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A Three-stage Approach for the Multi-period Green Home Health Care Problem with Varying Speed Constraints

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ABSTRACT: *In this paper, we address an environment-friendly approach to solve the Green Home Health Care (GHHC) routing and assignment problem. The approach aims to reduce fuel consumption to minimize carbon-di-oxide emissions. The Home Health Care (HHC) routing and assignment problem is a very complex problem due to the multi-factors and criteria that must be taken into consideration during the planning. The main of this work is to find an efficient working plan on a weekly basis, respecting continuity of care, with environmental concern, which ensures the satisfaction of both patients and caregivers and considers most of HHC constraints. The proposed approach is a three-stage methodology; the first stage is a multi-objective programming model that minimizes the total traveled distance and fuel consumption with varying speed. In the second stage, we introduce an assignment heuristic, and the third stage is an Integer Linear Programming (ILP) model that aims to balance caregivers' workload. The small and medium instances are solved using CPLEX optimizer studio and show that better route planning and minimum fuel consumption is achieved with varying speed concept.*

KEYWORDS: *Green home health care, multi-objective optimization, integer linear programming, human resource planning, routing problem, continuity of care.*

1 INTRODUCTION

HHC is a wide variety of health care services that are provided to patients at home. The HHC agencies receive requests from new patients every day, and need an efficient planning to manage their caregivers.

The increased costs of the subsequently required treatments pressure the primary care facilities to offer care services at home to reduce charges. The goal of these programs is to reduce the hospitalization rate and congestion (Lanzarone and Matta, 2012).

The HHC services improve patients' living conditions, particularly for those requiring assistance and medical treatment (Fikar et al., 2017).

In this paper, we discuss related optimization problems that occur in the HHC. During a planning horizon, a set of patients must be allocated to a group of qualified caregivers according to the treatment they need. The problem asks to schedule the patients according to their request and required care regarding their time window, i.e. the patient may not be available all through the day.

In addition, the patients are allocated by taking into consideration the compatibility between patient and caregivers' expertise. They may also have requests that must be taken into account, for example: caregiver preferences,

gender, language, etc. For this reason, we take into account the affinity between the caregiver and the patient.

We take into consideration the learning care factor (Gillan et al., 2013) which represents the experience gained by the caregivers through the planning horizon while giving the care to patients. This experience allows the caregivers to be more efficient because they become more accustomed to the patients. Hence, the time required for care to be given would be systematically reduced. The learning care is improving by the continuity of care, i.e., the patients are assigned to a limited number of caregivers during the planning horizon, which makes the problem more difficult and challenging to solve. Moreover, the health of the patients improves through the planning horizon, in consequence, the time required by the patient decrease.

The HHC transport system is designed to transform caregivers by cars to their patients. With regard to these organizational activities, one of the majorities of Green House Gaze (GHG) emission is the emission of CO_2 . In real life, a vehicle is not able to travel at a constant speed. It is expected to travel under a maximum and minimum speed limit. Experiments made with constant and varying speed show that fuel consumption is reduced using varying speed constraints (Poonthalir and Nadarajan, 2018).

In this paper, we discuss the fuel-GHHC with varying speeds that uses triangular distribution to minimize both the traveled distance of the routes and fuel consumption. To maintain caregivers' job satisfaction and service quality in the HHC, one of the objectives considered is to "master the overload risk" by balancing the caregivers' workload to reduce the excessive assignment and to satisfy the majority of patients by allowing them to be visited, if it is possible, by their preferred caregivers. To achieve the workload balancing, we have adopted (Cappanera and Scutella, 2015) technique to maximize the minimum utilization factor caregiver in the planning horizon in order to ensure a fair workload for all caregivers.

The quality of service requisites, the workload of each caregiver on each period, i.e., the sum of the daily service times and traveling times of the caregiver, cannot exceed the duration of the caregiver workday are taking into consideration.

This paper addresses a new environmental-friendly approach for the routing problem in the GHHC through reducing fuel consumption that leads to minimizing carbon dioxide with varying speed constraint and the satisfaction of both patients and caregivers in the home health care multi-period problem.

The main contribution of this work is developing a new approach for the GHHC; we take into consideration simultaneously the set of the following criteria:

- Balanced workload among caregivers
- Affinity between the patient and the caregiver
- Minimizing the total consumption of the fuel
- Minimizing the distance between the patients

And the following constraints:

- Adequacy between patient's needs and caregiver's skills
- Availability of patients
- Precedence of care
- Synchronization of cares
- Continuity of the care
- Maximum daily workload of the caregivers
- Varying speed routes

The remainder of the paper is organized as follows. Section 2 presents a literature review of the works related to the HHC. Section 3 is devoted to describe the problem and present the models, variables, and parameters. Computational results are given in Section 4. Finally, conclusions are given in Section 5 with future work perspectives.

2 LITERATURE REVIEW

Different studies related to the human resources planning (Cissé et al., 2017). At the strategic level, the districting problem considers the division of the region into districts to reduce the workload and the travel workload of the nurses according to several criteria for example the balancing of workloads among the designed districts. (Benzarti, 2012) developed two mathematical models of the districting problem. Resource dimensioning is done

at a tactical level, tackles the issue of defining the level of resources available at HHC and distributing the services to the districts.

Two major issues arise on the operational level: the caregiver assignment issue and the routing and scheduling issue for home health services.

In this paper, we address an operational problem related to assignment and routing problem aiming at assigning the patients to the caregivers and define the order and the time in which visits of caregivers to patients should be performed.

(En-nahli et al., 2015) developed a multi-objective mixed-integer linear for a daily HHC management by taking into consideration the affinity between the patients and the staff together and the skill constraints. The four objectives in the work were the cost, workload level, satisfaction level, and waiting time. (Cappanera and Scutella, 2015) developed a mixed linear integer to manage nurses' workload and reduce their waiting time. In their model, the authors find the idea of pattern to plan several visits to the same individual during the week. (Bertels and Fahle, 2006) presented a combination of linear programming, constraints programming and metaheuristics for a HHC problem that considers the staff rostering and vehicle routing components while minimizing transportation costs and maximizing satisfaction of the patients and nurses. (Moussavi et al., 2019) proposed a metaheuristic approach to the integration of worker assignment and vehicle routing problems, the work consist on finding the optimal services schedules for each one of the staff members so that the total and individual distance traveled by the staff is minimized. (Shi et al., 2017) proposed a heuristic algorithm integrated into a hybrid genetic algorithm and a Monte Carlo method to address the HHC routing and scheduling problem with fuzzy demand.

(Ben Bachouch et al., 2008) developed a mixed linear programming model of vehicle routing problem while respecting the availability of patients, breaks meals for staff, and shared visits to minimize the total distance traveled by the nurses. (Ehmke et al., 2015) considered the problem as a vehicle routing issue with time windows, in their case. They suggested a solution to guarantee the quality of service provided to all customers while the purpose of the problem is the classic VRP objective which is the cost of routing. Moreover, the paper studies the stochastic travel times. (Lanzarone et al., 2012) proposed mathematical programming models to balance the caregiver' workload under different categories. They considered the care's continuity constraint, caregiver's skills, and the districts where the patients and the caregivers belong. The patients' demands are considered either in a deterministic or stochastic way. (Kergosien et al., 2009) developed a Mixed Integer Linear Programming (MILP) for the HHC planning, they consider the problem as an extension of Multiple Travelling Salesman Problem with Time Window (mTSPTW) that aims to reduce costs of travel times between patients with additional constraints specific to the HHC: patients' availability, skills of

caregivers, preferences of the patients for caregivers, synchronization of multiple treatments for the same patient.

The problem discussed in this paper is a variant of the problem of multi-period human resources' planning in which one-period assignment has an effect on assignments for next periods. (Moussavi et al., 2017) presented a sequencing assignment model for weekly human resource planning. They proposed two metaheuristic approaches to solve the Sequencing Generalized Assignment Problem (SGAP).

The green vehicle routing problem (GVRP) was proposed by (Erdogan and Miller-Hooks, 2012). The objective of the problem is to devise low cost route for a set of homogenous vehicles stationed at a depot. Each vehicle takes a tour serving a set of geographically distributed customers with limited fuel capacity and time. The Fuel GVRP (FGVRP) with varying speed was proposed by (Poonthalir and Nadaraja, 2018) and it is used in this paper. The GVRP is a single objective problem that aims to reduce total route cost. While, the FGVRP is a bi-objective problem that aims to reduce both route cost and fuel consumption.

Experiments prove that varying speed reduce fuel consumption which lead to reduce carbon-di-oxide emissions (Poonthalir and Nadaraja, 2018).

In the literature, less environmental/green interest addressed to HHC. (Fathollahi-Fard et al., 2018) proposed a first GHHC approach using bi-objective optimization. The approach uses a number of modification and hybrid versions of metaheuristics and four heuristics. Later, (Fathollahi-Fard et al., 2019) introduced a GHHC and solve the problem using modified simulated annealing algorithms.

In this work, a new GHHC approach for the multi-period consists of three-stage methodology. The decomposition reduces the computational time required to solve the problem. The first stage aims to determine the packages needed in each day. The second and third stage aims to assign the packages defined in the first stage to the suitable/available caregivers while balancing the workload and maintaining the continuity of care.

3 PROBLEM DESCRIPTION AND MODELING

We consider a set of patients needing heterogeneous health care services. The problem consists in routing and scheduling caregivers to patients over a multi-period planning horizon taking into account multiple constraints involving, for example, patients' time windows and preferences, caregivers' skills and working hours, continuity of care, and workload balance. In addition, some patients may need to be serviced by two caregivers at the same time. The learning care factor is also considered in our work, which is expressed by the gradual reduction of the treatment duration as the caregiver becomes familiar with tasks performed for the same patient.

Triangular distribution:

A triangular distribution is a continuous probability distribution shaped like a triangle. It is defined by:

a: the minimum value, where $a \leq c$,

c: the peak value, where $a \leq c \leq b$,

b: the maximum value, where $b \geq c$.

The probability density function for a triangular distribution is defined as follows:

$$f(x) = \begin{cases} 0 & x < a \\ \frac{2(x-a)}{(b-a)(c-a)} & a \leq x \leq c \\ \frac{2(b-x)}{(b-a)(b-c)} & c \leq x \leq b \\ 0 & x > b \end{cases}$$

Triangular distribution is more flexible than normal distribution (Poonthalir and Nadaraja, 2018). Using triangular distribution is best interpreted. As vehicle speed fluctuates between a minimum and a maximum speed, which will travel at any of the most possible speed.

To know the average speed between an initial speed limit a and a maximum speed limit b , one has to calculate:

$$E(X) = \int_a^b xf(x)dx$$

The following example calculates the average speed between 30miles/hour and 40 miles/hour (Poonthalir and Nadaraja, 2018):

$$\begin{aligned} E(X) &= \int_{30}^{40} xf(x)dx \\ E(X) &= \int_{30}^{37} x \frac{2(x-30)}{(40-30)(37-30)} dx \\ &\quad + \int_{37}^{40} x \frac{2(40-x)}{(40-30)(40-37)} dx \\ E(X) &= 32 \text{ miles/gallon} \end{aligned}$$

The previous example shows the average speed between a minimum speed limit $a = 30$ and a maximum speed limit $b = 40$ and 37 be the most likely speed limit (Poonthalir and Nadaraja, 2018).

The approach proposed in this paper consists of three-stages; the first stage aims to determine the packages (routes) that caregivers perform with taking into consideration several constraints. In the second and third stage, we assign the packages to the suitable caregivers and balance the workload.

3.1 Mathematical modeling

3.1.1 First stage

We first propose the following multi-objective model that aims to determine the packages on one period and considers minimizing both distance and fuel

consumption. We assume that patients cannot be assigned to all packages; using this technique will assure the continuity of care in the approach.

We consider a complete directed network $G = (I, E)$ having I nodes corresponding to the cares required by the patients, plus an extra node (node 1), which is used to denote where the caregivers start their tour from node 1 and arrive in node 1.

3.1.1.1 Parameters:

K: Set of packages

I: Set of cares

NAP_i: Set of the unavailable packages for care i (The packages that care i cannot be assigned to)

s_i: Service time at care i

t_{ij}: Traveling time from node i to node j , $(i, j) \in E$

[A_i, B_i]: Respectively the earliest and the latest service time for the care i (related to the time window of the patient required care i)

S: Set of cares that require two caregivers ($S \subset K$)

MAXWL_k: The maximum daily workload for the package k

δ_i: The ratio of time decreased from care time s_i of care i this ratio define the learning care

M: A high value

F: Maximum fuel capacity

ord_i: Order of precedence of care i (if care i has to be planned before care j we have $ord_i \geq ord_j$)

I_i: One if the care i requires one caregiver. Two if the care requires two caregivers

dis_{ij}: Distance between node i and j

sp_{ij}: Average expected speed between i and j calculated using the triangular distribution (Miles/hour)

mpg: The total miles travelled per gallon (Miles/Gallon)

FCGH_{ij}: Fuel consumption in gallons per hour between nodes i and j (Gallon/hour) ($FCGH_{ij} = \frac{sp_{ij}}{mpg}$)

3.1.1.2 Decision variable

$$x_{ijk} = \begin{cases} 1 & \text{if the care } j \text{ is assigned after care } i \\ & \text{in the package } k \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ik} = \begin{cases} 1 & \text{if the care } i \text{ is assigned to the} \\ & \text{package } k \\ 0 & \text{otherwise} \end{cases}$$

AT_{ik}: Arrival time of the package k to the node i

RT_{ik}: Remaining time at node i of package k (Time left for package k at node i)

f_{jk}: Remaining fuel at node j of package k

3.1.1.3 Multi-objective programming model

Objective function:

$$\text{minimize } \sum_{k \in K} \sum_{(i,j) \in E} x_{ijk} \text{dis}_{ij} \quad (1)$$

$$\text{minimize } \sum_{k \in K} \sum_{(i,j) \in E} x_{ijk} \frac{\text{dis}_{ij}}{sp_{ij}} \text{FCGH}_{ij} \quad (2)$$

Constraints:

$$\sum_{k \in K} y_{jk} = I_j \quad \forall j \in I | j \neq 1 \quad (3)$$

$$\sum_{j \in I | j \neq 1} x_{1jk} \leq 1 \quad \forall k \in K \quad (4)$$

$$\sum_{j \in I | j \neq 1} x_{j1k} \leq 1 \quad \forall k \in K \quad (5)$$

$$\sum_{k \in N \setminus P_i} y_{ik} = 0 \quad \forall i \in I | i \neq 1 \quad (6)$$

$$y_{jk} = \sum_{i \in I | i \neq j} x_{ijk} \quad \forall k \in K, \quad \forall j \in I | j \neq 1 \quad (7)$$

$$\sum_{i \in I} x_{ijk} = \sum_{i \in I} x_{jik} \quad \forall k \in K, \quad \forall j \in I | j \neq 1 \quad (8)$$

$$AT_{jk} \geq A_j \quad \forall k \in K, \quad \forall j \in I | j \neq 1 \quad (9)$$

$$AT_{jk} \leq B_j \quad \forall k \in K, \quad \forall j \in I | j \neq 1 \quad (10)$$

$$f_{jk} \leq f_{ik} - \frac{dis_{ij}}{sp_{ij}} \frac{sp_{ij}}{mpg} x_{ijk} + (1 - x_{ijk})F \quad \forall k \in K, \quad \forall (i, j) \in E | j \neq 1 \quad (11)$$

$$\sum_{(i,j) \in E} ((s_i(1 - \delta_i)) + t_{ij}) x_{ijk} \leq MAXWL_k \quad \forall k \in K \quad (12)$$

$$AT_{jk} \geq AT_{ik} + ((s_i(1 - \delta_i)) + t_{ij}) x_{ijk} - (1 - x_{ijk})M \quad \forall k \in K, \quad \forall (i, j) \in E | j \neq 1 \quad (13)$$

$$f_{1k} = F \quad \forall k \in K \quad (14)$$

$$AT_{jk} = AT_{jk}' \quad \forall k, k' \in K, \quad \forall j \in S \quad (15)$$

$$RT_{1k} = MAXWL_k \quad \forall k \in K \quad (16)$$

$$ord_i \geq ord_j \times x_{ijk} \quad \forall k \in K, \quad \forall (i, j) \in E | (i, j) \neq 1 \quad (17)$$

$$RT_{jk} \leq RT_{ik} - ((s_i(1 - \delta_i)) + t_{ij}) x_{ijk} + (1 - x_{ijk})M \quad \forall k \in K, \quad \forall (i, j) \in E | j \neq 1 \quad (18)$$

$$x_{ijk} \in \{0,1\} \quad \forall k \in K, \quad \forall (i, j) \in E \quad (19)$$

$$y_{ik} \in \{0,1\}$$

$$AT_{ik} \geq 0$$

$$RT_{ik} \geq 0$$

$$f_{ik} \geq 0$$

Objective (1) aims to minimize travel distance. Objective (2) aims to minimize fuel consumption. Constraints (3) guarantee the number of caregivers that a care needs. Constraints (4) ensure that at most one care can be performed after the fictive care 1. Constraints (5) ensure that at most one care can be performed before the fictive care 1. Constraints (6) guarantee restriction of package for cares (This will assure the continuity of care in the planning). Constraints (7) guarantee that if a care is assigned to a caregiver, the care has a successor (Linking between routing and assignment variables). Constraints (8) are the classical flow conservation constraints on the routing variables. Constraints (9) and (10) ensure that the start time of the cares respect a time window. Constraints (11) gives the remaining fuel level at nodes based on the distance between i and j and the average expected speed between i and j . Constraints (12) assure that the workload of each caregiver in each day, expressed as the sum of the service times and traveling times does not exceed the duration of a workday. Constraints (13) calculate the arrival time of the package to the care. Constraints (14) ensure that the fuel level reaches its maximum capacity depot. Constraints (15) ensure that the care must be start at the same time for cares that require synchronization (needs two caregivers). Constraints (16) ensure that the workload of packages reaches its maximum at the depot. Constraints (17) guarantee the precedence of cares. Constraints (18) give the remaining time at nodes based on the travel time between i and j and the service time. The decision variables of the problem are given in constraints (19).

3.1.1.4 Weighted sum approach for multi-objective optimization

One of the most popular techniques to solve multi-objective optimization problems is the weighted linear aggregation. The problem becomes a single objective. This single objective function is considered as a sum of objective functions multiplied by weighting coefficients. The model is transformed into a mixed integer linear programming model and described as:

$$\text{minimize } \gamma = \alpha \times F_1 + \beta \times F_2$$

Subject to:

(3)-(19)

Where,

$$F_1 = \sum_{k \in K} \sum_{(i,j) \in P_k} x_{ijk} \times dis_{ij} \quad \text{And,}$$

$$F_2 = \sum_{k \in K} \sum_{(i,j) \in P_k} x_{ijk} \times \frac{dis_{ij}}{sp_{ij}} \times FCGH_{ij}$$

The normalization of objectives is required to get a consistent optimal solution (Grodzevich et al., 2006).

$\alpha = \rho_1 \times \theta_1$, and $\beta = \rho_2 \times \theta_2$ where $(\rho_1 + \rho_2 = 1)$

The normalization factor is calculated as follows:

Where $\theta_1 = \frac{1}{\min\{F_1\}}$ and $\theta_2 = \frac{1}{\min\{F_2\}}$

$\min\{F_1\}$, $\min\{F_2\}$ are respectively the minimum of F_1 and F_2

The decision maker chooses the weights ρ_1 and ρ_2 according to the importance of each objective function. Since the problem is multi-objective, we can get a set of optimal solutions from the Pareto Front. The weighted sum approach ensures finding points on the Pareto front by varying each time the weights ρ_1 and ρ_2 and solving the model (En-nahli et al., 2015).

3.1.2 Second Stage

In the second stage, we define a “category”; which is group of packages of first stage that contains the same patients in the planning horizon. To define the number of caregivers required in each category, we fix the day with the maximum number of packages that a category requires.

The number of categories is limited, due to the limited number of packages that a patient can be assigned to (the continuity of care constraint).

To decide the caregivers to assign to each category, and according to the affinity and the skill required by the patients, we propose the following heuristic:

Heuristic.1

Input

- **SC**: Set of categories
- **N**: Set of caregivers
- **Aff**: Affinity between the caregiver and the patients
- **SK**: Skill of the caregiver
- **SR**: Skill required by the patients

For all i in SC

while (the number of caregivers required by the category isn't reached)

X : $a = rand(N)$ (Choosing randomly a caregiver)

if ($SR(patients(i)) \leq SK(a)$ & $Aff(patients(i), a) \neq 0$ & a has never been assigned)

Assign $a \rightarrow i$

else go to X

Heuristic1 is proposed to assign the caregivers to the suitable categories according to the affinity between the patients and the caregivers, as well as, the skills required by the patients.

In the following stage, we aim to assign the caregivers to each package and to balance the weekly workload.

3.1.3 Third Stage

In this level of the approach, we focus on the caregivers assigned to each category and balance their weekly workloads.

3.1.3.1 Parameters

N: Set of caregivers

K: Set of packages

D: Set of days in the planning horizon

WL_n: Workload of package n

P_{jd}: 1 if package j is in day d , 0 otherwise.

3.1.3.2 Decision variables

$$z_{jnd} = \begin{cases} 1 & \text{if the package } j \text{ is assigned to the caregiver } n \text{ on day } d \\ 0 & \text{otherwise} \end{cases}$$

L: The minimal operability factor of the caregiver that we aim to maximize in order to ensure a fairness workload

L_n: The operability of the caregiver n during the planning horizon, given by the following formula:

$$\frac{\sum_{d \in D} \sum_{j \in J} z_{jnd}}{|D| \times WL_n} = L_n \quad \forall n \in N$$

Objective function:

$$\text{maximize } L \quad (20)$$

Constraints:

$$L_n \geq L \quad \forall n \in N \quad (21)$$

$$\sum_{n \in N} z_{jnd} \leq P_{jd} \quad \forall j \in K, \forall d \in D \quad (22)$$

$$\sum_{d \in D} \sum_{j \in K} z_{jnd} \leq 1 \quad \forall n \in N \quad (23)$$

Objective (20) aims to balance workload. Constraints (21) ensure that the workload of each caregiver is greater than the operability factor that we aim to maximize; it guarantees a fair workload for all caregivers and avoids solutions where a given caregiver has a workload less than others. Constraints (22) guarantee that the packages are assigned to the days given by the first stage model. Constraints (23) ensure that a caregiver is assigned to at most one package during a day.

4 COMPUTATIONAL EXPERIENCE

The model is implemented using CPLEX Optimization Studio12.6, in an Intel® Core™ i5 and 6 Go Ram. The heuristic.1 is implemented using C++. We have generated various instances to show the performance of the approach introduced for small and medium instances.

4.1 Data generation:

We have generated patients and caregivers' instances as shown in Table.1.

P.X.C.Y denotes an instance with **X** patients and **Y** caregiver.

Instances	Caregivers	Patients
1	4	12
2	10	24
3	15	48
4	18	60

Table.1 Instances

The duration of time windows of patients' availability varies between 90min and 180min. The considered skills required by the patients vary between 1 (usual cares) and 3 (advanced cares).

Caregivers who have "skill 3" can treat all cares. Caregivers with "skill 2" can treat patients requiring skill 2 and 1. The patients may need several cares per day: one, two, or three. Some patients do not need any care on a day. The cares have an order that must be taken into account, (+) denotes that the patient requires the care, (-) otherwise. (SYN) is the synchronization of cares; it denotes that the cares require two caregivers at the same time. The following Table.2 shows the care required by the patient on a day for instance (P.12.C.4).

	Care α	Care β	Care γ
P1	(before γ) +	-	+
P2	-	SYN +	-
P3	+	-	-
P4	(after β) +	SYN+	-
P5	-	-	-
P6	+	-	-
P7	(before γ) +	-	+
P8	-	-	+
P9	-	SYN (after γ) +	+
P10	-	-	-
P11	+	-	-
P12	-	-	+

Table.2 Data of cares required by patients on a day for Instance (P.12.C.4)

As mentioned in Section 2. Generally, the speed of the vehicle fluctuates between 30 and 60. This range is considered according to the literature (Poonthalir and Nadaraja, 2018). It is taken in an interval of 10 from 30 to 60 as [30 40 50 60].

To calculate the expected speed within the interval 30-60, one has to calculate the average speed within each interval and take the average.

4.2 Computational results:

In the following, we solve the problem using CPLEX optimize studio, let α be route cost and β be the fuel consumption.

Firstly, we take ($\beta = 0$) and minimize α as shown in column 2 of Table 3. Then, we take ($\alpha = 0$) and minimize β with constant and varying speed (column 3 and 5 of Table 3). The learning care factor is ($\delta = 0$).

Instance	Route traveled distance (Miles) ($\beta = 0$)	Fuel consump- tion with constant speed (Gallon) ($\alpha = 0$)	Speed	Fuel con- sumption with vary- ing speed (Gallon) ($\alpha = 0$)	Speed
P.12.C.4	11.21	1.86	40	1.77	39.25
P.24.C.10	22.796	3.77	40	2.77	41.29
P.48.C.15	37.19	6.28	40	5.78	40.02
P.60.C.18	45.36	6.98	40	5.01	37.55

Table.3 Fuel consumption with varying and constant speed

Table 3 shows the results obtained with varying and constant speed. We obtain a decrease in the fuel consumption when varying speed is used. Hence, the di-oxide emission is decreased.

Secondly, we solve the problem using the weighted sum and normalization approach described in Section 3, we take $\rho_1=0.5$ and $\rho_2=0.5$.

Instance	Cost with con- stant speed	Cost with vary- ing speed
P.12.C.4. $\delta.0.2$	1.073242	1.06963
P.24.C.10. $\delta.0.4$	1.09705	1.052
P.48.C.15. $\delta.0.4$	1.0073	0.893
P.60.C.18. $\delta.0$	0.9958	0.801

Table.4 Results of the weighted sum approach

In Table 4 the problem is solved using the weighted sum and normalization approach. The learning care factor takes ($\delta = 0$, $\delta = 0.2$ and $\delta = 0.4$).

The instance P.12.C.4. $\delta.0$ denotes 12 patients and 4 caregivers with leaning factor $\delta = 0$.

Experimental results show the decrease in fuel consumption when varying speed.

The weighted sum approach ensures finding points from the Pareto Front by varying the weights and solving the problem.

5 CONCLUSION

In this paper, we introduced a fuel consumption approach with varying speed constraints to solve the GHHC problem. We presented a literature review of the works related to the HHC. A three-stage methodology composed of a multi-objective programming model, a heuristic, and an ILP model is introduced to solve the multi-period GHHC considering several constraints and criteria that make the problem more challenging to solve. We are working on a GHHC problem-solving approach based on a multi-objective Genetic Algorithm.

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