Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

A Home Health Care Planning Problem with Continuity of Care And Flexible Departing Way for Caregivers ⋆

Wenheng Liu * **Mahjoub Dridi** * **Hongying Fei** ** **Amir Hajjam El Hassani** *

* *Nanomedicine Lab,Univ. Bourgogne Franche-Comté ,UTBM,F90000,Belfort,France (e-mail: Wenheng Liu,Mahjoub Dridi,Amir Hajjam El Hassani@utbm.fr).*
** *School of Management, Shanghai University, 99 ShangDa Road, BaoShan District, Shanghai 200444, China (e-mail: Feihy@shu.edu.cn)*

Abstract: This paper formulates a mixed-integer programming model for a mid-term home health care routing and scheduling problem with considering several real-life constraints, such as continuity of care, time window, qualification of caregivers, and a flexible departing way for caregivers. Three sub-objectives: operational cost, the satisfaction of patients, and workload balancing of caregivers are merged with the weights as the objective function. The model is addressed by a commercial solver Gurobi through the randomly generated instances inspired by Periodic Vehicle Routing Problem with Time Windows (PVRPTW) benchmark. Computational results present that this problem can be solved efficiently. Furthermore, the relationship between sub-objectives and optimal results is discussed by changing weight allocation. This work offers HHC managements a proper method to respect practical constraints, achieve optimal objectives as well as find the optimal solution efficiency.

Keywords: Home Health Care,Multi-Day Planning Horizon,Continuity of care, Vehicle Routing

1. INTRODUCTION

Home health care(HHC) is a wide range of health care services that can be given in personal home for an illness or injury; it is usually more convenient, less expensive, and just as effective as care you get in a hospital or skilled nursing facility. In recent years, the health care industry has become one of the largest sectors of the economy, mainly in North America and Europe (Emiliano et al., 2017). The trend of the demand for HHC services raises due to aging populations, the increase of chronic diseases, and the development of innovative technologies. Consequently, HHC companies are expected to reduce costs, improve service quality, and enhance productivity.

According to the survey of HHC companies(Harris, 2005; Shi et al., 2019), the primary operational process of HHC can be summarized as three phases: (1) The HHC company gathers necessary information from patients and caregivers; (2) The company makes the planning to decide which patient should be served by which caregiver on which day and the visit order of caregivers, the planning is done with the consideration of peculiar constraints (e.g., time window of patients, which imposes that a patient must be visited during this time interval) to achieve the objective (e.g., minimize the operational cost); (3) Caregivers serve the patients based on the designed route on the planned day. Generally speaking, this problem is called the home health care routing and scheduling problem (HHCRSP) (Fikar and Hirsch, 2017; Cissé et al., 2017). For the HHC company, it is hard to find high-quality solutions manually when the data scale is enormous. Hence, it is important for HHC companies to solve this problem efficiently.

In actual life, a mid-term HHCRSP is more practical to conduct multi-day planning for the HHC company. Continuity of care is a peculiar feature in mid-term HHCRSP, which means that patients require only one same caregiver to serve them during the planning period; this caregiver is named the reference caregiver. Continuity of care issue plays a significant role in not only developing a good relationship between caregivers and patients but also avoiding potential information loss among caregivers. However, only a few studies consider continuity of care in the HHC nurse-to-patient assignment problem(Carello and Lanzarone, 2014; Lin et al., 2016). Hence, it is of significance to research this issue in HHCRSP. In addition, since there may be a considerable workload gap among caregivers when the continuity of care is taken into account, workload balancing is also needed to be involved in maintaining the satisfaction of caregivers. Usually, a strict workload balancing is hard to obtain, this constraint is embedded in the objective function and also considered as a soft constraint(Bredström and Rönnqvist, 2008; Decerle et al., 2019).

Most literature in the HHCRSP assume that caregivers start and end their work at a single depot(Grenouilleau et al., 2019; Moussavi et al., 2019), while the multiple depots problem is less studied. In the context of HHC,

⋆ The first author thanks the China Scholarship Council for financial support gratefully (Contract N.201801810101).

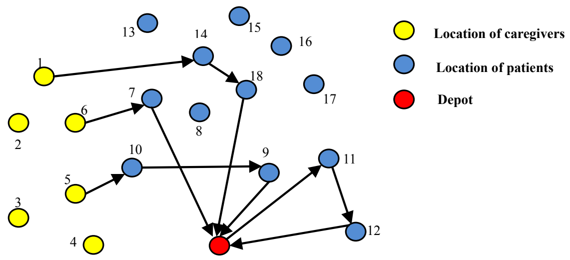


Fig. 1. Flexible departing way for caregivers

a multi-depot HHC service case was first proposed in (Akjiratikarl et al., 2007). Then Kergosien et al. (2009) studied a problem that covered both single and multiple depots by dissociating the starting and ending locations for each caregiver. In their problem, a caregiver can start and end at their home for the visit, Trautsamwieser et al. (2011) introduced three kinds of routes based on their origin and destination: routes start and end at the hospital, routes start and end at caregiver's location, and routes start and end at caregiver's location but the distance between the caregiver's location and the patient are not counted. Although multiple departing ways of caregivers are already researched, most assumption of them is not suitable in practical operation for the HHC company. In this paper, according to the reality of a HHC company (Institute Montclair) in France, we present a flexible departing way for caregivers, i.e., caregivers can depart either from their homes or from the location of the HHC company (also called depot), though all of them must finally return to the depot, see Fig. 1.

To sum up, compared with the existing literature, the main contributions of this study include two aspects: (1) a novel mathematical model for the mid-term HHCRSP with considering less studied continuity of care and a flexible departing way for caregivers issues is presented; (2) several experiments are conducted to evaluate the model, and the relationship between sub-objectives and optimal results is explored.

The rest of this study is organized as follows: Section 2 gives the problem statement. The mathematical model is described in Section 3. Section 4 illustrates the numerical results based on Gurobi and discusses the results with instances under different weight allocation. Finally, conclusions and perspectives are given in Section 5.

2. PROBLEM STATEMENT

In this section, the mid-term HHCRSP is defined. Given a set of patients who are to be served at home during the upcoming several days and a set of caregivers with various skills, the goal is to obtain a feasible schedule and several routes on a multi-day period for each caregiver. Each patient is visited at most once a day and can be served once or several times in the prefixed days within their time window; the patient's demands are deterministic during the planning period. Each caregiver has a contract working time, and all the visits should be completed within this period, contract working times can be deemed the time window of caregivers. Caregivers can use two kinds of transportation modes (the private car or the rented car provided by the HHC company). Only the caregivers qualified for the service of a patient can be allocated to serve this patient. In addition, each caregiver has the same basic salary, he/she will get additional income based on their working time. Finally, the caregivers will work at the company if there are no service tasks on some days,.

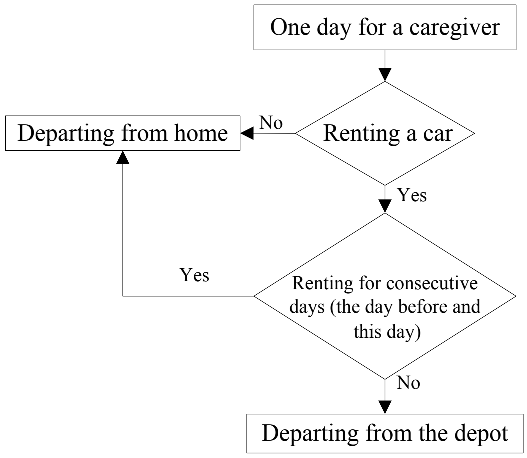


Fig. 2. Judging flow chart for the flexible departing way

Flexible departing way depends on whether caregivers choose private or rented cars for their visits. Caregivers depart from their homes if they use the private car, and if caregivers need the rented car for consecutive days, they also start the work from home so that rental cars can be maintained at home for the work of the coming day. Only if caregivers need a rented car one day, but the day before they choose the private car, the depot is the origin of the route since caregivers need to get the rented car first. The judging flow chart is presented in Fig. 2. In general, caregivers send a request to the company about which day they need a rented car and which day they can use the private car, the company rents the cars based on this request for the next planning horizon.

In this study, two types of patients and three different continuity of care requirements are considered, and the set of patients is partitioned into five subsets: (1) follow-up patients who require hard continuity of care, they are already under treatment during the last horizon, and their reference caregiver cannot be changed; (2) newly admitted patients who require hard continuity of care, they start their treatment during the upcoming horizon, and their reference caregiver cannot be changed; (3) patients who do not require continuity of care, their reference caregiver can be changed without any penalty; (4) follow-up patients who require partial continuity of care, they are already under treatment during the last horizon and can be reassigned to more than one capable caregivers; (5) newly admitted patients who require partial continuity of care, they start their treatment during the upcoming horizon and can be reassigned to more than one capable caregivers. The reassignment appears because the HHC company needs to balance workloads among caregivers or because there are not enough caregivers available sometimes. Since it is preferable not to change the reference caregiver for patients who require partial continuity of care, each reassignment will incurs a penalty cost to show patients' dissatisfaction.

The objective of HHC company often pursued is to minimize the total operational cost, and maximize the satisfaction of patients and caregivers. In this study, the total operational cost is represented by the wage of caregivers, which corresponds to their total working time of the car. The satisfaction of patients is defined by the penalty cost of reassignment for patients who require partial continuity of care, the lower the penalty cost, the higher the satisfaction. The satisfaction of caregivers is indicated by the workload balancing, which is associated with maximal working time difference during the planning horizon among caregivers; the smaller the difference, the higher the satisfaction.

3. MATHEMATICAL MODEL

Notations used in this study are listed as follows:

Sets:

K= {1, 2,...,m}: Set of caregivers;

D= {1, 2,...,m}: Set of the caregivers' address;

P= {m, m+1,...,m+n}: Set of locations where each location is associated with one patient;

P_c^1: Set of follow-up patients who require hard continuity of care,$P_c^1 \subset P$;

P_c^2: Set of newly admitted patients who require hard continuity of care,$P_c^2 \subset P$;

P_{nc}: Set of patients who do not require continuity of care,$P_{nc} \subset P$;

P_{pc}^1: Set of follow-up patients who require partial continuity of care,$P_{pc}^1 \subset P$;

P_{pc}^2: Set of newly admitted patients who require partial continuity of care,$P_{pc}^2 \subset P$;

V={0,1,...,m,m+1,...m+n,m+n+1}: Set of all locations where 0 is the origin of the routes if caregivers depart from the depot, m+n+1 is the destination of all routes, both 0 and m+n+1 represent the depot.

T= {1, 2,...,t}: Set of days covered by the planning horizon;

Parameters:

i,j: Index of the locations which correspond to the location mentioned in this problem;

k: Index of caregivers;

t: Index of days;

s_i^t: Service duration of patient i on day t;

t_{ij}: Travel time from location i to location j;

q_i^k: Binary constant, equals 1 if caregiver k is qualified to serve patient i;

w_i^k: Binary constant, equals 1 if caregiver k depart from their home's location i, 0 otherwise;

z^{kt}: Binary constant, equals 1 if caregiver k needs a rented car on day t, 0 otherwise;

d_i^t: Binary constant, equals 1 if the patient at location i requires a service on day t;

r_i^k: Binary constant, equals 1 if patient $i \in P_c^1 \cup P_c^2$ is initially assigned to caregiver k, 0 otherwise;

[PL_i^t,PU_i^t]: Lower/Upper bound time window of node i on day t;

A_i: Reassignment number of patient i in the planning horizon;

C^W: Wages of caregivers per time unit;

C^R: Penalty cost of a reassignment;

α: Weight of total wages of caregivers;

β: Weight of penalty cost for reassignment;

δ: Weight of workload balancing;

M: A sizeable positive constant;

Decision variables:

x_{ij}^{kt}: Binary variable, equals 1 if caregiver k travel from location i to location j on day t, 0 otherwise;

y_i^{kt}: Binary variable, equals 1 when patient i is allocated to caregiver k on day t, 0 otherwise;

mm_i^k: Binary variable, equals 1 when patient i is assigned to caregiver k, 0 otherwise;

ts_i^{kt}: Time point when caregiver k starts to work at location i on day t;

W: Workload balancing variable, which equals the maximal working time difference during the planning horizon among caregivers;

H_i^t: Artificial variable for constructing the sub-tour elimination constraint;

3.1 Working time of caregivers

In this study, the working time of a caregiver is defined as the sum of total traveling time and total service duration of his/her visiting route. The working time wt_k^t of caregiver k on day t is formulated as equation (1).

$$wt_k^t = \sum_{i \in V} \sum_{j \in V} x_{ij}^{kt} t_{ij} + \sum_{i \in P} y_i^{kt} s_i^t \quad \forall t \in T, k \in K \tag{1}$$

The workload balancing corresponds to the maximal working time difference during the planning horizon among caregivers. Hence, workload balancing W is formulated as equation (2).

$$\sum_{t \in T} wt_k^t - \sum_{t \in T} wt_l^t \le W \quad \forall k, l \in K, k \ne l \tag{2}$$

The mathematical formulation is given by:

$$Min \left(\sum_{k \in K} \sum_{t \in T} \alpha C^W wt_k^t + \sum_{i \in P_{pc}^1 \cup P_{pc}^2} \beta C^R A_i + \delta W \right) \tag{3}$$

Subject to:

$$\sum_{j \in P} x_{0j}^{kt} + \sum_{i \in D} \sum_{j \in P} x_{ij}^{kt} \le 1 \quad \forall t \in T, k \in K \tag{4}$$

$$\sum_{j \in P} x_{ij}^{kt} \le w_i^k \quad \forall i \in D, t \in T, k \in K \tag{5}$$

$$\sum_{j\in P} x_{0j}^{kt} + \sum_{i\in D}\sum_{j\in P} x_{ij}^{kt} = \sum_{j\in P} x_{j(m+n+1)}^{kt} \quad \forall t\in T, k\in K \tag{6}$$

$$\sum_{j\in P} x_{0j}^{kt} = z^{kt}\left(1 - z^{k(t-1)}\right)\sum_{j\in P} x_{j(m+n+1)}^{kt} \quad \forall t\in T, t\neq 1, k\in K \tag{7}$$

$$\sum_{j\in P} x_{j(m+n+1)}^{k1} = z^{k1}\sum_{j\in P} x_{0j}^{k1} + \left(1 - z^{k1}\right)\sum_{i\in D}\sum_{j\in P} x_{ij}^{kt} \quad \forall k\in K \tag{8}$$

$$\sum_{j\in V} x_{ij}^{kt} = \sum_{j\in V} x_{ji}^{kt} = y_i^{kt} \quad \forall i\in P, t\in T, k\in K \tag{9}$$

$$d_i^t = \sum_{k\in K} y_i^{kt} \quad \forall i\in P, t\in T \tag{10}$$

$$\sum_{i\in V} x_{ij}^{kt} \leq q_j^k \quad \forall j\in P, t\in T, k\in K \tag{11}$$

$$mm_i^k \geq y_i^{kt} \quad \forall i\in P, t\in T, k\in K \tag{12}$$

$$\sum_{k\in K} mm_i^k = 1 \quad \forall i\in P_c^1\cup P_c^2 \tag{13}$$

$$\sum_{k\in K} mm_i^k \geq 1 \quad \forall i\in P_{pc}^1\cup P_{pc}^2\cup P_{nc} \tag{14}$$

$$mm_i^k = r_i^k \quad \forall i\in P_c^1, k\in K \tag{15}$$

$$A_i = \sum_{k\in K} mm_i^k\left(1 - r_i^k\right) \quad \forall i\in P_{pc}^1 \tag{16}$$

$$A_i = \sum_{k\in K} mm_i^k - 1 \quad \forall i\in P_{pc}^2 \tag{17}$$

$$PL_i^t\sum_{j\in V} x_{ij}^{kt} \leq ts_i^{kt} \leq PU_i^t\sum_{j\in V} x_{ij}^{kt} \quad \forall i\in V, t\in T, k\in K \tag{18}$$

$$ts_i^{kt} + s_i^t + t_{ij} + \left(x_{ij}^{kt} - 1\right)\times M \leq ts_j^{kt} \quad \forall i,j\in V, t\in T, k\in K \tag{19}$$

$$H_i^t - H_j^t + x_{ij}^{kt}(n+1) \leq n \quad \forall i\in P, t\in T, k\in K \tag{20}$$

$$x_{ij}^{kt} = 0 \quad \forall i\in D\cup\{0, m+n+1\}, t\in T, k\in K \tag{21}$$

$$x_{ij}^{kt}\in\{0,1\} \quad \forall i,j\in V, t\in T, k\in K \tag{22}$$

$$y_i^{kt}, mm_i^k\in\{0,1\} \quad \forall i\in P, t\in T, k\in K \tag{23}$$

The objective function (3) aims at minimizing the total wage of caregivers during the planning horizon, the penalty cost of reassignments for patients who require partial continuity of care and the maximal working time difference during the planning horizon among caregivers, three sub-objectives are influenced by the weight $\alpha, \beta\ and, \delta$, respectively, the relationship of these three weights is defined in equation (24).

$$\alpha + \beta + \delta = 1 \tag{24}$$

Constraints (4) (5) guarantee that caregivers depart either from their homes or the depot. Constraint (6) ensures that each caregiver must return to the depot after completing their works. Constraints (7) and (8) identify whether a caregiver departs from their home or the depot. Constraint (9) ensures the balance of the caregivers, if a caregiver visits one patient, he/she must also leave this patient. Constraint (10) guarantees that each patient is served on the day he/she requires service. Constraint (11) imposes that caregivers is qualified for the patients they serve. Constraints (12) to (14) show the continuity of care, constraint (12) sets the variable mm, constraint (13) assures that patients with hard continuity of care requirement only be assigned to one same caregiver during the planning horizon, constraint (14) guarantees that patients who require partial or no continuity of care can be assigned to more than one capable caregivers. Constraint (15) makes sure those follow-up patients who require hard continuity of care do not change their assignment at the beginning of the consider planning horizon. Constraint (16) computes the number of reassignment of follow-up patients who require partial continuity of care. Constraint (17) computes the number of reassignment of newly admitted patients who require partial continuity of care. Constraint (18) ensures the feasibility of each visit based on the time windows. Constraint (19) assures that each caregiver has adequate time to travel between two consecutive locations. Constraint(20) is applied to eliminate sub-tours. Constraint (21) avoids the route establishment between caregivers' homes to the depot. Constraints (22)-(23) represent the feasibility of decision variables, respectively.

4. EXPERIMENTAL RESULTS

In this section, we validate the model by the commercial solver Gurobi. Considering that there is no similar model in the literature. Therefore, we generate the instances inspired by PVRPTW instances(Cordeau et al., 2001). In order to calculate the objective value, we suppose that the penalty cost is 50 for a reassignment, and the payment is 0.1 per time unit for each caregiver, time window of depot and location of caregivers are [0,1000], other parameters not included in PVRPTW instances are generated randomly. Since the studied problem covers all the constraints of the general PVRPTW, and PVRPTW has been proven to be NP-hard, our problem is also NP-hard. In recent years, some commercial programming solvers, such as Gurobi and CPLEX, have been developed to help researchers to find the optimal solution of the problems that can be formulated as linear programming models, and these tools are quite efficient especially for small-size instances in an NP-hard problem. Therefore, in this study, eight instances were adopted from original instances with up to 9 caregivers and 16 patients. Gurobi (Gurobi 8.1.0) is used to obtain optimal solutions to validate the constructed model on a PC with Intel Core i7-8700 CPU, 32 GB RAM, 3.2 GHz and Linux system.

We first assume all the weights of objective function are same ($\alpha = \beta = \delta$), and optimal results are shown in table 1. Where "*Nb*" represents the label of the instances, and "*K*" and "*N*" present the number of caregivers and patients, respectively. "*T*" is the planning horizon. The optimal results are presented in the second column, "*Best*" denotes the objective value, "*V1*" the wages of caregivers, "*V2*" the penalty cost of reassignment, "*V3*" the workload balancing. The last column represents the computational time. The results show that the studied problem can be solved by Gurobi in a acceptable time; obviously, it is more efficient to use our model to do planning than manually. Here we also give the solution of an example instance k3n8t4 in table 2.

Table 1 shows the optimal results when all the weights are the same. However, in real life, different HHC companies may decide the primary objective variously (e.g., a company considers the patient's satisfaction is the most vital objective to be pursued, but another company thinks the operational cost is the principal things). In order to help HHC managers make the proper decision to obtain the optimal solution, we further discuss the relationship between different weight allocations and optimal results. In summary, 15 combinations of weight allocation are defined. Each weight corresponds five possible values 0, 0.1, 0.25, 0.4 and 1. Different weight allocations reflect the importance of sub-objectives, the higher the weight value, the more critical the corresponding sub-objective (e.g., $\alpha - \beta - \delta$ equals 0.5-0.4-0.1 indicates that the company considers operational cost as the most crucial objective than the satisfaction of patients and workload balancing of caregivers). The weight value equals 0 when the corresponding sub-objective is not considered.

The detailed optimal results with different weight allocation are presented in table 3. We can see that optimal results are influenced by the weight values, in order to explore the connection between each weight and the optimal results, the variation of objective value and computational time under the weight value is presented in Fig.3 and Fig.4, respectively. It is noted that since certain weight allocations keep the same weight value of α, β, δ, hence, the average value is calculated. For example, there are two weight allocations with $\alpha = 0.1$, so the objective value for the instance k3n8t4 with $\alpha = 0.1$ is obtained by (31.34+31.58)/2=31.46, and the computational time is (1.12+1.44)/2=1.28.

As shown in Fig.3 (a), while the weight α increase, the objective value is raised as well for all instances. Fig.3 (b) presents that the decrease of the objective value with the increase of weight β for all instances. Fig.3 (c) indicates that the lowest objective value always appears at $\delta = 0.1$, but there is no apparent correspondence between the objective value and weight δ. In Fig.4 (a), it is evident that the variation of the computational time does not follow a specific function of the value of weight α. A negative correlation between the computational time and weight β can be seen in Fig.4 (b). Finally, in Fig.4 (c), most of the instances obey a positive correlation between the calculation time and weight δ. To sum up, we can get some exciting finding, generally speaking, a company consider: (1) the more critical the operational cost, the larger the objective value; (2) the more important the satisfaction of patient, the smaller the objective value and the shorter the computational time; (3) the more critical the workload balancing, the longer the computational time.

Table 1. Optimal Results

Nb	K	N	T	Best	V1	V2	V3	CT(s)
1	3	8	4	99.76	94.98	0	4.78	1.57
2	6	12	4	155.37	98.21	49.95	7.21	2.35
3	6	13	4	161.94	140.09	16.65	5.20	18.6
4	9	16	4	178.74	129.79	0	48.95	9.79
5	4	6	6	117.30	96.33	0	20.97	0.41
6	4	7	6	115.36	110.90	0	4.46	1.10
7	5	10	6	145.50	129.92	0	15.58	1.38
8	8	14	6	270.86	192.96	0	77.9	10.82

Table 2. Detailed Routes of Instance K3N8T4

Day	Caregiver1	Caregiver2	Caregiver3
1	Home-4-5-Depot	Home-6-10-Depot	Home-7-9-Depot
2	Depot-4-5-Depot	Depot-6-8-Depot	Depot-10-11-7-Depot
3	Home-4-5-Depot	Home-6-8-Depot	Home-10-11-9-Depot
4	Home-4-5-Depot	Home-6-8-Depot	Home-11-7-9-Depot

5. CONCLUSIONS AND PERSPECTIVES

This paper proposes a mathematical model for multi-objective mid-term HHCRSP with considering several new practical constraints such as a flexible departing way for caregivers and continuity of care. Experimental results present that Gurobi is able to solve such a problem in a acceptable time. Different weight allocation is proposed to discuss the relationship between the weight value of the objective function and optimal results. This study can help HHC company managers make proper decision to satisfy the real-life constraints, achieve the optimal objective as well as find the optimal solution efficiency.

There are two improvements need to be done in the future. (1) More detailed weight allocation criteria are necessary to be explored, which require to the real-life instances to evaluate the performance of the model; (2) Since many uncertain factors exist in the HHC management, such as patient's demand might be cancelled temporarily; some urgent demands need to be added during the horizon. Then a stochastic model needs to be constructed for tackling the uncertain constraints, and high-quality meta-heuristics will be developed to solve the stochastic model in the future.

REFERENCES

Akjiratikarl, C., Yenradee, P., and Drake, P.R. (2007). Pso-based algorithm for home care worker scheduling in the uk. *Computers & Industrial Engineering*, 53(4), 559–583.

Bredström, D. and Rönnqvist, M. (2008). Combined vehicle routing and scheduling with temporal precedence and synchronization constraints. *European journal of operational research*, 191(1), 19–31.

Carello, G. and Lanzarone, E. (2014). A cardinality-constrained robust model for the assignment problem in home care services. *European Journal of Operational Research*, 236(2), 748–762.

Cissé, M., Yalçındağ, S., Kergosien, Y., Şahin, E., Lenté, C., and Matta, A. (2017). Or problems related to home health care: A review of relevant routing and scheduling problems. *Operations Research for Health Care*, 13, 1–22.

Cordeau, J.F., Laporte, G., and Mercier, A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. *Journal of the Operational research society*, 52(8), 928–936.

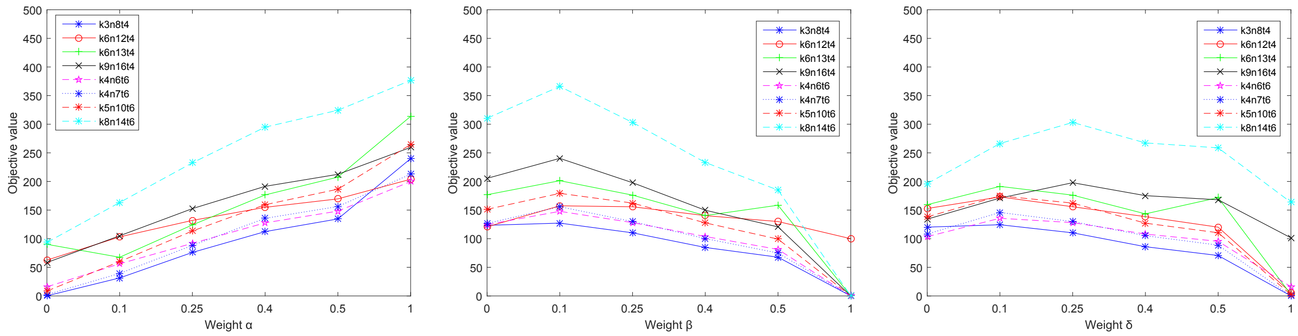
Decerle, J., Grunder, O., El Hassani, A.H., and Barakat, O. (2019). A memetic algorithm for multi-objective optimization of the home health care problem. *Swarm and evolutionary computation*, 44, 712–727.

Emiliano, W., Telhada, J., and do Sameiro Carvalho, M. (2017). Home health care logistics planning: a review and framework. *Procedia Manufacturing*, 13, 948–955.

Fikar, C. and Hirsch, P. (2017). Home health care routing and scheduling: A review. *Computers & Operations Research*, 77, 86–95.

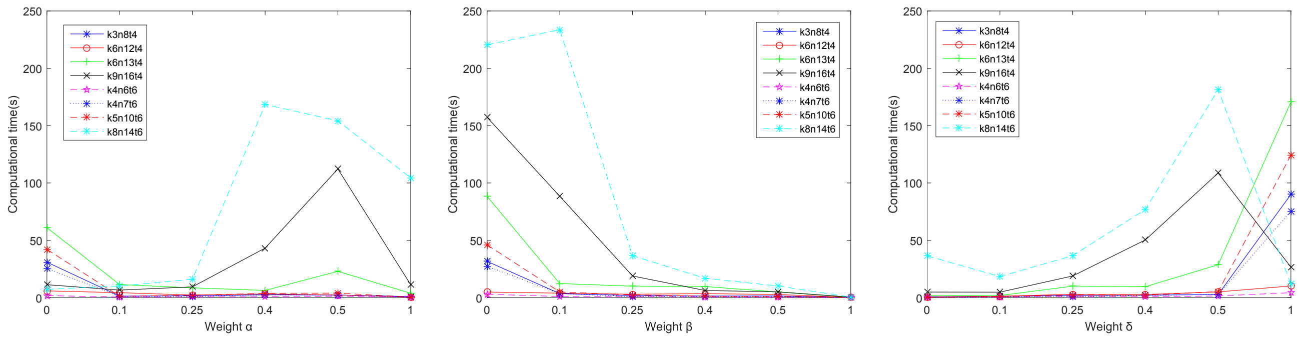
Table 3. Optimal Results Under Different Weight Allocation

$\alpha-\beta-\delta$	k3n8t4		k6n12t4		k6n13t4		k9n16t4		k4n6t6		k4n7t6		k5n10t6		k8n14t6	
	Best	CT(s)	Best	CT(s)	Best	CT(s)	Best	CT(s)	Best	CT(s)	Best	CT(s)	Best	CT(s)	Best	CT(s)
1-0-0	239.9	0.95	203.87	0.4	313.71	3.8	259.52	11.32	199.78	0.52	212.71	0.36	264.53	0.43	376.57	104.47
0.5-0.5-0	120.74	0.95	154.37	0.48	164.55	0.52	142.84	2.75	111.03	0.33	111.88	0.33	149.57	0.44	211.97	4.47
0.5-0.4-0.1	137.82	1.29	180.27	0.67	210.91	1.99	186.97	5.6	149.49	0.59	160.49	0.76	192.93	0.97	291.47	20.09
0.5-0.25-0.25	143.41	1.82	189.54	3.16	226.75	7.61	224.74	24.25	160.39	0.78	169.87	0.89	206.77	1.42	344.4	54.25
0.5-0.1-0.4	140.68	3.17	171.12	3.05	221.59	13.57	252.67	94.28	162.08	1.01	171.88	2.62	196.51	3.36	383.13	147.01
0.5-0-0.5	130.12	3.87	152.61	3.99	214.28	90.7	255.16	433.95	158.12	3.95	167.13	6.5	186.79	13.31	391.2	545.15
0-1-0	0	0.23	100	0.16	0	0.31	0	0.42	0	0.14	0	0.12	0	0.23	0	0.4
0.4-0.5-0.1	111	1.11	165.83	1.65	171.91	1.62	154.98	3.87	121.86	0.44	131.22	0.49	156.84	0.93	241.09	16.59
0.25-0.5-0.25	74.89	1.5	141.92	1.73	122.72	4.66	134.19	5.27	88.06	0.36	86.61	1.08	109.23	1.06	203.35	13.12
0.1-0.5-0.4	31.34	1.12	105.97	2.35	65.25	5.48	97.77	6.37	54.1	0.4	38.66	0.98	57.73	0.76	151.52	6.83
0-0.5-0.5	0.48	2.46	81.93	7.2	268.12	12.07	73.5	6.7	31.46	0.82	6.7	0.95	23.14	1.77	116.96	9.65
0.1-0.4-0.5	31.58	1.44	100.32	6.21	69.88	17.27	112.47	6.71	58.21	0.53	40	0.94	62.41	1.57	174.91	13.44
0.25-0.25-0.5	77.15	1.78	122.06	2.68	125.48	12.32	170.94	13.45	95.8	0.93	89.96	0.95	117.69	3.12	261.83	18.76
0.4-0.1-0.5	113.8	3.74	143.79	4.71	181.08	10.91	228.02	82.47	133.576	0.94	139.92	4.36	161.94	6.46	348.75	320.25
0-0-1	0.12	90	5.71	10.11	2.48	170.57	101.55	26.56	16.176	4.25	0.23	75.2	2.52	124.16	163.58	11.72
Average	90.2	7.7	134.62	3.24	157.25	23.56	159.69	48.26	102.68	1.07	101.82	6.44	125.91	10.71	244.05	85.75



(a) (b) (c)

Fig. 3. The variation of objective value depending on weight α, β *and*, δ



(a) (b) (c)

Fig. 4. The variation of computational time depending on weight α, β *and*, δ

Grenouilleau, F., Legrain, A., Lahrichi, N., and Rousseau, L.M. (2019). A set partitioning heuristic for the home health care routing and scheduling problem. *European Journal of Operational Research*, 275(1), 295–303.

Harris, M.D. (2005). *Handbook of home health care administration*. Jones & Bartlett Learning.

Kergosien, Y., Lenté, C., and Billaut, J.C. (2009). Home health care problem: An extended multiple traveling salesman problem. In *Proceedings of the 4th multidisciplinary international scheduling conference: theory and applications (MISTA 2009)*, 85–92.

Lin, M., Chin, K.S., Wang, X., and Tsui, K.L. (2016). The therapist assignment problem in home healthcare structures. *Expert Systems with Applications*, 62, 44–62.

Moussavi, S.E., Mahdjoub, M., and Grunder, O. (2019). A matheuristic approach to the integration of worker assignment and vehicle routing problems: Application to home healthcare scheduling. *Expert Systems with Applications*, 125, 317–332.

Shi, Y., Boudouh, T., and Grunder, O. (2019). A robust optimization for a home health care routing and scheduling problem with consideration of uncertain travel and service times. *Transportation Research Part E: Logistics and Transportation Review*, 128, 52–95.

Trautsamwieser, A., Gronalt, M., and Hirsch, P. (2011). Securing home health care in times of natural disasters. *OR spectrum*, 33(3), 787–813.