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A bi-objective home health care routing and scheduling by multi-directional local search

ZHAO Jiao ¹, WANG Tao ², MONTEIRO Thibaud ¹

¹ Univ Lyon, INSA-Lyon, DISP, EA4570, 69621 Villeurbanne cedex, France,
jiao.zhao@insa-lyon.fr, thibaud.monteiro@insa-lyon.fr

² Université Jean Monnet de Saint Etienne, DISP, EA4570, 42300 Roanne, France,
tao.wang@univ-st-etienne.fr

Résumé. This paper models the routing and scheduling problem in home health care as bi-objective problem by minimizing two conflicting objectives: traveling cost and satisfaction of patients. It extends the classical constraints of the vehicle routing problem by considering the qualification and workload of caregivers. A mixed-integer programming model is developed for the problem. Motivated by the challenge of computational time, multi-directional local search framework embedded with adaptive large neighborhood search and metaheuristic is proposed to solve the problem. Our data set for computational experiment is based on Solomon data set. Three kinds of metrics for evaluating the Pareto optimal sets reveal this approach can fit different types of instances.

Mots clés: routing and scheduling problem, multi-objective problem, multi-directional local search.

Introduction

Demand for Home Health Care (HHC) has been increasing in recent years as the preference of the elderly for aging in place has grown. Depending on the individual patient's situation, provided care can range from nursing care to specialized medical services. It helps decreasing hospital admissions and duration while patients can accept treatment in familiar surroundings. The integration and coordination of health service delivery network is a complex task and managers have to face many logistics decisions. Network design, transportation management, staff management, inventory management are described as different logistic function in HHC. The planning horizon can be classified by three levels depending on the time horizon from the long-term to the short-term, namely strategic, tactical and operational [Gutiérrez et Vidal, 2013]. The short-term daily activities in HHC services are shown in Fig. 1. Once patients have their medical treatment prescription and when service time, staff qualifications, frequencies and hours for each medical procedure are defined, decision-makers assign qualified caregivers to patients according to the requested services. Then they decide to schedule a route for each caregiver satisfying the available time of patients. Finally, each caregiver performs their medical service, starting from the home health care facility, visiting patients in a planned sequence before returning to the origin.

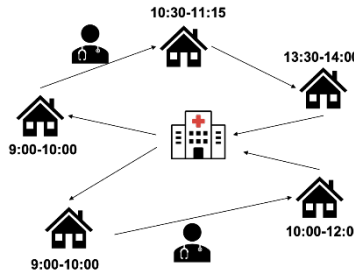


Figure 1: Typical activities in daily home health care services.

These activities in home health care can be planned in tactical and operational level and belongs to transportation management. The transportation service accounts for a large part of company's cost and poses the challenge to the efficiency. Caregivers should arrive and leave within the available time of patients. But HHC companies may not be capable to provide service for all patients in their available time. All of patients can be covered by schedule if some of them can start and end service outside the available time. But too much delay for patients decreases the service quality and patients' satisfaction while too much waiting time for caregivers leads to increasing working hours.

In this study, the routing and scheduling problem in HHC is modeled as a vehicle routing problem with time windows (VRPTW) which aims to determine the most cost-efficient routes considering time windows. Each caregiver is assigned to a set of patients in one route. The available time of patients respects a fixed time interval for receiving care service, called time windows. The patients must be visited within hard time windows. Caregivers are not permitted to perform service if they arrive or leave beyond time window. Soft time windows can be violated at the cost of a penalty.

This paper aims to get cost-efficient routes while improving the service quality and satisfaction of patients and caregivers. Fewer times that arrival and departure times are beyond the time windows indicate better satisfaction of patients and caregivers. The first contribution is the modelling of the routing and the scheduling problem. It is modelled as a bi-objective problem considering operational constraints by mixed integer liner programming formulation. The second contribution is related to the solution approach. An Adaptive Large Neighborhood Search (ALNS) based multi-directional local search (MDLS) are proposed to solve the problem. Six types of destroy and repair operators are embedded in ALNS. Experiments with different types of instances have been done.

The rest of this paper is organized as follows. Section 2 overviews the literature related to the vehicle routing and scheduling problem in home health care activities. Section 3 addresses the model with two objective functions. A multi-objective solution methodology is proposed in Section 4. The parameters setting, computational experiments and result analysis are presented in Section 5. Finally, conclusion of this paper and perspective of future studies are summarized in the last section.

1 Related works

We focus on home health care routing and scheduling problems (HHC-RSP) on a daily planning horizon in this paper. This problem is an extension of VRPTW which is proved to be NP-hard problem. Its tasks consist of the partitioning of the customer set and the routing of each vehicle respecting time window. Vehicle starts from the depot, moves once to each customer, finally return to the depot. The HHC-RSP consists on designing optimal delivery routes from a center location to a set of geographically distributed patients with various constraints, resulting optimization problems are complex and, hence, of high interest to stakeholders. It has features [Fikar et al., 2017]: (1) temporal dependency and disjunctive services; (2) continuity, patients are assigned to a restricted set of care workers; (3) care workers' skills and patients' requests. In HHC-RSP, more attention is drawn on the patients and caregiver's requirement and availability compared with VRPTW. Various constraints and objectives which are used in different articles due to the authors' country's home care management. Exact, heuristic and metaheuristic methods are mainly used to solve this problem.

[Shahnejat-Bushehri et al., 2019] took into account precedence and synchronization constraints. Two kinds of caregivers provided primary tasks and synchronized services that can be defined as simultaneous or precedence tasks. Two meta-heuristics applied in two phrases. A variable neighborhood search-based heuristic is used to get a feasible solution that has to observe assignment constraints, working time restrictions, time windows, and mandatory break times [Trautsamwieser et al., 2011]. The constraints in existing research also include the

matching the skills of caregivers and patients [Bertels and Fahle, 2006], balance of the workload [Manerba and Mansini, 2016], visit incompatibility [Nikzad et al., 2021], multiple modes of transportation [Hiermann et al., 2015] and the time-dependent travel time [Rest and Hirsch, 2016].

In many situations, decision-makers want to consider other aspects while reducing costs. Many objectives have to be optimized at the same time. Weighted sum, bounded objective function and lexicographic method of the objective functions are the intuitive methods for single objective optimization. In game theoretic approach, objective functions are assumed as the players who are ultimately controlled by decision-maker and can be expected to reach an agreement, meaning the game is co-operative [Rao, 1987]. Single solution method can be used if the decision-maker's preference is known. It's better for them to make decision from a set of solutions when they can't express their preference explicitly. Pareto points can be gotten by normal-boundary intersection [Das and Dennis, 1998] and genetic algorithms.

The recent advance in the HHC research has moved to explore the multi-objective optimization method to obtain a Pareto frontier instead of a weighted objective function. Two kinds of objectives including distance and penalties applied to care and the synchronization visit were combined to be a single objective function by [Decerle et al., 2018]. Genetic algorithms and local search provided good results while being flexible to the instance type. [Grenouilleau et al., 2019] minimized the weighted sum of travel time, a score of continuity of care, overtime, idle time and penalty for unscheduled patients, etc. A set partitioning heuristic method solved a linear relaxation of a set partitioning model using the columns generated by the large neighborhood search. Three objective functions are minimized considering travel cost, inconsistency a workload balance. An artificial bee colony metaheuristic was proposed to get non-dominated solutions to provide effective alternative solutions for managers in HHC companies [Yang et al., 2021].

In most of these papers, arriving time exceeding the time window means worse satisfaction of patients. It is more reasonable that the time window means the available time of patients. There will also be a penalty if caregivers perform service and then leave from patients' home after the time window. Therefore, we define patients' satisfaction as minimizing the number of times that arrival and leaving time is beyond time window. Although improving service quality and patients' satisfaction is as important as reducing the cost, there is still inadequate related research, which motivates us to introduce a bi-objective model to reconcile the interest of different stakeholders in HHC. Different levels of caregivers are needed according to the severity of the patients' health condition. We assume a fixed number of caregivers to be assigned in daily working. A certain number of patients to be served by one caregiver is limited for balancing. We first consider these properties together. Although there are many metaheuristics existing in the literature, the study using ANLS based MDLS is still inadequate. Decision-makers can select their preferred solution from Pareto optimal set according to different operation situation. This approach has fewer hyper parameters compared to genetic algorithms.

2 Problem statement

In this section, a mathematical model and its components representing the extension of VRPTW in HHC will be formulated. From the perspective of graph theory: let $G = (V, A)$, where $V = \{0\} \cup N = \{1, 2, \dots, n\}$ is the vertex set, and represents the depot and the patients to serve. $A = \{(i, j) \in V, i \neq j\}$ is the set of arcs. The arrival and departure time instant of caregivers, the travel time t_{ij} for each arc $(i, j) \in A$ and service time δ_i for each patient i are given. Travel time is equal to the cost c_{ij} . It is assumed that all caregivers leave the depot at time instant 0. Time window of each patient $[e_i, l_i]$ is defined as the earliest time and the latest time of starting service that can be tolerant by patient. The decision-makers aim to find a minimum-cost tour that serves the vertices once and satisfy the side constraints of arc $R \subseteq A$.

Caregiver $k \in K$ starts from the facility, moves once to each patient, finally return to the depot. Each caregiver has qualification Q_k . Three levels of qualifications $Q = \{1,2,3\}$ are defined in this paper. Each patient $i \in N$ distributes in a different location. Each patient has demand for different levels of caregivers D_i according to their health condition. If the caregiver arrives before e_i , the service will be started until reaching e_i ; if the caregiver arrives after e_i , the service will be started immediately. The caregiver will leave after serving for δ_i . The departure time can be calculated as $dt_{ik} = \max(at_{ik}, e_i) + \delta_i$. The service capacity of HHC companies may not be sufficient to provide services for all patients in some cases. Therefore, some patients can't be served in any feasible solutions if caregivers must visit all patients within time windows (hard time window). That caregivers arrive too early or leave too late will increase the workload and decline the patients' satisfaction. Penalty cost is included in objective functions when the caregiver arrives or leaves beyond the time window. The decision variables of this model are summarized in Table 1.

Notation	Definition
x_{ijk}	Binary decision variable, 1 if caregiver k moves from i and j , 0 otherwise
at_{ik}	Continuous decision variable, arrival time of caregiver k at patient i 's location
dt_{ik}	Continuous decision variable, departure time of caregiver k at patient i 's location
P_{ik}	1 if the caregiver arrives earlier than the earliest time of time window or end service later than the latest time of time window, 0 otherwise

Table 1: Decision variables

The objective functions and constraints are formulated as follows:

$$\min \sum_{i,j \in V} \sum_{k \in K} c_{ij} x_{ijk} \quad (1)$$

$$\min \sum_{i \in N} \sum_{k \in K} P_{ik} \quad (2)$$

$$P_{ik} = \begin{cases} 1, (\sum_{j \in V} x_{ijk}) * at_{ik} < e_i \text{ or } (\sum_{j \in V} x_{ijk}) * dt_{ik} > l_i \\ 0, \text{else} \end{cases} \quad (3)$$

$$at_{jk} = dt_{jk} + t_{ij} \quad (4)$$

$$dt_{ik} = \max(at_{ik}, e_i) + \delta_i \quad (5)$$

$$P_{ik} \leq \sum_{j \in V, i \neq j} x_{ijk} \quad (6)$$

$$s.t. \sum_{k \in K} \sum_{j \in N, i \neq j} x_{ijk} = 1, \forall i \in N \quad (7)$$

$$\sum_{i \in V, i \neq j} x_{ijk} = \sum_{i \in V, i \neq j} x_{jik}, \forall k \in K, \forall j \in V \quad (8)$$

$$\sum_{j \in N} x_{0jk} = 1, \forall k \in K \quad (9)$$

$$dt_{ik} + t_{ij} \leq (1 - x_{ijk})M + at_{jk}, \forall i \in N, \forall j \in N, \forall k \in K, i \neq j \quad (10)$$

$$dt_{ik} + t_{ij} \geq at_{jk} - (1 - x_{ijk}) * M, \forall i \in N, \forall j \in N, \forall k \in K, i \neq j \quad (11)$$

$$at_{jk} \leq t_{0j} + (1 - x_{0jk}) * M, \forall j \in N, \forall k \in K \quad (12)$$

$$at_{jk} \geq t_{0j} - (1 - x_{0jk}) * M, \forall j \in N, \forall k \in K \quad (13)$$

$$dt_{0k} = 0, \forall k \in K \quad (14)$$

$$(\sum_{j \in V, j \neq i} x_{ijk}) * D_i \leq Q_k, \forall i \in N, \forall k \in K \quad (15)$$

$$a \leq \sum_{i \in N} \sum_{j \in V} x_{ijk} \leq b, \forall k \in K \quad (16)$$

$$x_{ijk} \in \{0, 1\} \quad (17)$$

$$at_{ik}, dt_{ik} \geq 0 \quad (18)$$

The first objective function (1) is to minimize the travel cost. (2)-(6) represent the penalty cost. If the arrival time and departure time are beyond the time window, the penalty is accumulated by 1. If the penalty is small, it means most of caregivers don't need to wait and most of patients can receive service on time and finish their service before latest time of time window. Caregivers and patients will be satisfied with such schedule. Constraint (7) ensures that caregiver is assigned to exactly one route. Constraint (8) means each caregiver visits the patient and then leaves the patient. Constraint (9) indicates caregivers start from the depot and return to the depot after finishing services. Constraints (10) – (14) guarantees the schedule feasibility and makes subtours impossible. Note that, for a given k , at_{ik} and dt_{ik} is meaningless whenever patient i is not visited by caregiver k . Caregivers can only perform the service if the qualification level is satisfied by constraint (15). Constraint (16) indicates each caregiver must serve a limited number of patients regarding to the working load balance. Constraints (17)-(18) set the domains of decision variables.

3 Solution methodology

In this section, multi-directional local search embedded with ALNS is detailed in order to solve the large-scale multi-objective vehicle routing problem.

3.1 Multi-directional local search algorithm

MDLS is first proposed by [Tricoire, 2012]. Each local search is used to single objective (direction) iteratively to improve the non-dominated front. Each local search works separately without considering the importance of the objectives. This strategy has less parameters and can get a well-spread set of solutions (shown in Fig.2). F denotes the set that contains the non-dominated solutions. The initial solution are constructed by saving algorithm which is a kind of constructive heuristic by merging the nodes with largest saving. In each iteration, a solution is randomly selected from F . ALNS is used to improve the solution of each objective. Record to record travel algorithm [Dueck, 1993] is used as an acceptance criterion. New solutions are added to F . Only non-dominated solutions are kept in F after one iteration by Deb non-dominated sorting method. The algorithm will stop after satisfying the stopping condition.

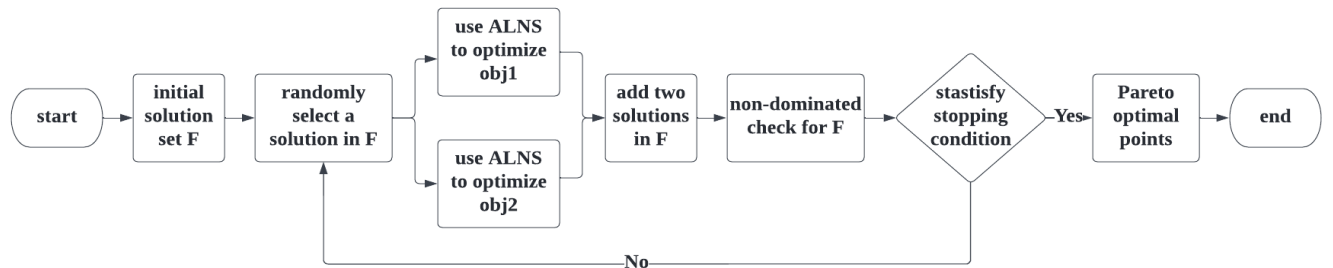


Figure 2: Structure of MDLS

Three destroy operators and three repair operators are embedded in ALNS (based on [Ropke and Pisinger, 2006]). We ensure the solutions after repairing are feasible by adding the constraints. To satisfy constraints (15) and (16), we choose a route that includes patients more than a to destroy. A removal list of patients is obtained after using destroy operators. When we insert the node in removal list into the route, we choose the route that qualification level of the caregiver satisfies the request of patient and include patients less than b to repair.

A certain number of nodes are randomly removed and inserted in routes in random destroy and random repair operators. These operators can be easily implemented and run faster than other operators. Worst destroy operator chooses the nodes with largest saving that appear to be placed in the wrong position in the solution, while relatedness destroy operator tends to select the nodes that are similar and can be easily exchanged. The relatedness of the first objective (1) can be calculated by $1/(c_{ij}/c_{max} + v)$, while the second objective (2) by $1/[(de_{ij} + dl_{ij})/t_{max} + v]$, where c_{ij} means the cost between node i and j , c_{max} means the largest cost of all pairs of i and j , de_{ij} and dl_{ij} denote the different of time window between i and j , if i and j are in the same route, v is equal to 0, 1 otherwise. We iteratively find the node with minimum cost position in the greedy repair operator. But for the nodes that are expensive to insert to the last iteration, there are not many chances for inserting the nodes because many of the routes are "full". The regret operator chooses the nodes from removal set by calculating $i = \arg \max_{i \in u} [\sum_{j=1}^k (\Delta f_i^j - \Delta f_i^0)]$, where u is removal set, Δf_i^j denotes the insertion value of node i in j^{th} cheapest insertion position. This method selects the insertion that will regret most if it isn't inserted now.

Only one destroy operator and one repair operator are chosen by probability $w_j / \sum_{i=1}^o w_i$ in one iteration, where w_j is the weight of j^{th} operator to be chosen, $i \in \{1, 2, \dots, o\}$. The entire search is divided into a number of segments. A segment is a number of iterations of the ALNS. w_j is automatically updated after a segment and is calculated by formula (19):

$$w_j = (1-r) * w_i + r * (\pi_i / \theta_i). \quad (19)$$

θ_i means the number of times we have attempted to use heuristic i during the last segment. The reaction factor r controls how quickly the weight adjustment algorithm reacts to changes in the effectiveness of the heuristics. The scores are r_1, r_2, r_3 under three kinds of acceptance criterion and evaluate how well the heuristic has performed recently. A high score corresponds to a better performance. More specifically, in record to record method, if the neighborhood solution generated by the destroy and repair operators is better than the current solution, the best solution and the sum of best solution and deviation, it is always accepted.

4 Computational study

For all the experiments, we have used an Intel(R) Core (TM) i5-10310U CPU (@ 2.21 GHz) CPU with 16GB of RAM memory. In this section, we first present our instances and then the results and analysis of numerical experiments. No benchmark results exist in the literature for our problem. Hence, we generate six different types (C1, C2, R1, R2, RC1, RC2) instances based on the Solomon data (Solomon, 1987) and compare metrics of them to test whether the algorithm fits for different types. Each type contains 25-nodes, 50-nodes and 100-nodes problems. Distance is Euclidean, and the value of travel time is equal to the value of distance between two nodes. The geographical data are randomly generated in problem sets R1 and R2, clustered in problem sets C1 and C2, and a mix of random and clustered structures in problem sets by RC1 and RC2. Problem sets R1, C1 and RC1 have a short scheduling horizon while the sets R2, C2 and RC2 have a long scheduling horizon. Patients' requirement for different levels of caregivers and service time are added randomly by manual. The longest service time accounts for fifty percent of the time window. We assume 3 caregivers are assigned to 25 patients, 5 caregivers to 50 patients, 10 caregivers to 100 patients.

In this paper, the metrics we use to compare different instances and evaluate the parameters setting include the number of Pareto optimal points (NUM), hypervolume indicator (HV) and spread metric (S). The solutions are scaled between 0 and 1 before calculating these metrics. Hypervolume indicator gives the volume x enclosed by a reference point and the solutions and is shown in following formula (20):

$$HV = \bigcup_{x \in A} V(x, R). \quad (20)$$

The reference point R is set to point (1,1) for two objective functions commonly. This metric measures the convergence and diversity. The larger hypervolume means the better quality of the solutions. Spread metric evaluates the diversity of solutions and is given by

$$sp = (d_f + d_l + \sum_{i=1}^{n-1} |d_i - \bar{d}|) / [d_f + d_l + \bar{d}(n-1)], \quad (21)$$

where d_f and d_l are the Euclidian distances between the extreme solutions in true Pareto front and non-dominated solutions (NDS). $\bar{d}$ is the average of all distance d_i , d_i is the Euclidean distance between one solution and the next nearest solution, $i \in [1, |NDS| - 1]$. We assume the extreme value of true Pareto front is (0,1) and (1,0). Smaller value indicates better distribution.

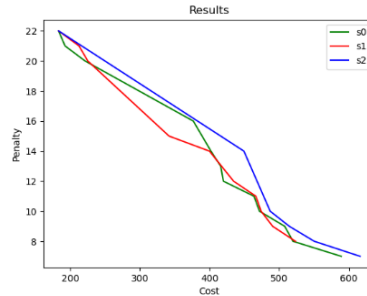


Figure2: Average results of C1 with 25 patients.

	s_0 (IA100, IM1000)				s_1 (IA100, IM100)				s_2 (IA200, IM50)			
	time(s)	NUM	HV	S	time(s)	NUM	HV	S	time (s)	NUM	HV	S
25	1220.61	8.03	0.45	0.05	65.48	6.37	0.34	0.07	63.43	5.23	0.30	0.11
50	1816.29	11.70	0.37	0.04	125.14	8.80	0.29	0.08	123.67	5.90	0.21	0.14
100	2493.35	17.73	0.34	0.03	378.53	12.10	0.28	0.04	373.46	6.60	0.18	0.10

Table 2: Result

The algorithm will stop after 100 thousand iterations in s_0 while 10 thousand in s_1 and s_2 . In s_1 , the number of iterations of ANLS (IA) is smaller while the number of iterations of MDLS (IM) is larger, and s_1 otherwise. Fig. 2 shows the Pareto solutions of one type of instance. Solutions of s_0 and s_1 dominate s_2 . Although some solutions of s_1 dominate some solutions of s_0 , there are more solutions in s_0 , and the solutions in s_0 are more evenly distributed. Table 2 shows the time of two settings are similar, and all of N, HV and S of s_1 have better performance than s_2 . Smaller number of iterations of ALNS is better. If larger number of iterations of ANLS is set, the algorithm tends to reach the “extreme” value of each objective function. But if it is smaller, the balance between two objectives is obtained so that the algorithm is able to find more possible values of two objectives gradually. The number of iterations of MDLS of s_0 is ten times as many times as s_1 . For s_0 , the three metrics are improved with the compared with s_1 . The values of three metrics are all in reasonable ranges which means solutions are well-spread and have good convergence and diversity. The proposed method fits every kind of instances.

Conclusion

We study a routing and scheduling problem in HHC optimizing travel cost and caregivers' and patients' satisfaction, considering the matching of patients' requests and qualification levels of caregivers, the workload constraints. This problem is modeled as a multi-objective problem. The computational tests demonstrate the suitability and the efficiency of the proposed ALNS based MDLS method. In real-life service, the service time is related to the physical condition of patient, the patients may need different types of service at one work day, so more practical constraints and the uncertain service time are needed to be considered in the future work.

References

- Gutiérrez, E. V. and C. J. Vidal (2013). Home health care logistics management: Framework and research perspectives. *Int. J. Ind. Eng. Manag.*, 4(3), 173-182.
- Fikar, C., and P. Hirsch (2017). Home health care routing and scheduling: A review. *Comput. Oper. Res.*, 77, 86-95.
- Shahnejat-Bushehri, S., R. Tavakkoli-Moghaddam, S. Momen et al. (2019). Home health care routing and scheduling problem considering temporal dependencies and perishability with simultaneous pickup and delivery. *IFAC-PapersOnLine*, 52(13), 118-123.
- Trautsumwieser, A., M. Gronalt and P. Hirsch (2011). Securing home health care in times of natural disasters. *OR spectrum*, 33(3), 787-813.
- Bertels, S., and T. Fahle (2006). A hybrid setup for a hybrid scenario: combining heuristics for the home health care problem. *Comput. Oper. Res.*, 33(10), 2866-2890.
- Manerba, D. and R. Mansini (2016). The nurse routing problem with workload constraints and incompatible services. *IFAC-PapersOnLine*, 49(12), 1192-1197.
- Nikzad, E., M. Bashiri and B. Abbasi (2021). A matheuristic algorithm for stochastic home health care planning. *Eur. J. Oper. Res.*, 288(3), 753-774.
- Hiermann, G., M. Prandtstetter, A. Rendl, J. Puchinger and G. R. Raidl (2015). Metaheuristics for solving a multimodal home-healthcare scheduling problem. *Cent. Eur. J. Oper. Res.*, 23(1), 89-113.
- Rest, K. D. and P. Hirsch (2016). Daily scheduling of home health care services using time-dependent public transport. *Flex. Serv. Manuf. J.*, 28(3), 495-525.
- Rao, S. S. (1987). Game theory approach for multiobjective structural optimization. *Comput. Struct.*, 25(1), 119-127.
- Das, I. and J. E. Dennis (1998). Normal-boundary intersection: A new method for generating the Pareto surface in nonlinear multicriteria optimization problems. *SIAM J. Optim.*, 8(3), 631-657.
- Decerle, J., O. Grunder, A. H. El Hassani, and O. Barakat (2018). A memetic algorithm for a home health care routing and scheduling problem. *Oper. Res. Health Care*, 16, 59-71.
- Grenouilleau, F., A., Legrain, N. Lahrichi and L. M. Rousseau (2019). A set partitioning heuristic for the home health care routing and scheduling problem. *Eur. J. Oper. Res.*, 275(1), 295-303.
- Yang, M., Y. Ni and L. Yang (2021). A multi-objective consistent home healthcare routing and scheduling problem in an uncertain environment. *Comput. Ind. Eng.*, 160, 107560.
- Tricoire, F. (2012). Multi-directional local search. *Comput. Oper. Res.*, 39(12), 3089-3101.
- Ropke, S., and D. Pisinger (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transp. Sci.*, 40(4), 455-472.