Crew Constrained Home Health Care Routing Problem with Time Windows and Synchronized Visits

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Abstract. Population aging, rise in the prevalence of chronic diseases worldwide, and growing health care costs have substantially increased the demand for home health care (HHC) in recent years. To gain a competitive advantage in the market and lower public expenditure, HHC service providers and governmental institutions mainly focus on increasing service quality while decreasing their costs. These objectives have resulted in various challenging optimization problems that have been widely studied in the past few years, including routing and scheduling problems. In this paper, we study an HHC routing and scheduling problem with time windows, where service is provided to patients requesting different types of care using a limited crew. We first provide the mixed integer programming formulation of the problem. Then, we perform a computational study to investigate the benefits of allowing synchronized visits to patients. Our results show that synchronized visits guarantee HCC service to all patients in some instances which are otherwise infeasible, and may reduce the total travel distance in other cases.

Keywords: Home health care · Synchronization · Vehicle routing problem

1 Introduction

The global increase of chronic diseases, population aging, and continuous changes in the health care systems are all implications of the significant increase in demand for home health care (HHC) services. Given a choice between care in an institution or at home, most people would prefer to stay in their own home (World Health Organization 2011). Older people (aged 65 or over) constituted 19.2% of the total population in the EU-28 in 2016, which indicates a 2.4% increase in the last decade. This increasing trend is projected to continue and reach 30% by the year 2080 (EUROSTAT 2015). The population of Americans aged over 65 is projected to more than double from 40.2 million in 2010 to 88.5 million in 2050 (Vincent and Velkoff 2010). Health spending accounts for nearly 10% of GDP in the European Union (OECD 2016), of which up to 5% is spent on HHC services (Genet et al. 2012). While the general view among Europeans is that health care services should be provided and controlled by the governments, the integration of HHC services into governmental institutions is a long-term process, so

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private companies have been filling the gap. In 2014, more than 4.9 million patients received service from home health agencies in the United States, and around 8% of the registered long-term HHC service providers had for-profit ownership (Harris-Kojetin et al. 2013).

The aim to reduce public expenditures without sacrificing from the service quality and to gain competitive advantage have made HHC routing and scheduling problems popular in the operations research (OR) literature in recent years. To lower costs, effective planning of HHC operations is a necessity. Optimizing the assignment of personnel by planning their travel routes and arrival time at each patient, and scheduling their working times are some of the challenging problems addressed by researchers within the HHC context. Although HHC routing and scheduling problems are relatively new, they are closely related to well-studied problems such as technician routing, logistics management, workforce routing, and scheduling problems. A comprehensive review of recent work on HHC routing and scheduling can be found in Fikar and Hirsch (2017).

In this paper, we extend the Crew Constrained Home Care Routing Problem with Time Windows (CC-HCRPTW) introduced by Tozlu et al. (2015). In this problem, limited HHC crew provide different types of care to patients within specific time windows. The HHC services offered to patients can be categorized into two groups. The first group includes services such as nursing, vaccination, blood pressure measurement, blood sugar measurement, insulin injections, etc., which are provided by a nurse. The second group includes assisting older people, home life aids, bathing, etc. An aide provides these services. Some of the patients need both of these services; hence, they should be served by both a nurse and an aide. It is also possible that the service required by a patient must be provided by two care providers simultaneously, e.g., when the patient is unable to move and needs a bath.

Some patients only require a single type of care which can be provided by a vehicle which rides only a nurse (or aide). A vehicle carrying both a nurse and an aide would be able to provide service to any patient type. The requirement of different types of services by a patient closely relates the problem at hand to the technician routing problem introduced by Dutot et al. (2007) where technicians with different skill levels are assigned to teams to meet the skill requirements of the interventions in the telecommunication sector. Although the assignment, scheduling and routing tasks in our problem are highly complex, which makes it a challenging combinatorial optimization problem, HHC service providers usually manage these complex tasks manually, which results in potentially sub-optimal solutions and high organizational efforts (Wirnitzer et al. 2016).

In this study, we introduce CC-HCRPTW with Synchronization (CC-HCRPTWSync) and highlight the advantages of allowing synchronized visits to patients. To the best of our knowledge, this particular vehicle routing problem (VRP) variant where synchronized visits are allowed has not been studied in the literature.

Bredström and Rönnqvist (2008) is the first study that addressed HHC routing and scheduling problem with time windows considering synchronization constraints. In this paper, the authors proposed a mathematical formulation for a real-world application considering minimization of total travel time, maximization of the sum of preferences of customers and minimization of the difference between the longest and the shortest service times among the vehicles to optimize the workload balance. A local branching approach was proposed to solve this multi-objective optimization problem. The authors also proposed a branch-and-price algorithm and constructed benchmark instances, of which 44 out of 60 were solved to optimality.

A generalization of VRP with synchronization was presented by Dohn et al. (2011), which is referred to as VRP with Time Windows and Temporal Dependencies. The authors study more general requirements such as maximum and minimum overlap and gap between the starting and ending time of visits in addition to standard synchronization. The objective function minimizes the total transportation costs. A branch-and-cut-and-price algorithm was proposed and tested on instances derived from the well-known benchmark instances of Solomon (1987) for VRPTW.

Our problem differs from those in the literature as we consider a heterogeneous fleet where the number of crew available is limited.

2 Problem Description and Formulation

Given a central office (depot) and a set of patients, the patients are classified as type 1, type 2 or type 3, where the type 1 patients need to be served by a nurse, type 2 patients by an aide and type 3 patients by both. The service time for a patient depends on the type of the patient and should start within the assigned time window. In other words, the time window restricts the earliest and latest time to start the service at that patient. The time-window constraint does not only provide a better quality service but also makes sure that time-sensitive HHC tasks such as insulin injection, blood taking, provision of medication are performed on time (Fikar and Hirsch 2017).

Based on the type of personnel it carries, a vehicle can also be classified as type 1, type 2, or type 3. A type-1, type-2, or type-3 vehicle carries a nurse, a home health aide, or both, respectively. As mentioned earlier, a type-3 vehicle can provide service to all types of patients, whereas a type-1 (type-2) vehicle can only serve type-1 (type-2) patients. Each vehicle starts its tour at the central depot, serves a set of patients and returns to the central depot before the end of the shift. We assume that the numbers of nurses and aides available are limited, i.e., we have two types of limited resources.

The aim is to minimize the total distance traveled while providing HHC to all the patients with an appropriate type of vehicle within the predefined time window. The distance minimization objective is used because the vehicles are generally provided by a third-party company and are charged by the total trip distance.

2.1 Mathematical Formulation

We begin by introducing the necessary notation. Let $V = \{1, \ldots, n\}$ denote the set of patients, and vertices 0 and $n+1$ denote the depot representing the start and end of each vehicle route, respectively. The sets including the depot are denoted as $V_0 = V \cup \{0\}$ and $V_{n+1} = V \cup \{n+1\}$ and the set including all the nodes is denoted as $V_{0,n+1} = V \cup \{0\} \cup \{n+1\}$. Thus, CC-HCRPTW can be defined on a complete directed graph $G = (V_{0,n+1}, A)$ with a set of arcs $A = \{(i, j) | i, j \in V_{0,n+1}, i \neq j\}$. Each arc $(i, j) \in A$ is associated with a distance d_{ij} and a travel time t_{ij}. A patient $i \in V$ is of type r_i, where $r_i \in \{1, 2, 3\}$.

Each patient is assigned a service time s_i and a time window $[e_i, l_i]$. The former indicates the amount of time units that service will be provided to the patient i, while the latter states that the care at patient i can start as early as e_i and as late as l_i. The time window for the depot is denoted by $[e_0, l_0]$, where e_0 is the start time of service from the depot and l_0 is the restriction on the latest time to arrive at the depot at the end of the shift. The set of patients of type r is denoted as T_r and $T_{r,0} = T_r \cup \{0\}$. If a nurse (aide) is assigned to a vehicle, it is called a type-1 (type-2) vehicle. A vehicle carrying both a nurse and an aide is referred to as a type-3 vehicle.

The binary decision variable x_{ijr} takes the value of 1 if arc (i, j) is traversed by a vehicle of type r, and 0 otherwise. The decision variable q_i keeps track of the arrival time to vertex i. The number of available nurses and aides are h_1 and h_2, respectively, and referred to as the crew (resource) limits. Thus, following Tozlu et al. (2015), the mixed integer program of the CC-HCRPTW can be formulated as follows:

$$\text{Minimize} \sum_{i \in V_{0,n+1}} \sum_{j \in V_{n+1}, j \neq i} \sum_{r \in R} d_{ij} x_{ijr} \tag{1}$$

subject to

$$\sum_{i \in V_0, i \neq j} x_{ij1} + \sum_{i \in V_0, i \neq j} x_{ij3} = 1, \forall j \in T_{1,0} \tag{2}$$

$$\sum_{i \in V_0, i \neq j} x_{ij2} + \sum_{i \in V_0, i \neq j} x_{ij3} = 1, \forall j \in T_{2,0} \tag{3}$$

$$\sum_{i \in V_0, i \neq j} x_{ij3} = 1, \forall j \in T_{3,0} \tag{4}$$

$$\sum_{i \in V_0, i \neq j} x_{ijr} = \sum_{i \in V_{n+1}, i \neq j} x_{ijr}, \forall j \in V, \forall r \in R \tag{5}$$

$$\begin{aligned} & q_i + x_{ijr}\left(t_{ij} + s_i\right) - L\left(1 - x_{ijr}\right) \leq q_j, \\ & \qquad \forall i \in V_0, \forall j \in V_{n+1}, j \neq i, \forall r \in R \end{aligned} \tag{6}$$

$$e_j \leq q_j \leq l_j, \forall j \in V_{0,n+1} \tag{7}$$

$$\sum_{j \in V_{n+1}} x_{0j1} + \sum_{j \in V_{n+1}} x_{0j3} \leq h_1 \tag{8}$$

$$\sum_{j \in V_{n+1}} x_{0j2} + \sum_{j \in V_{n+1}} x_{0j3} \leq h_2 \tag{9}$$

$$x_{ijr} \in \{0, 1\}, \forall i \in V_0, \forall j \in V_{n+1}, j \neq i, \forall r \in R \tag{10}$$

$$q_i \geq 0, \forall i \in V_{0,n+1} \tag{11}$$

The objective function (1) minimizes the total distance traveled. Constraints (2)–(3) ensure that the care is provided to the patients exactly once by a vehicle carrying the appropriate personnel. Constraints (2) make sure that type-1 patients are served by a type-1 or type-3 vehicle, whereas Constraints (3) guarantee the service to type-2 patients by a type-2 or type-3 vehicle. Constraints (4) enforce that only type-3 vehicles provide care to type-3 patients. Flow conservation is ensured by Constraints (5) while time feasibility for arcs leaving patients or the depot is satisfied by Constraints (6). Constraint (7) make sure that the time windows of the patients and depot are not violated. Sub-tours are eliminated by maintaining the schedule feasibility concerning time considerations through Constraints (6) and (7). Constraints (8) and (9) guarantee that the total crew assigned to the vehicles does not exceed the available number of nurses and aides, respectively. Binary decision variables are defined in Constraints (10), and the non-negativity restriction on the arrival times is imposed by Constraints (11).

The model can be easily modified to handle other relevant objective functions, such as minimizing the total number of health care personnel (12) or the total number of vehicles (14) as follows:

$$min \sum_{i \in V_{n+1}} \left(x_{0j1} + x_{0j2} + 2x_{oj3}\right) \tag{12}$$

$$min \sum_{i \in V_{n+1}} \sum_{r \in R} x_{ojr} \tag{13}$$

3 CC-HCRPTW with Synchronization

It is possible to use limited resources more efficiently by serving a type-3 patient by type-1 and type-2 vehicles simultaneously. Essentially, by allowing synchronization, we are enlarging the feasible region. A similar idea was suggested by Labadie et al. (2014). A type-3 patient who needs both a nurse and an aide can be served by a type-1 and type-2 vehicles simultaneously. Furthermore, with an easy but eloquent modification to our model, synchronized visits can be imposed by replacing Constraints (4) with the following constraints:

$$\sum_{i \in V_0, i \neq j} x_{ij3} + \frac{1}{2}\left(\sum_{i \in V_0, i \neq j} x_{ij1} + \sum_{i \in V_0, i \neq j} x_{ij2}\right) = 1, \forall j \in T_{3,0} \tag{14}$$

$$\sum_{i \in V_0, i \neq j} x_{ij1} \leq 1, \forall j \in T_{3,0} \tag{15}$$

$$\sum_{i \in V_0, i \neq j} x_{ij2} \leq 1, \forall j \in T_{3,0} \tag{16}$$

Constraints (14) makes sure that a type-3 patient is served either by a single type-3 vehicle or by a pair of type-1 and type-2 vehicles visiting her simultaneously. Constraints (15) and (16) guarantee that only one vehicle of type 1 and type 2 visits a type-3 patient.

Figure 1 highlights how allowing synchronized visits can reduce the number of vehicles and crew needed to provide service to a set of patients. Patients 1 and 2 are of type-1 and need to be served by a nurse, while patients 4 and 5 are type-2 and need an aide. Patient 3 is a type-3 patient who requires both a nurse and an aide. The solution

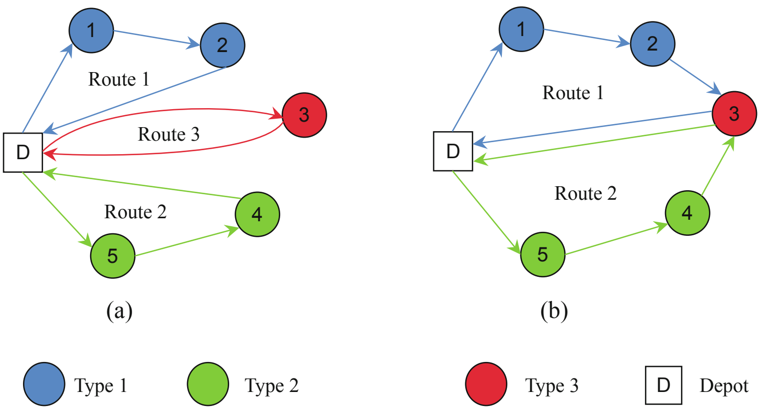

Fig. 1. An illustrative example of CC-HCRPTW and CC-HCRPTWSync: (a) synchronized visits are not allowed, (b) synchronized visits are allowed

in Fig. 1(a), where synchronized visits are not allowed, shows that a type-1 vehicle provides service to patients 1 and 2 through Route 1, a type-2 vehicle serves patients 4 and 5 through Route 2, and a type-3 vehicle serves patient 3 through Route 3. In total, three vehicles accompanied by two nurses and two aides are required to provide service to the patients. In Fig. 1(b), where synchronized visits are allowed, a type-1 vehicle serves patients 1 and 2 while a type-2 vehicle serves patients 4 and 5, and both vehicles simultaneously provide service to patient 3 before returning to the depot at the end of their routes. Note that the service at a synchronized patient begins within its time windows when both resources are present, meaning that one of the vehicle types may have to wait for the other to arrive to begin the service. One can notice that the number of vehicles needed to serve all the patients is reduced by one when synchronization is allowed. Moreover, only one nurse and one aide are needed, which shows a more effective utilization of available resources. CC-HCRPTW is infeasible for any instance where the available resources (h_1, h_2) are less than (2,2) (i.e. (1,1), (1,2) and (2,1) cases) whereas the corresponding CC-HCRPTWSync versions are all feasible. This also shows the benefit of allowing syncronized visits to patients under tight resources.

4 Experimental Design

4.1 Instance Generation

To show the advantages of synchronization, we selected a subset of Solomon 25-node instances, namely R201, RC101, RC105, adapted them to our problem. We used the same coordinates and time windows as in Solomon data and ignored the demand information. To make the data compliant to our problem, we needed to assign each customer a type and a corresponding service time. The types are assigned such that the probability of synchronized visits is relatively high. Each instance was expanded into five groups, namely G1, G2, G3, G4, G5, in which the percentage of patients with care types 1, 2 and 3 differs as given in Table 1.

Table 1. Percentage of each care type in instance groups

Group	Type of care		
	1	2	3
G1	60%	32%	8%
G2	48%	36%	16%
G3	48%	28%	24%
G4	32%	28%	40%
G5	28%	24%	48%

In the first group of instances, 60% of the patients require type-1 care only, 32% require type-2 care only, and the remaining 8% require both type-1 and type-2 cares. Similarly, the information for the other groups is as given in Table 1. The service times of type-1, type-2, and type-3 patients are 10, 40, and 45 min, respectively.

Determining the number of available nurses and aides is a challenging problem. On the one hand, if the crew constraints are too tight, we may end up with infeasible instances. On the other hand, if these constraints are too loose, the instances may no longer become challenging.

To determine meaningful crew sizes, we first solved the HCRPTW model by minimizing the total amount of each resource separately as well as minimizing the sum of resources by using CPLEX solver. Minimizing the sum of the resources provides us a "lower bound" on the number of resources. The "upper bound" is obtained by minimizing the total traveled distance. For each instance, we then determine four different crew settings following these lower and upper bounds for the number of nurses and aides. In the first setting, the crew size h_1 and h_2 are set to the optimal resources obtained from minimizing the total distance traveled. For the second setting, the resource limits are set to the optimal resource values obtained from minimizing the sum of h_1 and h_2. For the remaining two settings, the resource limit is tight in one resource type and loose in the other. Thus, the total number of instances we generated is $3 \times 5 \times 4 = 60$.

4.2 Experimental Environment and Parameter Settings

The MILP was coded in Java and solved using IBM ILOG CPLEX Version 12.6.2. For all experiments, we used a 64-bit server equipped with Intel Xeon E5-2640 v3 2.6 GHz processor running on a Windows 7 Professional virtual machine with 16 GB RAM.

5 Results

In this section, we compare the results for CC-HCRPTW with those obtained for CC-HCRPTWSync. Note that the objective function value (ofv) of CC-HCRPTW is an upper bound for the ofv of CC-HCRPTWSync. When the crew sizes are limited, allowing synchronized visits can improve the optimal ofv of CC-HCRPTW, and in some cases, an infeasible instance with a specific crew configuration can become feasible. Table 2 shows the results for 10 selected instances among 60. The computation times are in seconds. We should note that in this paper, we only present the results of problems that benefit from the utilization of synchronized visits. In all of our instances, either a single patient or at most two type-3 patients are visited simultaneously by a type-1 and type-2 vehicle. For larger instances, the probability of having more patients visited simultaneously may increase.

Table 2. Advantages of allowing synchronized visits

Instance	h1	h2	No sync			Sync			
			Status	ofv	Time	Status	ofv	Time	imp. (%)
P1	2	2	Optimal	71781	8.59	Optimal	67284	18.76	6.68
P2	4	7	Optimal	80357	0.15	Optimal	70937	0.11	13.28
P3	6	6	Optimal	82493	0.14	Optimal	78171	0.31	5.53
P4	7	7	Optimal	77754	7.00	Optimal	77280	30.50	0.61
P5	7	8	Optimal	75483	0.55	Optimal	75343	0.81	0.19
P6	5	6	Infeasible			Optimal	72380	3.21	
P7	6	7	Infeasible			Optimal	71026	0.20	
P8	6	6	Infeasible			Optimal	88228	0.92	
P9	5	5	Infeasible			Optimal	69024	184.93	
P10	5	6	Infeasible			Optimal	73099	520.79	

In instances P1–P5, we observe that the total distance traveled can be reduced by up to 13.28%. On the other hand, instances P6–P10, which are infeasible in the case of CC-HCRPTW become feasible when synchronized visits are allowed. Note that an instance may be feasible for different sets of crew sizes in CC-HCRPTWSync whereas all the corresponding CC-HCRPTW cases are infeasible because synchronized visits are not allowed. One such example is instance P8 for which CC-HCRPTW is infeasible for resource levels (5,6), (6,6) and (6,7) where the first number indicates the number of nurses and the second the number of aides. This shows that allowing synchronized visits can enable the service provider company to successfully offer service to patients, especially when the number of nurses and aides are limited or low on a specific day.

6 Discussion and Conclusion

In this study, we first discussed the Crew Constrained Home Care Routing Problem with Time Windows and formulated its mathematical programming model. Next, we extended this problem by allowing synchronized visits to the patients and presented its mathematical programming formulation.

For this problem, we created challenging instances involving 25 patients by solving the HCRPTW model with different objectives to determine different resource levels.

We performed computational tests to investigate the benefit of allowing synchronized visits. Our results revealed improvements in 10 instances out of 60. In five instances that are infeasible to CC-HCRPTW, feasible optimal solutions are obtained by allowing synchronized visits. In the remaining five instances, CC-HCRPTWSync improves the objective function value of that of CC-HCRPTW. It should note that the advantages of synchronized visits can be more significant in real-world large size problems, which would offer more opportunity to visit patients simultaneously.

Further research on this topic may focus on performing computational experiments on an extended set of data. Since the problem is intractable for large size instances, a heuristic/metaheuristic method can be devised to tackle CC-HCRPTW as well as its extension to CC-HCRPTWSync.

Finally, the problem has several interesting extensions which deserve further investigation, e.g. vehicle routing where the personnel is allowed to use multiple modes of transport, vehicle routing with split service when a type-3 patient can be served by a nurse and an aide at different times, vehicle routing where the fleet is comprised of electric vehicles, as well as the time-dependent and stochastic VRP variants of the problem.

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