Computing and Informatics, Vol. 41, 2022, 288–308, doi: 10.31577/cai_2022_1_288

# HOME HEALTH CARE SCHEDULING PROBLEM UNDER UNCERTAINTY: ROBUST OPTIMIZATION APPROACHES

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**Abstract.** This paper deals with the home health care service (HHCS) which is defined as a set of medical, paramedical and social services delivered to patients in their domicile rather than in hospital. To support decision making in HHC, optimization models have been used. However, several of those models are deterministic and do not address the dynamical and uncertainty aspects of the system and variability of some patient data. The HHC scheduling problems are facing more and more complex and specific constraints. These constraints have to be respected, meanwhile the problem objective is optimized under parameters uncertainties. This paper aims to formulate a model that integrated home care scheduling problem while taking into account human aspect – the behavior of patients, and also another aspect like travel time uncertainty and dynamic behavior of involved medical team and social actors in HHC. Robust approaches are adopted to model and handle this uncertainty.

**Keywords:** Home health care, robust optimization, scheduling, uncertainties

## 1 INTRODUCTION

Home Health Care (HHC) is an emerging offer in developing countries. It allows to patients suffering from serious diseases, acute or chronic illness to benefit from medical and paramedical treatment at their homes [1].

The concept of "HHC" was launched in the United States of America in 1947 and in France in 1951. This growth is due to economics factors related to hospitals' over-crowding and willingness to keep health costs under control. On the other side, it is due to human factors linked to the increase of life expectancy, the aging of population and the occurrence of chronic diseases.

HHC was acknowledged in 2009 as full-fledged health care institution which means that the home health care is subject to the same obligation as traditional hospitalization. It is forced to ensure quality, safety, permanence and continuity of care for patients by involving many actors such as medical team, paramedical and social team, support cell, social actors, etc.

The major issue of HHC structure is the improvement of patient care, while ensuring efficiency for the health insurance. Therefore, HHC needs to upgrade the skills and competencies within its operational area: management, organization, care while taking into consideration specific constraints of the home operation.

We are particularly interested to improve schedule planning for the home health care problem. The question is to respond to patient's demand while organizing the activities and interventions of all involved teams. Reducing costs, waiting time, wasted time and ensuring quality of service are also among the issues of such system [2]. Reaching these objectives and ensuring relevant HHC systems require the use of powerful tools and models for decisions making.

Furthermore, this problem is often subject to different types of uncertainties which are related to patients, caregivers and other involved actors in HHC or its environment. In reality, the optimizing process is hampered by the uncertainty of the data. It is therefore necessary to establish methodologies which take into account perturbations in the optimization process. For these reasons, we turn to robust optimizing that can provide solutions for problems subject to uncertainties. To do so, a special mathematical model called robust routing problem with time windows is proposed in order to schedule and optimize giving home care services to patients. Through the developed model we aim to maximize activities of caregivers and minimize routing travel time as well as ensuring the best resource for each care activity. We aim also to minimize the dependency level of each routes. The basis of this model is elicited from [3] who have designed HHC for routing problem.

To the best of our knowledge, our model is the first model to incorporate

1. integration of some realistic feature to the model such as uncertainty in the travel time of routing problem and
2. applied robust approaches to face this uncertainty.

The contribution of the paper is summarized as follows:

- In the proposed model a break is taken into account, which is more realistic by allowing caregivers to have some pause during their work.
- In this study, the uncertainty in the travel time of caregivers is a realistic assumption (breakdown, accident, change in scheduling of care activities facing a more urgent case).

The rest of the paper is organized as follows. In Section 2, the related literature is reviewed. Section 3 gives the mathematical formulation of the HHC problem. This section presents two optimization approaches we propose to resolve the problem while taking into account the uncertainty aspect. Future work about the development of a collaborative solution for coordinating HHC activities is addressed in Section 4. Finally, the work is concluded by the Section 5.

## 2 LITERATURE REVIEW

Home Health Care (HHC) problem can be defined as a set of human and material resources used to give required services (e.g. medical, paramedical, cleaning, drug delivery) to patients in their homes. This emerging service sector gained a big attention by researchers and practitioners during the last decades due to several challenging problems raised by this new alternative to traditional hospitalization.

A large number of research works has emerged recently to optimize one or more criteria by considering different class of specific constraints for this service problem in health sector. In the first part of this section, we will focus on a set of 37 research papers published between 2008 and 2020 and dealing with the deterministic HHC problem. This papers set allowed us to identify:

1. The considered optimization criteria, which are:
   - Time (e.g. travel, waiting, uptime, overtime)
   - Costs (e.g. travel, waiting, assignment, resources)
   - Traveled distances (e.g. CO2 emissions).
   - Workload balance (e.g. number of patients, time duration).
   - Patient preference (e.g. nurse assignment, unavailability)
   - Caregiver preference (e.g. lunch break, unavailability)

- Unsatisfied services (e.g. dissatisfaction rate)
- Number of used caregivers (e.g. use rate)

2. The specific and/or common constraints to which the problem is subjected to are as follows:

   **TW:** The abbreviation of time windows. This class of constraints has been considered either for drug delivery or for patient (resp. caregivers) availability (resp. unavailability).

   **Simultaneously:** It means simultaneous synchronization constraint. Sometimes several resources are required simultaneously to ensure the service, such as the bath if the patient is dependent and a single person is not sufficient.

   **Preferences:** Include patient and caregivers preferences. These preferences are generally regarding assignment and time visits.

   **Qualification:** Define if some specific qualifications are required for the caregivers assigned to patient. In some cases of severe burns, the assigned nurse should have the skills to change the patient's bandage.

   **Synchronization:** It concerns notably precedence synchronization. In fact, sometimes, a patient requires several service activities which should be well organized. For example, a dependent patient should receive his toilet before the doctor visit.

   **Periodicity:** This class of constraints defines how many times some activities are repeated such as drug delivery or a recurrent service for patients suffering from long-term disease like dialysis.

3. Some different approaches to model and solve the considered problem, and mainly:

   - Exact approach's, called also exact algorithms which consists on solving the problem to optimality. This approach is very well used in literature to solve real case problems or small sized instances (i.e. branch and bound).
   - Metaheuristic approach's, is a heuristic algorithm that can provide a good optimizing solution in acceptable computational time but the optimality of the solution is not guaranteed. Thanks to this identification, a classification is provided in Table 1.

In the previous studies dealing with the addressed problem, most of them have been focused on the deterministic case. However, in the real world, it is a matter of uncertainties and it is usually hard to know precise decisions and thus, they are made in the face of hazards and indecisions.

Given the aspect of planning problems, a consideration of uncertainties and robust optimizing approaches may be useful to find good quality solution for scheduling problem.

Uncertainty can be defined as a situation in which available data and information is incomplete, insufficient or absent. It can be caused also from a doubt about the

| Ref. | Optimization criteria | | | | | | | | Constraints | | | | | | Solution Approach | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Time | Cost | Distance | Work-load | Patient's Pref. | Caregiver's Pref. | Unsatis-fied | # Care-givers | TW | Simulta-neously | Prefe-rences | Qualifi-cation | Synchro-nization | Perio-dicity | Exact | Metaheu-ristic |
| [4] | x | | | x | | | | | x | | | x | | | x | |
| [5] | x | | | | | | | | x | | | | | x | x | x |
| [6] | x | | | | | | | | | | | x | | | x | |
| [7] | x | | | x | | | | x | x | x | | x | | | x | x |
| [8] | | x | | | | | | | x | | | | | | x | x |
| [9] | | x | | | | | | | x | | x | x | | | | x |
| [10] | | x | | x | | | x | | x | | | x | | x | x | x |
| [11] | x | | | | | | | | x | | | | | | x | |
| [12] | x | | | x | | | x | | x | x | | x | | | x | x |
| [13] | | x | | | | | | | x | | | x | | | x | x |
| [14] | x | | | | | | | | x | x | | | | x | | x |
| [15] | | x | | | x | | x | | x | | | x | | | | x |
| [16] | | x | | | | | | | x | | | | | | | x |
| [17] | | x | | | | | | | x | | | x | | | x | |
| [18] | | x | | | | | | | x | | | x | | x | x | x |
| [19] | x | x | | | | | | | x | | | x | | | | x |
| [20] | | x | | | | | | | x | | x | | | | x | |
| [21] | x | | | | | | | | x | x | | x | | | x | x |
| [22] | x | | | | x | | | | x | | x | x | | | x | x |
| [23] | | x | | | x | | | | x | | | x | | x | x | |
| [24] | | | x | | x | x | | | x | | x | x | | x | | x |
| [25] | | x | | | x | x | | | x | | x | x | | | | x |
| [26] | | x | | | x | | | | x | x | | x | x | | x | |
| [27] | | x | | | | | | | x | x | | | | x | | x |
| [28] | | x | | | | | | | x | x | | | x | | | x |
| [29] | x | | | | | | | | x | | | | | x | | x |
| [30] | | x | | | | | | | x | x | | x | | | | x |
| [31] | | | | | | | | x | x | | | x | | x | x | |
| [32] | x | x | | | x | x | | | x | | | x | | x | x | |
| [33] | x | | | | | | | | x | x | | x | | | x | |
| [34] | x | | x | | | | x | | x | | | x | | x | | x |
| [35] | | x | | | | x | x | | x | | | | x | | x | |
| [36] | x | | | | x | x | | | x | | | x | x | | | x |
| [37] | x | | | | x | x | | | x | | | x | x | | x | x |
| [38] | x | | | | | | | | x | | | | | | x | |
| [39] | | | x | x | | | | | | | | x | | | x | x |
| [40] | x | x | | | x | | | | x | | | | | x | | x |

Table 1. Classification of the literature review on HHC

availability of a resource (human or material) after an unexpected change in the system.

In case of unavailability of an information or a resource, risk analysis methods are often used. Nevertheless, in the majority of cases studied, uncertainty is characterized by a random law.

To formulate and resolve these kinds of problems, stochastic optimization methods are used. In other cases, the uncertainty cannot be represented by a probability law. To face this lack and limit, in this situation, robust optimization methods are more suitable and useful.

One of the most popular frameworks for planning and scheduling under uncertainties is stochastic programming [41, 42, 43]. Uncertainty can be represented using a number of discrete scenario to represent future states. A challenged approach can be considered as developed in [44] about a multi-stage stochastic linear programs (M-SLP) to model planning and uncertainties. Also, chance constraint programming is another possibility to model this problem. However, these two approaches have a lot of drawbacks: i) the number of scenario increase with the number of uncertain parameters, ii) this leading to an increase in the problem size.

Determining the probability law related with each variables or random parameter can be a particularly difficult and sometimes the impossible task. Hence, a recent methodology of operational research (RO)-robust optimization-remains a necessity to deal with these issues. This field has seen a gaining increasing and development during the last two decades.

Among the non-probability uncertainty models identified in the literature, we first identified the discrete scenario modeling where uncertain parameters are represented by a finite set of discrete values [45]. In this study, problems are modeled by continuous intervals or more generally by convex sets. This method is widely used in robust optimization [45, 46, 47]. Our contribution through this paper is focused on this second category with the representation of uncertainty by intervals.

The first robust optimization model was developed in [48] where the authors proposed a linear optimization model to construct a solution that is feasible for all data that belongs to a convex set. The model treats column-wise uncertainty in linear programming problems, where each uncertain parameter has to be taken equal to its worst case value in the set. The drawback of this approach is that the solutions produced are too conservative. Therefore, the obtained solutions are robust but too far from the optimal solution.

The topic of over-conservatism was discussed in [49]. The authors have proposed less conservative models by considering linear programs with an ellipsoidal structure of uncertainty. The robust problem gathered is in the form of conic quadratic problems. This means that the robust counterpart does not maintain the complexity of the initial nominal problem.

Bertsimas and Sim have presented in [47] a particular technique adapted to polyhedral uncertainty that leads to a robust counterpart by controlling the degree of conservativeness of the solution.

In recent years, robust approaches were interested in solving real applications. In [50], the authors have presented an overview of research work on Vehicle Routing Problems (VRP) with more realistic constraints. Based on this approach, we are mainly interested in this paper in robust approaches applied to the VRP with or without time windows (R-VRP, R-TSP and R-TSPTW).

Several studies have discussed the uncertainty of demand in the VRP [51, 52], the RSCP [53, 54]. Others have proposed a robust optimization model form the VRPTW with uncertainties on time services [55, 56], uncertainties on the travel times [57]. In [58], the authors have examined the robust TSP with paths belonging to a set of values, and in [59] the case of the TSP with uncertainty on the distance between nodes has been studied. Furthermore, Minoux has considered the robustness of the inventory management scheduling problem [60, 61, 62]; and transportation problems was studied in [63].

Several studies have focused on home health care organization and scheduling in terms of coordination and cooperation of all involved caregivers [64, 21, 65, 66]. As developed in these research works, different models and platforms have been developed to reach an effective organization of home care activities. The common point and addressed issue of all these works is to ensure the efficiency in which distributed care interventions are managed while involving different participant and ensuring patient satisfaction as well.

In [64] a solution, called Plas'O'Soins, and aimed to address the home health care problem by providing an interactive ICT platform to improve coordination and continuity of care within homecare organizations. It supports care specification as well as scheduling of the care plans using taking into account many constraints like human resources, medical constraints and geographical distribution of patients. The authors of [21], have addressed the problem of routing and scheduling HHC service under precedence and coordination constraints. Taking into account that the patients may receive multiple caregivers, the objective is to find the minimal round for vehicles, while satisfying all the caregivers and without violating customers' time windows. The same for [65] and [66] where the authors have proposed mathematical algorithms for HHC daily planning while ensuring the satisfaction of all the stakeholders (caregivers, patients, other social actors, etc.).

To bring our contribution in this field of HHC, our work in this paper focuses mainly on the short term caregivers round problem where travel time uncertainty is considered. This contribution is based on the development of two robust approaches to solve uncertain problems in HHC framework.

## 3 PROPOSED MODEL

The problem we are dealing with in this paper is the organization of HHC activities. The model proposed is an extension of the multiple traveling salesman problem with time windows (m-TSPTW). This section will present the problem statement.

Then, the mathematical formulation, and finally, two new robust approaches will be presented.

### 3.1 Problem Statements

A care activity $i \in A$ is performed at patient's home by a resources $k \in R$ in given time windows $[a_i, b_i]$. Each patient is characterized by a level of dependence $N_i$ and a degree of competence which is defined between patients and resources. The degree of competencies is a real value arranged between "0" and "1". Regarding resource's type, if the grade is closed to one this means that the compatibility is high and so activity can be performed. Otherwise, it cannot be realized. To perform an activity, one or more resources may be required.

In this model, two fictive activities will be considered: the first one "0" represents the beginning of activities and the second one is $n_{A+1}$ which represents the final activity.

These two fictive activities are characterized by a degree of competence and service's duration null. The time windows in the fictive activities represent the planning horizon. Besides, the breaks should be taken during the day between 12 h and 13 h.

### 3.2 Deterministic Model

Our model is inspired by the work presented in [3] for which we have added the breaks for caregivers. This new parameter requires a new reformulation of the problem, and of course new models and solutions which are different from those presented in [3]. The following notations are required for the model formulation:

- $R = \{1, \ldots, n_R\}$ – Set of caregivers.
- $A = \{0, \ldots, n_{A+1}\}$ – Set of activities. The activities "0" and "$n_{A+1}$" are the fictitious activities.
- $nb_i$ – Number of resources needed to realize the activity $i \in A$.
- $[a_i, b_i]$ – Time window to perform activity $i \in A$.
- $N_i$ – Level of dependence for a person receiving activity $i \in A$.
- $C_{jk}$ – Degree of competence between activity $j \in \{1 \ldots n_A\}$ and resource $k \in \{1 \ldots n_R\}$.
- $t_i$ – Duration of the activity $i \in A$.
- $D_{ij}$ – Travelling time between activity $i$ and $j$.
- $M$ – High value.

#### 3.2.1 Decisions Variables

The decisions variables of this model are $x_{ijk} = 1$ if the resource $k \in R$ performs the activity $i \in A$; 0 otherwise. $Z_i$ is the starting date for activity $i \in A$.

### 3.2.2 Problem Formulation

Mathematical model is developed in this subsection to organize tours of care activities. The objective function is a linear mixture of three parameters as given by Equations (1), (2) and (3).

- Minimize the total traveling times:

$$\text{minimize T}=\sum_{i=0}^{n_A}\sum_{j=1}^{n_{A+1}} D_{ij}\sum_{k=1}^{n_R} x_{ijk}. \tag{1}$$

- Minimize the gap between the best resource for an activity and the resource to achieve the activity

$$\text{Minimize } C=\sum_{i=0}^{n_A}\sum_{j=1}^{n_R}(1-C_{jk})\sum_{k=1}^{n_{A+1}} x_{ijk}. \tag{2}$$

- Minimize the level of dependence of each route (B is defined by a constraint (4))

$$\text{Minimize } B. \tag{3}$$

The problem constraints are modelled as follows:

$$\sum_{i=1}^{n_A}\sum_{j=1}^{n_{A+1}} N_i x_{ijk} \leq B_i \qquad \forall k \in \{1,\dots,n_R\}, \tag{4}$$

$$\sum_{j=1}^{n_{A+1}}\sum_{k=1}^{n_R} x_{ijk} = nb_i \qquad \forall i \in \{1,\dots,n_A\}, \tag{5}$$

$$\sum_{i=0}^{n_A}\sum_{k=1}^{n_R} x_{ijk} = nb_j \qquad \forall j \in \{1,\dots,n_A\}, \tag{6}$$

$$\sum_{j=1}^{n_A} x_{0jk} = 1 \qquad \forall k \in \{1,\dots,n_R\}, \tag{7}$$

$$\sum_{i=1}^{n_A} x_{i(A+1)k} = 1 \qquad \forall k \in \{1,\dots,n_R\}, \tag{8}$$

$$\sum_{i=0}^{n_A} x_{ilk} = \sum_{j=1}^{n_{A+1}} x_{ljk} \qquad \forall k \in \{1,\dots,n_R\}\, \forall i \in \{1,\dots,n_A\}, \tag{9}$$

$$z_j \geq z_i + t_i + D_{ij} + (x_{ijk}-1)M, \tag{10}$$

$$\forall k \in \{1,\dots,n_R\} \quad \forall i \in \{0,\dots,n_A\} \quad \forall j \in \{1,\dots,n_{A+1}\},$$

$$z_i \geq a_i \qquad \forall i \in \{1, \ldots, n_{A+1}\}, \tag{11}$$

$$z_i \leq b_i - t_i \qquad \forall i \in \{1, \ldots, n_{A+1}\}, \tag{12}$$

$$\sum_{i=0}^{n_A} x_{ijk} \leq C_{jk} M \qquad \forall i \in \{1, \ldots, n_{A+1}\} \quad \forall k \in R, \tag{13}$$

$$\sum_{i=P+1}^{n_A+n_R} \sum_{j=1}^{n_A+n_R+1} x_{ijk} = 1 \qquad \forall k \in \{1, \ldots, n_R\}, \tag{14}$$

$$\sum_{i=0}^{n_A} \sum_{j=n_A+1}^{n_A+n_R} x_{ijk} = 1 \qquad \forall k \in \{1, \ldots, n_R\}. \tag{15}$$

The constraint (4) determines the components of B that represents the value of objective function defined by (2). B is defined as an upper bond of the global dependency level. The global dependency level of a tour represents the sum of dependency levels of each patient visited on the tour. Constraint (5) ensures that the number of resources performing an activity is correct. Constraint (6) guarantees that all resource performing activities will exist from patient's home. Constraint (7) pushes that the activities begin by fictive activity "0" and constraint (8) forces that the activities finish by the fictive activity $nA + 1$. Constraint (9) guarantees the flow's conservation. Constraint (10) checks that travel time between two activities is taken into consideration. Constraints (11) and (12) assure that all activities are released and completed during the time windows. Compatibility resources/activities is respected according to constraint (13). Constraints (14) and (15) ensure that each resources have one break during the day.

In order to catch travel time uncertainty and study the resulting impact on caregiver's scheduling, two robust approaches developed by [47] and [48] were adopted. In the following, the main concepts required for deriving robust models proposed are exposed.

### 3.3 First Robust Formulation

The first robust optimization model was developed by Soyster [48]. His idea was to evaluate solution by choosing the worst case scenario. Nevertheless, by seeking for a valid solution independently of uncertain data values, we are limited to conservative solution the value of which is very far from the optimal solution of initial deterministic program.

To be more realistic, it is common to assure some uncertainty in travel times. We define the uncertainty set as being the interval number for each one of them. Formally, travel time belongs to $\left[\bar{D}_{ij} - \hat{D}_{ij}, \bar{D}_{ij} + \hat{D}_{ij}\right]$, where $\bar{D}_{ij}$ represents the nominal value of $D_{ij}$ and $\hat{D}_{ij}$ represent its maximum deviation. We consider $\zeta_{ij} \in$

$[-1, 1]$ a variable which construct the uncertain part such as:

$$D_{ij} = \bar{D}_{ij} + \hat{D}_{ij}\zeta_{ij}\zeta_{ij} \in [-1, 1], \forall i, j \in [0 \dots n_{A+1}]. \tag{16}$$

So, Equations (2) and (10) become respectively:

$$\min \left( \sum_{i=0}^{n_A} \sum_{j=1}^{n_{A+1}} \sum_{k=1}^{n_R} \bar{D}_{ij} x_{ijk} + \max_{\zeta_{ij} \in [-1,1]} \left\{ \hat{D}_{ij} x_{ijk} \zeta_{ij} \right\} \right), \tag{17}$$

$$z_j \geq z_i + t_i + \bar{D}_{ij} + (x_{ijk} - 1) * M + \max_{\zeta_{ij} \in [-1,1]} \left\{ \hat{D}_{ij} \zeta_{ij} \right\}. \tag{18}$$

According to Soyster's approach, we replace objective function by (19) and we add constraint (20) to our model.

$$\min \left( \sum_{i=0}^{n_A} \sum_{j=1}^{n_{A+1}} \sum_{k=1}^{n_R} x_{ijk} (\hat{D}_{ij} + \bar{D}_{ij} \right), \tag{19}$$

$$z_j \geq z_i + t_i + \bar{D}_{ij} + (x_{ijk} - 1) * M + \hat{D}_{ij} \zeta_{ij}. \tag{20}$$

### 3.4 Second Robust Formulation

Bertsimas and Sim (2004) present a new technique particularly suitable for polyhedral uncertainty that leads to linear robust counterparts while monitoring the level of conservatisms of the solution.

The authors stipulate that the worst case scenario cannot simultaneously affect all uncertain coefficients. Therefore, they introduce the concept of budget of uncertainty $\Gamma \in [0, n]$ which represents the maximum range of the uncertain travel time that can simultaneously deviate from their nominal values.

When ($\Gamma = 0$, nominal value is considered, and ($\Gamma = n$ leads to considering the problem with the greatest travel time. The purpose of setting the parameter $\Gamma$ is to restrict the travel time that are greater than the nominal one. Therefore, according to its prediction, the decisions maker is free to choose any value of the budget of uncertainty $\Gamma$ in the interval $[0, n]$ and solve the robust problem.

The robust problem is the following:

$$\min \left( \sum_{i=0}^{n_A} \sum_{j=1}^{n_{A+1}} \sum_{k=1}^{n_R} \bar{D}_{ij} x_{ijk} + \max_{\substack{\sum_i \sum_j \varphi_{ij} \leq \Gamma \\ 0 \leq \varphi_{ij} \leq n}} \left\{ \hat{D}_{ij} x_{ijk} \varphi_{ij} \right\} \right) \quad \forall i, j \in A, \tag{21}$$

$$z_j \geq z_i + t_i + \bar{D}_{ij} + (x_{ijk} - 1) * M + \max_{\substack{\sum_i \sum_j \varphi_{ij} \leq \Gamma \\ 0 \leq \varphi_{ij} \leq n}} \left\{ \hat{D}_{ij} \varphi_{ij} \right\} \quad \forall i, j \in A \tag{22}$$

where the uncertainty set $U(\Gamma)$ is defined by:

$$U(\Gamma) = \left\{ D_{ij} \in \mathbb{R}^n : D_{ij} = \bar{D}_{ij} + \hat{D}_{ij}\varphi_{ij} / \varphi_{ij} \in Z(\Gamma) \right\} \quad \forall i, j \in A \tag{23}$$

and

$$Z(\Gamma) = \left\{ \varphi_{ij} \in \mathbb{R}^n / \sum_{i=1}^{n_A} \sum_{j=1}^{n_A} \varphi_{ij} \leq \Gamma, 0 \leq \varphi_{ij} \leq n \right\} \quad \forall i, j \in A. \tag{24}$$

Considering (20) and (21), we rewrite the problem as:

$$\begin{aligned} &\min \left( max \left\{ \hat{D}_{ij}\varphi_{ij} \right\} \right) \quad \forall i, j \in A, \\ &\sum_{i=1}^{n_A} \sum_{j=1}^{n_A} \varphi_{ij} \leq \Gamma, \\ &0 \leq \varphi_{ij} \leq n. \end{aligned}$$

Then, by applying the strong duality theorem, we can substitute inner optimization problem by its dual:

$$\begin{aligned} &\min \Gamma\alpha + \sum_{i=1}^{n_A} \sum_{j=1}^{n_A} r_{ij} \quad \forall i, j \in A, \\ &\alpha + r_{ij} \geq \hat{D}_{ij}, \\ &\alpha, r_{ij} \geq 0. \end{aligned}$$

The robust problem becomes:

$$\min \left( \Gamma\alpha + \sum_{i=1}^{n_A} \sum_{j=1}^{n_A} r_{ij} + \sum_{i=0}^{n_A} \sum_{j=1}^{n_{A+1}} \sum_{k=1}^{n_R} x_{ijk}\bar{D}_{ij} \right) \quad \forall i, j \in A, \tag{25}$$

$$z_j \geq z_i + t_i + \bar{D}_{ij} + (x_{ijk} - 1) * M + \hat{D}_{ij}\zeta_{ij} \quad \forall i, j \in A, \tag{26}$$

$$\alpha + r_{ij} \geq \hat{D}_{ij} \quad \forall i, j \in A, \tag{27}$$

$$\alpha, r_{ij} \geq 0 \quad \forall i, j \in A. \tag{28}$$

## 4 FUTURE WORK AND PERSPECTIVES

With the interests of improving the HHC and managing the flow of information concerning the patients, everyone agrees that HHC approach, in general, has reached a stage where it is more than necessary to cross a new stage in order to be able to address the new challenges to be faced for next decades. This new stage is imposed by technological and digital evolutions and transformations (big data, Internet of Things, cloud computing, etc.).

The expansion of new communication and information technologies and the evolution of logistics activities and emergence of HHC services entail the need of restructuring, relocating and grouping in the forms of interest and management centres. The ultimate aim is to facilitate the interactions of all involved actors and performing common activities concerning HHC such as cares, housework, catering, etc. efficiently (see Figure 1).

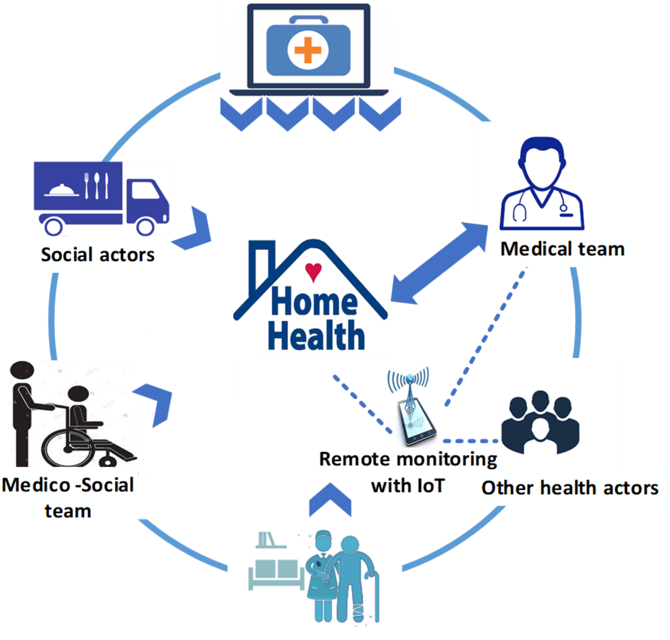


Figure 1. HHC system architecture

To do so, it is required to develop organizational solutions allowing to have the right service in the right place and at the right time. Figure 1 presents an architecture of such solution that will be developed in our future research as a continuation of our current work presented in this paper. It is a collaborative platform that will integrate the proposed optimal solutions in this paper in order to further contribute to improving stakeholder performance and managing activities successfully. This platform will be based on the deployment and integration of new information and communication technologies, and on the adoption of new management and planning methods based on optimization models as developed in this paper.

This solution, based on the emergence of new efficient, reliable and quality services, should make it possible to achieve objectives such as:

- facilitate the services and logistics activities of the involved actors (mobility, management, coordination, planning, etc.),
- responsiveness managing, adaptability, agility and reconfigurability,

- management and sharing of resources (material and human) in a more organized and optimal way,
- facilitate decision-making,
- gain in terms of time and efficiency.

The information sharing approaches and platforms we have developed recently in [67] and [68], for the management of logistics flows and transportation services, will be adapted and served as a basis of this new platform (Figure 1). This is a promising solution for managing HHC daily activities and scheduling tasks and associated services which are often fluctuating.

## 5 CONCLUSIONS

This paper deals with the formulation of new optimization models for a home health care scheduling problem. These models take into account uncertainties in the management of activities of caregivers within HHC. Two robust formulations are proposed and can be solved easily using Cplex solver.

Due to the NP hardness of the considered problem, the proposed MIP models are able to solve instances with more than 20 patients approximately. So, as perspective, we will develop a metaheuristic approach to solve large problem instances. And as aforementioned, we will focus in our future work on the development and implementation of a collaborative platform for information and resources sharing in HHC systems. Based on the obtained optimal solutions from optimization models associated with new technologies, this innovative platform will gear to improvement of the quality of the healthcare for patients while involving different, complementary and distributed actors.

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