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The application of Adaptive Large Neighbourhood Search in Home Health Care Routing and Scheduling Problem

Le Minh Thao Nguyen[1,*], Nguyen Ky Phuc Phan[1] and Hoai Phuong Le[2]

[1] School of industrial and engineering management, International University, Vietnam National University
[2] Faculty of Mechanical Engineering, Ho Chi Minh City University of Technology (HCMUT), VNU-HCM

Abstract

Due to an aging population, a significant increase in demand for Home Health Care (HHC) services in most developed and developing countries. This paper addresses the considerations of costs including transportation cost, caregiver's cost and patients' load. To mitigate the issue, the objective is to minimize the costs and considerate the patient's load. The resource is defined as an arrangement for patient's load. The deterministic model is solved by CPLEX, and the Adaptive Large Neighborhood Search based on heuristics.

Keywords: Home Health Care, Routing and Scheduling, Adaptive Large Neighborhood Search

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1. Introduction

Nowadays, home healthcare is becoming more and more developed due to an aging population, rates of chronic illness and increasing hospital costs. According to the health report in 2015 of (WHO and Course 2017), the number of humans is expected to live to 77, 15 of these years would be passed with some kind of disability [1]. Moreover, the proportion of elderly people is not only peaking in European countries, but it is also tended to go up further in the following years [9]. Hence, HHC assists old people to be independent to daily activities including bathing, eating, and dressing. In addition, in the system of hospitals, it contributes to medical consultations, medicine and medical equipment distribution, abortive sample collection, management of leftover pharmaceuticals and equipment, and repair and maintenance of home-use equipment, especially in COVID-19 pandemic in 2020. The vast majority of patients could not go to the hospital or medical clinics because of the tough situation of the pandemic so that HHC became important achieve the highest quality of life possible, all through care given in the comfort and familiarity of home. The system allowed to be effective to manage dynamic situations.

The Home Health Care Routing and Scheduling Problem (HHCRSP) is a significant optimization challenge in the delivery of home healthcare services. In addition to routing constraints and time-window restrictions, Home Health Care Routing and Scheduling Problem (HHCRSP) are highly affected by several operational. Synchronization constraints do not only emerge when certain treatments require more than one caregiver to perform tasks simultaneously, but it is also related to failure to align service start times which results in infeasibility under challenging time windows. Set-up and arrangement time is concerned by another important corner, referring to the preparation, handling, and post-caring assistance required before or after each service. While

*Corresponding author. Email: minhthao.theresa@gmail.com

synchronization and setup constraints are mainly on temporal feasibility, they do not fully capture the care intensity burden associated with each patient. Effected by practical requirements observed in home health care organizations, this study adopts the concept of patient load, which represents the additional workload and arrangement effort imposed on caregivers when delivering specific services. This factor directly influences several points such ass workload balance, caregiver assignment, and feasible route construction which complement classical synchronization, setup constraints and leading to a more realistic representation of HHCRSP scenarios. Moreover, researchers have recently been quite interested in the Home Health Care Routing and Scheduling Problem (HHC). There are several parallels between VRPWTW and the home healthcare planning problem, which is really a variation of it. First of all, Liu et al. use a route-based mathematical model to handle the variability in the caregiver's travel time and the patient's service time [4]. This model uses a discrete approximation technique in conjunction with the branch and price (B&P) algorithm to produce a solution. Next, the home health care routing and scheduling problem (HHCRSP) is a well-known problem that is combined by the NP-hard problems including the nurse rostering problem [2] and the vehicle routing problem with time frames (Bräysy and Gendreau 2005) [3]. In addition, the simultaneous delivery and pick-up challenge with stochastic travel and service times in HHC was examined by Shi et al. [8].

This study aims to accomplish the following primary goal by using metaheuristics and other strategies: Reduce the overall travel distance during the allotted time slots, lowering the overall expense of hiring caregivers while still meeting the needs of the patient. To achieve the main objective, this investigation must meet the following requirements. The first point is the collection required data from Ho Chi Minh City, such as patient location, vehicle, and other related information. Next, it is considered significant and subsidiary constraints to obtain the optimal solution within the allocated time. After constructing a mathematical model, it is essential to execute tests to confirm its logic using IBM ILOG CPLEX software. To test with large-scale datasets, it is applied to Adaptive Large Neighborhood Search metaheuristics.

2. Methodology

2.1. Problem statement

The growth of demand for Home Health Care (HHC) services, especially during and after the COVID-19 pandemic, highlights the need for efficient routing and scheduling of caregivers. In particular, in Vietnam, challenges arise from dynamic patient needs, caregiver skill matching, time constraints, and high transportation costs. Existing models lack the flexibility and scalability to address these complexities in real-time. This study aims to develop an integrated optimization approach to minimize operational costs while ensuring timely, high-quality care in urban settings.

The set of patients is denoted by N={1,2,3,...,n},where n is the number of patients. For each patient i, a preferred time window is defined as $[\boldsymbol{a_i}, \boldsymbol{b_i}]$,where $\boldsymbol{a_i}$ and $\boldsymbol{b_i}$ are, respectively, the earliest and latest possible service times of the visits. The caregiver's set is denoted by K={1,2,3,...,c} and set of services is denoted by S={1,2,3,...,q}. The duty length for each caregiver k is given by $[d_k,e_k]$ where $\boldsymbol{d_k}$ and $\boldsymbol{e_k}$ are, respectively, the earliest and latest service times.

The problem is to minimize the transportation cost, traveling cost, and consider the patient's load. The patient's load is arranged before or after the service. The services requested by patients are satisfied by qualified caregivers. After the service are finished, the caregivers would be back to the Home Health Care Center.

2.2. Mathematical formulation

Table 1. Set of indices

Set	Definition
N	Set of patients
N^0 and N^{n+1}	Set of patients including the HHC centre, which is represented by artificial nodes 0 and n + 1 where $N = N^0 \cup \{0\}$ and $N^{n+1} = N \cup \{n+1\}$
K	Set of caregivers
S	Set of service and skills
P	Set of all locations of patients $\{1, \dots P\}$

Table 2. Set of parameters

Parameters	**Definitions**
n	Number of patients
c	Number of caregivers
q	Number of services (skills)
M	Large positive number
$[a_i, b_i]$	Patients' time windows
$[d_k, e_k]$	Caregivers' time windows
c_{ij}	Transportation cost between patients i and j
δ_{is}	Equals 1 if the patient $i \in N$ requires the service operation $s \in S$
Δ_{ks}	Equals 1 if the caregiver K is qualified to provide the service operation $s \in S$
λ_i	Equals 1 if service operations requested by the patient i must be simultaneous
pc_k	Preference vector for caregiver k, equal to 1 if caregiver k can provide special service, 0 if they provide normal service
pc_k	Preference vector for patient i, equal to 1 if patient i chooses special service, 0 if they decide normal service
E	The arrangement duration

tc	Traveling cost
l_i	Service time
eb	The earliest time that all caregivers can start the arrangement
lb	The latest time that all caregivers can start the lunch break
d_{ij}	Distance from node i to node j
ec	The earliest time that all caregivers can start the service
lc	Latest time that all caregivers can finish the service
ep_i	The earliest time that the service for patients i can be started
lp_i	The latest time that the service for patients i can be started
W_{max}	Maximum working hours for all caregivers
W_{min}	Minimum working hours for all caregivers
P_{max}	The minimum number of patients that all caregivers can serve
P_{min}	The minimum number of patients that all caregivers can serve
c_k	Cost of using caregiver k

Table 3. Set of decision variables

Decision variables	Definitions
x_{ijk}	Equals 1 if the caregiver k visits the patient j after the patient i, 0 otherwise
y_{ijk}	Equals 1 if the service operation s is provided by the caregiver k to the patient i, 0 otherwise
$\widetilde{S_{ik}}$	Start time of a service operation at the patient i provided by the caregiver k
$S1_{ik}$	Arriving time of caregiver k to node i
TL_k	The starting time of arrangement
Y^a_{ik}	Binary variable, equal to 1 if caregiver k takes a break at patient i after service; 0 otherwise, $\forall i \in N, k \in C$
Y^b_{ik}	Binary variable, equal to 1 if caregiver k takes a break at patient i before service; 0 otherwise, $\forall i \in N, k \in C$

Minimize Z=
$\sum_{k=1}^{x}\sum_{i=0}^{n}\sum_{j=0}^{n+1} c_{ij}x_{ijk} + \sum_{i\epsilon N}\sum_{j\epsilon P}\sum_{k\epsilon C} x_{ijk}t_c + \sum_{j\epsilon P}\sum_{k\epsilon C} c_k x_{0jk}$
s.t

$\sum_{i=0}^{n}\sum_{k=1}^{c} x_{ijk} = \sum_{s=1}^{q} \delta_{is}$ $j\epsilon N$	(1)
$\sum_{i=0}^{n+1}\sum_{k=1}^{c} x_{ijk} = \sum_{s=1}^{q} \delta_{is}$ $i\in N$	(2)
$\sum_{i=0}^{n} x_{i,n+1,k}=1$ $k\epsilon K$	(3)
$\sum_{j=1}^{n} x_{i,j,k}=1$ $k\epsilon K$	(4)
$\sum_{i=0}^{n} x_{imk}=\sum_{j=1}^{n+1} x_{mjk}$ $m\varepsilon N, k\epsilon K$	(5)
$\tilde{S}_{ik} + \sum_{s=1}^{q} \tilde{t}_{is}\, y_{iks} + \tilde{T}_{ij} \le \tilde{S}_{ik} + (1 - x_{ijk})M$ $j\epsilon N^{n+1}, k\epsilon K$	(6)
$\tilde{S}_{ik} \le \sum_{s=1}^{q} y_{iks}\, M$ $i \in N, k \in K$	(7)
$\sum_{j=1}^{n+1} x_{ijk} = \sum_{s=1}^{q} y_{iks}$ $i \in N, k \in K$	(8)
$2y_{iks} \le \delta_{is} + \Delta_{ks}$ $i \in N, k \in K, s \in S$	(9)
$\sum_{s=1}^{q} y_{iks} \le 1$ $i \in N, k \in K$	(10)
$\sum_{k=1}^{c} y_{iks} \le 1$ $i \in N, s\epsilon S$	(11)
$d_k \le \tilde{S}_{0k}$ $k \in K$	(12)
$\tilde{S}_{(n+1)k} \le e_k + o_k$ $k \in K$	(13)
$(\sum_{s=1}^{q} y_{iks} - 1)M + a_i \le \tilde{S}_{ik}$ $i \in N, k \in K$	(14)
$\tilde{S}_{ik} + \sum_{s=1}^{q} \tilde{t}_{is}\, y_{iks} \le b_i + v_i + (1 - \sum_{s=1}^{q} y_{iks})M$ $i \in N, k \in K$	(15)
$\sum_{i\epsilon P} Y^b_{ik} + \sum_{i\epsilon P} Y^a_{ik} = 1$ $\forall k\epsilon K$	(16)
$Y^b_{ik} + Y^a_{ik} \le \sum_{i\epsilon N} x_{ijk}$ $\forall k \in K\ \forall j \in P$	(17)
$TL_k + EY^b_{ik} \le S_{jk} + (1-Y^b_{ik})lb$	(18)
$S1_{ik} + (t_{ij} + l_i)(x_{ijk} + Y^b_{ik} - 1) \le TL_k + (2 - x_{ijk} - Y^b_{ik})lp_i$ $\forall k \in K\ \forall j \in P,\ \forall (i \ne j) \in P$	(19)
$TL_k + (t_{ij} + E)(x_{ijk} + Y^a_{ik} - 1) \le S1_{ik} + (2 - x_{ijk} - Y^a_{ik})lb$ $\forall k \in K\ \forall j \in P,\ \forall (i \ne j) \in P$	(20)
$S1_{ik} + l_i + Y^a_{ik} \le TL_k + (1 - Y^a_{ik})\, lp_i$ $\forall k \in K\ \forall i \in P$	(21)
$eb \le TL_k \le lb$ $\forall k\epsilon K$	(22)
$\sum_{v=1}^{c} \tilde{S}_{iv} - \sum_{s=1}^{q} \delta_{is}\tilde{S}_{ik} \le (2-\lambda_i - \sum_{s=1}^{q} y_{iks})M$ $i \in N, k \in K$	(23)
$\sum_{v=1}^{c} \tilde{S}_{iv} - \sum_{s=1}^{q} \delta_{is}\tilde{S}_{ik} \le (\lambda_i + \sum_{s=1}^{q} y_{iks} - 2)M$ $i \in N, k \in K$	(24)
$x_{ijk} = 0$ $i \in N, k \in K$	(25)
$\tilde{S}_{ik} \ge 0$ $i \in N, k \in K$	(26)
$v_i \ge 0$ $i \in N$	(27)
$o_k \ge 0$ $i \in N$	(28)
$x_{ijk} \in \{0,1\}$ $i \in N, j \in N, k \in K$	(29)
$y_{iks} \in \{0,1\}$ $i \in N, k \in K, s \in S$	(30)

The objective function (1) is to minimize the total transportation cost. Constraints (2) and (3) state that each patient will be visited by a group of caregivers, the number will depend on the kind of services requested. Constraints (4) and (5) state that each caregiver leaving the HHC centre to visit assigned patients must get back there. Constraints (6) impose route continuity for the patients assigned to a caregiver k. Constraints (7) determine the service operations' starting time of the patient j with respect to the service operations' completion time of the patient i. Constraints (8) initialize the starting time to zero if the caregiver k is not assigned to the patient i. Constraints (9) define the variables y_{iks} , the caregiver k is assigned to the patient i if after having visited the patient i the doctor will visit the next patient j or return to the HHC center. Constraints (10) ensure the qualification of the caregiver k to provide the service operation s requested by the patient i. Constraints (11) ensure

that each caregiver provides a single service operation to an assigned patient i. Constraints (12) guarantee that for a patient i, each service operation is provided by only one caregiver. Constraints (13) and (14) ensure the respect of caregivers' time windows. Constraints (15) and (16) guarantee the respecting of patients' availability periods. Constraint (17) determines whether caregiver k should start to make an arrangement of patients' load before or after visiting node i. Constraint (18) denotes that the hospital arranges patients' loads if the caregiver visits that patient. Constraint (19) - (22) ensure that the pauses for caregivers to arrange patients before and after services begin at the proper times. Constraint (23) ensures that the start time of the patients' load of arrangement must happen in the defined time window. Constraints (24) and (25) ensure caregivers' starting time synchronization if a patient's requested services must be simultaneous. Constraints (26) - (31) are the domains of the decision variables.

2.3 Data Processing

There are three types of data including Home Health Care, patients and caregivers shown in Table 4, Table 5, and Table 6 below.

2.3.1 HHC Centre Information

Table 4. HHC Centre Information

ID	**0**
Longitude	**106.65**
Latitude	**10.79**
d_k	**420**
e_k	**1020**
a_i	**690**
b_i	**780**
W_{max}	**480**
W_{min}	**60**
E	**30**
tc	**15**
P_{max}	**7**
P_{min}	**1**

2.3.2 Patient Information

Table 5. Patient's information

ID	Longitude	Latitude	ep	lp	l
1	106.60851	10.80958	510	600	45
2	106.66566	10.75154	660	720	60
3	106.62413	10.76593	570	660	45
4	106.63769	10.79949	510	570	60
…	…	…	…	…	…

2.3.3 Caregiver Information

Table 6. Caregiver's information

k	pc	c
1	0	$15
2	1	$25
3	0	$15

2.3.4 Traveling time and traveling distance

The traveling distance between each node will be calculated by using the Haversine formula. It is shown in the traveling distance matrix in kilometres. Besides, the traveling time is calculated by assuming that the speed of each caregiver when moving in Ho Chi Minh City is 40km/h. It is presented on the traveling time matrix in minutes.

2.4. Assumption

The Home Health Care Routing and Scheduling Problem (HHCRSP) is defined under the following assumptions. First of all, the working time is from 7.00 AM to 5.00 PM covered in in one HHC Centre in one day. Next, each caregiver must start the route from the centre and return to the node. Besides, all patients must be visited. Each patient will be served within a different time window. In addition, no cancellation and lateness are allowed. Furthermore, the Haversine formula calculates the travel distance between node i and node j, and the travel time is calculated by assuming the speed of the caregiver is 40km/h. The proposed mixed-integer linear programming (MILP) is used to formulate the daily HHCRSP.

2.5. Adaptive Large Neighbourhood Search

Since the MILP model, by using CPLEX, cannot handle large datasets, ALNS is developed to solve this problem. Below is the pseudocode of ALNS:

Input:
- Graph G = (N, A) with nodes (N) and arcs (A)
- Parameters: max_iterations, destroy_repair_methods
- Constraints: (1) to (31)
- Objective function: Minimize travel cost and the number of caregivers used
- Initial solution S
- Distance matrix and time matrix
Output:
- Best feasible solution S_best and its cost
BEGIN
1. Initialize:
- S_current ← Initial feasible solution (construct using greedy or heuristic method)
- S_best ← S_current
- T ← Initial temperature
- Iteration ← 0
- Initialize weights for destroy and repair methods
2. Evaluate the initial solution:
- f(S_current) ← Evaluate objective function
- f(S_best) ← f(S_current)
3. WHILE Iteration < max_iterations DO:
a. Select destroy and repair methods:
- Select destroy_method and repair_method using adaptive weights
- Update weights based on their success rates
b. Generate novel solutions:
- S_destroyed ← destroy_method(S_current)
- S_candidate ← repair_method(S_destroyed)
c. Check the feasibility of S_candidate:
d. Apply simulated annealing:
- Δf ← f(S_candidate) - f(S_current)
- Accept S_candidate IF:
- Δf < 0 (improved solution), OR
- exp(-Δf / T) > random(0, 1) (worse solution with probability)
- IF S_candidate is accepted THEN:
- S_current ← S_candidate
- Update S_best:
- IF f(S_candidate) < f(S_best) THEN:
- S_best ← S_candidate
e. Update temperature:
- T ← T × cooling_rate
f. Increment iteration:
- Iteration ← Iteration + 1
4. Return
- S_best and f(S_best)
END

The specifics of each step are presented as follows:

Step	Description
1	Generate an initial feasible solution using a greedy heuristic
2	Initialize operator weights and Simulated Annealing parameters
3	While termination condition not met
3.1	Select destroy and repair operators based on adaptive weights
3.2	Apply destroy operator to partially remove patients
3.3	Apply repair operator to reinsert removed patients
3.4	Check feasibility with respect to routing, time windows, synchronization, and patient load
3.5	Accept or reject solution using Simulated Annealing criterion
3.6	Update best solution and operator scores
3.7	Update temperature according to cooling schedule
4	Return the best feasible solution

3. Result and Discussion

3.1 Numerical experiments

The model formulation is implemented in optimization programming language (OPL) and solved using ILOG CPLEX 20.1.0 in aggressive mode. The experimental evaluation is presented according to the use of IBM ILOG CLPEX Optimization Studio and ALNS algorithm, Python in Spyder environment on 11th Gen Intel(R) Core (TM) i7-1185G7 3.00GHz (8 CPUs), ~3.0GHz.

3.1.2 Test instances

It is assumed to be a dataset including 10 patients and 3 caregivers. It is presented the route of three caregivers which indicates the patients each caregiver served. The results are shown below in Table 7. In Figure 1, the convergence graph shows the objective is 755.85 with iteration 1000 which means the minimize cost with 10 patients and 3 caregivers is 755.85.

Table 7. Overall route representation by CPLEX

Caregiver 1	HHC Centre – Patient 3 – Patient 2 – Patient 10 – Patient 7 – HHC Centre
Caregiver 2	HHC Centre – Patient 4 – Patient 6 – HHC Centre
Caregiver 3	HHC Centre – Patient 5 – Patient 8 – Patient 1 – Patient 9 – HHC Centre

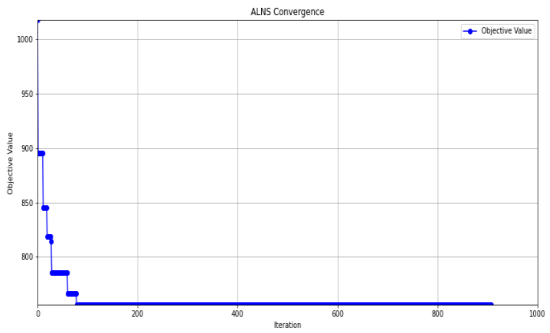

Figure 1. Convergence graph

3.2 Result

To check the results, it is necessary to have test instances which indicate in Table 8. In the small-scale set, the objective value of MILP run by CPLEX is compared to this of ALNS. Besides, the GAP in each data set is calculated after that which satisfies the condition lower than 10 percent. To evaluate the solution quality, the proposed ALNS results are compared with solutions obtained by ILOG CPLEX 20.10. For instances where CPLEX is able to reach optimality within the imposed computational limits, the reported CPLEX objective value corresponds to the optimal solution. In these cases, the optimality gap between the upper and lower bounds is equal to zero. For larger instances where CPLEX does not converge to proven optimality, the solver reports both the best feasible solution and the best bound. The optimal gap is computed as the relative difference between these bounds and expressed in percentage. This information is used to assess the quality of the heuristic solutions obtained by ALNS relative to the best-known CPLEX bounds. Next, in the larger scale data set, it is checked by increasing the iteration which helps to find the best objective in Table 9.

Table 8. Test instances

Instance	MILP		ALNS		GAP	
	Objective value	Time (s)	Objective Value	Time (s)	Objective Value	Time
Size_10	702.015	1.92	755.86	1.65	7.67 %	>99 %
Size_11	768.086	2.18	814	1.51	5.97 %	>99 %
Size_12	825.95	2.48	871.36	1.61	5.49 %	>99 %
Size_13	933.02	2.81	941.49	1.36	0.9%	>99 %
Size_14	937.117	2.27	1023.63	1.63	9.23 %	>99 %

Table 9. Result of objective value

Instance	Objective Value				
	Iteration 2000	Iteration 4000	Iteration 6000	Iteration 8000	Iteration 10000
Size_20	1586.47	1507.38	1621.66	1557.32	1580.74
Size_40	2765.61	2531.62	2753.23	2643.36	2493.26
Size_60	3633.08	3367.29	3426.03	3425.39	3324.47
Size_80	4760.12	5003.22	5105.41	4543.75	4970.28

The GAP values obtained range from 0.9 percent to 9.23 percent across the tested instances. For smaller problem sizes, the proposed ALNS algorithm achieves relatively low GAP values due to several points including a limited combinatorial search space, fewer interactions among routing, synchronization, and patient load constraints. Nonetheless, a higher GAP is observed for size 14. This deviation can be explained by the rapid growth in problem complexity as the number of patients increases. In particular, size 14 is introduced to be a significantly larger number of feasible routing combinations, stronger interactions between patient load arrangements and time window constraints. Furthermore, more frequent synchronization requirements among caregivers are considered. These factors considerably not only enlarge the solution space but also making it more challenging for the metaheuristic to converge to near-optimal solutions within a reasonable computational budget. Nevertheless, the obtained results remain acceptable for medium-scale HHCRSP instances and demonstrate the robustness of the ALNS approach under increasing problem complexity.

3.3 Discussion

From a practical implementation perspective, the proposed solution is well appropriate to the deployment in a near real-time home healthcare planning environment. In practice, patient load factors may fluctuate due to unexpected conditions such as changes in patient health status, additional preparation requirements, or extended post-service arrangements. The proposed ALNS framework is not only inherently flexible but also can accommodate such variations by dynamically updating patient load parameters and re-optimizing routes within a short computational time. Furthermore, when changes occur during daily operations, the system can be re-executed using the current solution as an initial state, allowing rapid adjustment of caregiver assignments and schedules while preserving feasibility with respect to time windows and synchronization constraints. This adaptability enhances the applicability of the proposed approach for real-world home healthcare systems, where uncertainty and operational variability are unavoidable.

4. Conclusion

Despite the rapid development of HHC services, it still faces many challenges. Service providers always want to meet the requirements and satisfaction of caregivers and clients without increasing the operational costs. Due to the need, the number of clients who require services at a specific period increases significantly daily, but the number of caregivers is limited. Therefore, it is essential to develop an optimal route in which caregivers serve clients that reduces costs and increases customer satisfaction.

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