit any patients. Constraint (7) is the classical flow constraint for the routing variables. Constraints (8) and (9) are related to care continuity. Constraint (8) links routing variables and assignments variables. A nurse can visit a patient only if he/she is assigned to that patient. Constraint (9) ensures that total assigned nurses to a patient are not more than allowed care continuity threshold. Constraint (10) states that if patient p' is visited by nurse n at day d after patient p , $X^{nd}_{p,p'}$ will be equal to 1 and constraint is transferred to $U^{nd}_p + (d_p + t^n_{p,p'}) \le U^{nd}_{p'}$. Thus $U^{nd}_{p'}$ is calculated based on service time (d_p), travel time ($t^n_{p,p'}$), and previous node visit time (U^{nd}_p). If $X^{nd}_{p,p'}$ equals to zero, constraint equals to $U^{nd}_p - U^{nd}_{p'} \le (b_p - a_{p'})$ determining an upper bound for $U^{nd}_p - U^{nd}_{p'}$. This constraint also prevents sub tour formation since it relates routing variables with a time relation. Constraint (11) ensures that time variables respect time windows and each visit is started within its allowed time window.

$$Min \quad \alpha \sum_{n \epsilon N'} O_n + \sum_{n \epsilon N'} \sum_{d \epsilon T} \sum_{p' \epsilon P \cup \{|P|+1\}} \sum_{p \epsilon P \cup \{0\}} c^n_{p,p'} X^{nd}_{p,p'} \tag{2}$$

$subject\ to:$

$$\sum_{d \epsilon T} \sum_{n \epsilon A_p} \sum_{p' \epsilon P \cup \{0\}} X^{nd}_{p',p} = v_p \qquad \forall\, p \,\epsilon\, P \tag{3}$$

$$\sum_{d \epsilon T} (U^{nd}_{|P|+1} - U^{nd}_0) - O_n \le h_n \qquad \forall\, n \,\epsilon\, N \tag{4}$$

$$\sum_{j \epsilon P \cup \{|P|+1\}} X^{nd}_{0,p'} = 1 \qquad \forall\, n \,\epsilon\, N, \forall\, d \,\epsilon\, T \tag{5}$$

$$\sum_{p \epsilon P \cup \{0\}} X^{nd}_{p,|P|+1} = 1 \qquad \forall\, n \,\epsilon\, N, \forall\, d \,\epsilon\, T \tag{6}$$

$$\sum_{p' \epsilon P \cup \{0\}} X^{nd}_{p',p} = \sum_{p' \epsilon P \cup \{|P|+1\}} X^{nd}_{p,p'} \qquad \forall\, n \,\epsilon\, N, \forall\, d \,\epsilon\, T, \forall\, p \,\epsilon\, P \tag{7}$$

$$\sum_{d \epsilon T} \sum_{p' \epsilon P \cup \{0\}} X^{nd}_{p',p} \le v_p R^n_p \qquad \forall\, n \,\epsilon\, N, \forall\, p \,\epsilon\, P \tag{8}$$

$$\sum_{n \epsilon N} R^n_p \le r_p \qquad \forall\, p \,\epsilon\, P \tag{9}$$

$$U^{nd}_p + (d_p + t^n_{p,p'}) X^{nd}_{p,p'} \le U^{nd}_{p'} + (b_p - a_{p'})(1 - X^{nd}_{p,p'}) \qquad \forall\, n \,\epsilon\, N, \forall\, d \,\epsilon\, T, \forall\, p \,\epsilon\, P \cup \{0\}, \forall\, p' \,\epsilon\, P \cup \{|P|+1\} \tag{10}$$

$$a_j \sum_{p \epsilon P \cup \{0\}} X^{nd}_{p',p} \le U^{nd}_p \le \tau - (\tau - b_p) \sum_{p' \epsilon P \cup \{0\}} X^{nd}_{p',p} \qquad \forall\, p \,\epsilon\, P, \forall\, n \,\epsilon\, N, \forall\, d \,\epsilon\, T \tag{11}$$

$$\sum_{s \in S_p} Y_{ps} \le 1 \qquad \forall\, p \,\epsilon\, P \tag{12}$$

$$\sum_{n \epsilon N} \sum_{p' \epsilon P \cup \{0\}} X^{nd}_{p',p} \le \sum_{s \in S_p} a_{sd} Y_{ps} \qquad \forall\, p \,\epsilon\, P, \forall\, d \,\epsilon\, T \tag{13}$$

$$X^{nd}_{p,p'} \in \{0,1\} \qquad \forall\, n \,\epsilon\, N, \forall\, d \,\epsilon\, T, \forall\, p \,\epsilon\, P \cup \{0\}, \forall\, p' \,\epsilon\, P \cup \{|P|+1\} \tag{14}$$

$$R^n_p \in \{0,1\} \qquad \forall\, n \,\epsilon\, N, \forall\, p \,\epsilon\, P \tag{15}$$

$$Y_{ps} \in \{0,1\} \qquad \forall\, s \,\epsilon\, S, \forall\, p \,\epsilon\, P \tag{16}$$

$$O_n \ge 0 \qquad \forall\, n \,\epsilon\, N \tag{17}$$

$$U^{nd}_p \ge 0 \qquad \forall\, p \,\epsilon\, P \cup \{0, |P|+1\}, \forall\, n \,\epsilon\, N, \forall\, d \,\epsilon\, T \tag{18}$$

It is obvious if patient p is not visited by nurse n, constraint equals to $0 \le U^{nd}_p \le \tau$ which means time variable can obtain any value. Constraint (12) and (13) are about periodic demands and service selection. Constraint (12) makes sure that one scenario can be assigned to a patient among all of patient's preferred scenarios. Constraint (13) assures that regarding to the assigned scenario (Y_{ps}), only allowable routing variables can have none-zero values. Finally Constraints (14)-(18) define decision variables types.

III. Solution Method

In this section a metaheuristic based on Simulated Annealing (SA) is proposed consisting of an initialization algorithm and three improving algorithms. The SA parameteres are defined in Table II.

TABLE II. ALGORITHM'S SYMBOLS

Symbol	Definition
l_d	Maximum patient numbers can or must be visited on day d
n_s	Number of scheduled nurses
p_d	Number of scheduled patients
π	The probabilty of assignig a patient with coresspunding element eqaul to 1
α	Temperature Coeffiecient
ρ	Omitted patients percentage in *SS* algorithm
m	Maximum allowed iteration number without improvement in *SS* algorithm
$Iter_{temp}$	Number of iteration in each temperature
$temp_c$	Current temperature
Δf	Change amount in objective function

A. Initialization Algorithm

To obtain an initial feasible solution, we should know available and forbidden patients for each uurse and in each day. For this purpose, a 3-dimensial matrix, named *Roster*, is constructed.

Roster matrix dimensions include patients, nurses, and days respectively. Each element of this matrix can have 0, 1, or 2 values under following conditions.

$$Roster_{p,n,d} = \begin{cases} 2, & \text{if patient } p \text{ must be visited on day } d \\ 1, & \text{if patient } p \text{ can be visited on day } d \\ 0, & \text{if patient } p \text{ must not be visited on day } d \end{cases} \quad \forall p \in P, \forall n \in N, \forall d \in T$$

Roster matrix is calculated based on nurses' skills, patients' needs, and patients' allowable scenarios. After each patient-nurse assignment, *Roster* is updated based upon other constraints. The initialization algorithm is as follows

Initialization Algorithm

<u>**Step 0:**</u> *Roster* Calculation, $d=0$;

While ($d < |T|$) **do**

- $d{+}{+}$;
- $n_s = p_s = 0$;
- **While** ($n_s < |N| \,\&\, p_s < l_d$) **do**
  - <u>**Step 1:**</u> select one nurse by using following rules in a lexicographic order: 1-nurse with maximum available working time, 2-nurse with maximum corresponding elements equals to 2 on day d, 3-randomly selection. Then $n_s{+}{+}$ and go to <u>step2</u>.
  - <u>**Step 2:**</u> select one patient that its corresponding element is 2 by using following rules in a lexicographic order: 1-farthest patient to selected nurse, 2-patient with lowest time window upper bound, 3-randomly selection. Then if assignment is feasible, patient with least additional cost is selected for next assignments. After each assignment, $p_s{+}{+}$ and check nurse available working time, if it is less than zero go to <u>step 1</u>. If there is no patient with element equals to 2 go to <u>step 3</u>. Step 3: if still no patient is assigned to selected nurse, select one patient that its corresponding element is 1 regard the order mentioned in step 2. Then if assignment is feasible, patient with least additional cost is selected for next assignments by the probability of π. After each assignment, $p_s{+}{+}$ and check nurse available working time. If it is less than zero, go to <u>step 1</u>.
- **End While**
- If there is any patient that its corresponding element is 2, select them in order of their numbers and assign them to nurses in order of their available times. If there is a patient that cannot be assigned to any patient, go to step 0.

End While

B. Improving Algorithms

1) Inter-Route Algorithm (IRS)

In this algorithm, the swappings of all pairs of paitents in each route are examined. According to the first-improvemetn strategy in costs, the corresponding swap is applied. If no improvement is found, the next route is examined. Also, uurses are selected respect to their number.

2) Intra-Route Algorithm (ORS)

Using *ORS* algorithm, the swappings of all pairs of paitents in each dar and among diffrenet nurses are are examined. Nurses are selected based on. Sawping applied to the solution based on the first improvement strategy. If no improvement is found, other routes in that day will be tested. In the next step, next days will be checked.

3) Scenario Swapping Algorithm (SS)

This algorithm examines the impact of changing patients' assigned scenario. In this procedure, p percent of patients are omitted from nurses' routes randomly. Then, at a random order, cost of assigning each scenario for all patients is calculated and best scenario is chosen for that patient. This algorithm iterates until no improvement or no any feasible solution is found at most *m* iteration. Moreover, if any feasible solution is not found in each iteration, p will be reduced by θ percent. Also, if feasible solution is found but without any improvement, p will be increased by θ percent. Finally, in case of any improvement, p will equals to its initial value.

C. SA Algorithm

In this section, SA algorithm, consisting of algorithms presented in previous sections, is explained. In SA algorithm, improving algorithms, described in Section *B*, is used as a local search procedure. Each algorithm is selected randomly with equal probability as it is needed. If a local search algorithm leads to improvement, its probability for being chosen in next iterations will be increased. The SA algorithm can be descibed as follows:

SA Algorithm

- Best Solution $=\infty$, Current Solution = *Initialization*, $temp_c = T_0$

While ($temp_c > T_f$) **do**

- **For** (i = 1 to $Iter_{temp}$) **do**
  - Current Solution improvement by one of the improving algorithms selected randomly;
  - accept worse answer by the probability $e^{\frac{-\Delta f}{temp_c}}$; if there is improvement, increase the probability of selected algorithm for being selected for subsequent iterations
  - **If** (Current Solution improves Best Solution)
    - Best Solution = Current Solution
  - **End If**
  - $i = i+1$;
- **End For**
- $temp_c = temp_c * \alpha$

End While

End

IV. Computional Results

In order to investigate the performance of the developed algorithms, we generated a set of random test instances. Four different sizes of patient numbers are considered including 10, 20, 40, or 80 patients. Also, residence of patients and nurses are determined by coordinates within the range of 1 to 1000, convertible based on each cities proportion. For each size of the problem, two different instances are generated. Also for each different instance, various states for some parameters are considered. These parameters are number of skills (2 and 4 skills), number of declared scenarios by patients (only one scenario, more than one scenarios, all of the scenarios), and number of nurses (slight, sufficient, and excessive). Other parameters are generated based on the appropriate distributions. According to the combination of different values of parameters, 84 instances are generated based on 8 different data. The developed algorithms are implied by using C++ programming language and applying IBM ILOG CPLEX 12.6 libraries. The computer, used for computational results, has these specifications: CPU Intel Corei5 2.27GHZ, Ram 4GB.

A. Parameter Tuning

As the proposed algorithm has several parameters, it is essential to find best parameter combination. For this purpose, 21 sample instances are selected, different combination of parameters are examined and results have been shown in Table I. In this table, the considerd values for parameters are mentioned in the first row while the best combination of parameters is displayed in the second row. Temperatures and iteration numbers are chose economically which means more iteration and more time-consuming parameters does not reach a significant improvement.

TABLE III. PARAMETER TUNNING

Algorithm	π	ρ	m	$Iter_{temp}$	θ
Combinations	50,70, 80,90	10,30, 50	50,100	5.10	10, 20
SA	70	50	100	5	10

B. Results of SA Algorithm

The results of the developed *SA* algorithm over 84 generated test instances are presented Table II. It should be mentioned that for each test instance, algortithm has been implemented five times. Also, the comparative results with CPLEX 12.6 are displayed in this table. In the three hours time limit, the software is only able to find feasible solution for only 43 instances where 18 solutions of them are optimal. Overally, the CPLEX software is ineffective for larger problems since the home care problem is NP-Hard. It can find feasible solution for 18 instances out of 24 instances with 40 patients where only 3 of them are optimal. It is worse for instances with 80 patients in which only for one instance out of 36 test instances a feasible solution are found.

TABLE IV. COMPARATIVE RESULTS OF *SA* ALGORITHM

Run	Average Gap (%)	Max Gap (%)	AverageTime (S)
Run 1	-7.65%	3.40%	50.25
Run 2	-8.10%	1.34%	47.42
Run 3	-7.93%	2.63%	51.34
Run 4	-8.05%	4.10%	47.62
Run 5	-7.85%	2.14%	48.54
Best of All Runs	-8.28%	0.84%	49.12

V. CONCLUSION AND FUTURE RESEARCHES

In this paper a new problem of home care are considered which studies all aspects of quality of service (QoS). Also another important point which is very vital to patient's comfort is taken to account by considering regular visits and scenarios.
As the problem is a type of vehicle routing problem and is NP-hard, exact methods and solvers are unable to find solution for it. Therefor a heuristic algorithm based on simulating annealing algorithm is proposed which is very effective in comparison to exact methods.
Since the developed algorithm is not able to find optimal solutions for some large scale instances, more hybrid algorithms may be developed to reach solution with better qualities. Furthermore, more local search algorithms can be applied to enhance the algorithm performance. These local search algorithms can be heuristic or based on exact mathematical programming methods. Another extension, being available for this problem, is considering possible disruption to schedules. For example, nurse absence and urgent treatments are some of eruptions. Some methods may be employed to decrease the effects of these disruptions.

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