MERGING SHORT-TERM AND LONG-TERM PLANNING PROBLEMS IN HOME HEALTH CARE UNDER CONTINUITY OF CARE AND PATTERNS FOR VISITS

SEMİH YALÇİndağ
Industrial Engineering Department, Yeditepe University
İstanbul, Turkey

ETTORE LANZARONE*
Department of Management, Information and Production Engineering
University of Bergamo, Dalmine (BG), Italy
(Communicated by Aviv Gibali)

ABSTRACT. Home Health Care (HHC) human resource management is a complex process. Moreover, as patients are assisted for a long time, their demand for care evolves in terms of type and frequency of visits. Under continuity of care, this uncertain evolution must be considered even when scheduling the visits in the short-term, as the corresponding operator-to-patient assignments could generate overtimes and unbalanced workloads in the long-term, which must be fixed by reassigning some patients and deteriorating the continuity of care. On the other hand, the operator-to-patient assignment problem under continuity of care over a long time period could generate solutions that are infeasible when the scheduling constraints are considered. We analyze the trade-offs between the two problems, to analyze the conditions in which they can be sequentially solved or an integration is required. In particular, we take an assignment and scheduling model for short-term planning, an operator-to-patient assignment model over a long time horizon, and we merge them into a new combined model. Results on a set of realistic instances show that the combined model is necessary when the number of patterns is limited and the variability of patients’ demands is high, whereas simpler models deserve to be applied in less critical situations.

1. Introduction. Home Health Care (HHC) denotes a wide range of health services provided at the patient’s home rather than in a hospital, which include several medical, paramedical and social services. It offers a better quality of life to patients while reducing the cost burden. On the one hand, HHC is beneficial for patients and their relatives because they can receive treatments in a familiar environment, where the risk of infections is also lower than in hospitals. On the other hand, hospitalization costs such as cleaning buildings and food are avoided. Therefore, HHC is a fast growing sector in Europe, North America and Japan, also driven by population growth and ageing, greater attention to user-centered services, technological

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* Corresponding author: Ettore Lanzarone.
developments, public investments to increase the level of well-being, and pressures to contain health care costs.

Unique characteristics make HHC resource planning different from that of other services, even within the health care sector. One of the main distinguishing features is the so-called continuity of care, which is pursued by several providers. Continuity of care means that the provider assigns each patient to a single operator per type and that this pairing should be maintained for a long time period, ideally for the entire patient stay. It is essential for maintaining a good quality of service, because patients do not deal with different operators and because the loss of information in the handover between operators is prevented. Therefore, it should be preserved at least for the most critical patients and those with specific needs.

In addition, HHC operators take care of critically ill patients and follow their care path for a long time. This increases their stress level and requires to properly manage shifts, workloads and tasks to limit the burnout risk. In particular, to reduce this risk, overtime should be kept to a minimum and workload should be balanced between similar operators. At the same time, non-stressed operators improve the quality of the service, and overtime reduction limits the service costs incurred by the provider.

Finally, patients are treated by the HHC service for a generally long period; therefore, their health conditions may change over time and their demand for care may evolve both in terms of type of service required at each visit and frequency of visits. When continuity of care is pursued, it is essential to take account of this uncertain evolution even when solving the short-term planning and scheduling problems. Otherwise, the determined operator-to-patient assignments could generate remarkable overtimes and highly unbalanced operators’ workloads over the long-term horizon. If this happens, to ensure a reasonable service level, issues must be fixed by reassigning some patients, thus deteriorating the continuity of care.

The operator-to-patient assignment problem under continuity of care, which must be solved over a long time period, is sometimes considered an independent problem to be solved before defining the detailed scheduling of visits. However, this could generate solutions that are infeasible when the scheduling constraints of visits are considered. One of the main scheduling constraints is to respect certain patterns for visits during the time horizon, to avoid visits too concentrated on a few consecutive days and long periods without visits. In detail, patterns represent the combinations of week days in which the visits can be provided, and each weekly number of visits is associated with a set of patterns. While scheduling with patterns, the shortest time horizon includes at least few days (usually a week) in order to link subsequent visits and impose their time distance. For example, for a weekly number of visits equal to 3, possible patterns can be “Monday, Wednesday and Friday”, “Tuesday, Thursday and Saturday”, and so on. Then, a specific pattern is assigned to each patient over the week, choosing from those associated with his/her weekly number of visits.

In this work, we analyze the trade-offs between short-term planning with patterns and long-term operator-to-patient assignment problem under continuity of care. Indeed, we analyze the conditions in which one of them can be considered the main problem to be solved first independently of the other, or an integration is required to avoid infeasibility and/or continuity of care detriment.

Operatively, we take from the literature an assignment and scheduling problem for the short-term planning, and an operator-to-patient assignment problem over a
long time horizon. The former (denoted as Problem I) provides assignment decisions with detailed scheduling information for the following week while taking into account the set of possible patterns for each number of visits, the maximum capacity of operators and the continuity of care within the week. The latter (denoted as Problem II) assigns the operators to the patients while preserving the continuity of care over the weeks based on the overall number of visits required by patients at each week and the maximum capacity of operators. Then, we merge them into a new combined problem (denoted as Problem III), which takes into account the specifications of both Problem I and Problem II.

Our idea to combine scheduling with patterns for visits and long-time assignments under continuity of care is general and covers several classes of HHC providers that pursue continuity of care. Then, when referring to the specific Problem I and Problem II used as starting points, a specific class of real providers is considered. Obviously, without continuity of care, there is no need to link different weeks as all visits in a week can be assigned independently of what decided for the previous week.

The behavior of these models has been tested on a set of realistic instances referring to the considered provider class. They have been generated by varying two parameters related to the key factors considered in our analysis: the flexibility of the patterns and the variability of patients’ demands. The former is in terms of the number of possible patterns associated with a weekly number of visits, the latter is related to the variability of the number of visits between consecutive weeks. Results show the trade-offs and the need to consider a combined approach (i.e., Problem III) when these factors become critical.

The paper is organized as follows. A literature review on HHC assignment and scheduling/routing problems in presented in Section 2. The addressed HHC scheduling and operator-to-patient assignment problems are presented in Section 3, while the associated mathematical models are detailed in Section 4. The computational experiments and the obtained results are described in Section 5. Finally, the discussion and conclusions of the work are drawn in Section 6.

2. Literature review. HHC human resource planning includes a number of application relevant problems that are widely addressed in the literature [7, 10, 12]. It includes several planning problems (levels) such as dimensioning the resources, partitioning the territory into districts, assigning patients to operators, scheduling the visits and routing the operators [15]. Some of these levels can be merged depending on the specific needs and requirements of the HHC provider, e.g., assignment, scheduling and routing problems can be merged all together [21], or assignment and scheduling problems can be merged while solving the routing problem at a later time [25], or resource dimensioning and operator scheduling problems can be put together [22, 20].

Merging levels is a complex process both in theory and in practice; however, it is worthy of consideration as it can be more problematic not to merge them and to use the output of any one level as an input for another, due to the conflicting requirements of the different problems. For instance, the aim of the operator-to-patient assignment problem is usually to keep the continuity of care over a long planning horizon, while the requirements associated with other planning levels are neglected [17]. On the other hand, when continuity of care is included in the scheduling problem, it is usually considered to find the best visiting plan over a short planning horizon rather than a longer one [25]. Although these problems can
be successfully managed independently in some HHC contexts, in other cases it can be problematic to determine short-term scheduling decisions based on long-term assignment decisions already established, and vice versa. For example, predefined assignments may prevent from finding a feasible schedule or worsen its quality.

In the literature, most of the works are devoted to the joint assignment, scheduling and routing problems for a short-term planning horizon. Moreover, several works address the stand-alone assignment problems for both short-term and long-term planning horizons. However, to the best of our knowledge, no work focuses on combining assignment and scheduling for long-term planning horizons. To prove this, we review in the following the relevant literature on HHC assignment and scheduling problems.

As for the operator-to-patient assignment problem, most of the available studies consider the continuity of care, which is indeed the most important feature of HHC, together with additional goals such as the minimization of the costs incurred by the provider, the minimization of the operators’ overtimes, and the workload fairness between colleagues [6]. Moreover, besides the continuity of care, the variability of patients’ demands is taken into account, as it is a critical factor that may affect quality and feasibility of the solutions [18, 5]. Demand variability is common to several health care facilities; however, it becomes more critical in the HHC context under continuity of care where patients are assisted for a long time. In fact, balancing or limiting the operators’ workloads in a planning period does not guarantee to balance or limit them in the next periods, as the demand from some patients may increase and that from some others may decrease [9, 13, 18, 8, 19]. The available studies consider both deterministic and stochastic approaches for the assignment problem [17]; moreover, assignment policies [14, 16] and robust programming approaches are also studied [5] to deal with demand uncertainty.

Several works deal with the scheduling problem, but almost all of them are in combination with the assignment and routing problems and consider a short-term planning horizon, i.e., one week [4, 3, 11, 21, 25, 23]. In fact, it is not useful to schedule for longer time horizons, as variations in patients’ demands and patient’s mix would require several modifications to the decided schedule if it had been decided too many days in advance. Only in [25], alternative models are developed for the assignment, scheduling and routing problems, where assignment and routing decisions are held in two consecutive stages and scheduling decisions are included in one or both stages. Among the listed studies, [4], [3] and [25] determine the schedules exploiting patterns as we are doing in this work. Continuity of care is also included in some of these works together with workload balancing, travel time minimization and preference maximization objectives. However, almost none of these studies consider the demand variability, as it happens in the stand-alone assignment problems.

Close to our work, as mentioned above, [25] present a model for the joint assignment and scheduling decisions under continuity of care, which does not include a long-term planning horizon (i.e., longer than one week) for managing the assignments in the presence of demand variability. On the other hand, [17] consider a long-term planning horizon with demand variability and continuity of care, while they do not include any scheduling decision. To overcome these limitations, in this work we merge these two models in order to combine the scheduling decisions for
the first week and the assignment decisions for all weeks. To the best of our knowledge, no other work integrates the scheduling decision into the assignment level considering variable patient demands over several planning periods.

3. HHC scheduling and operator-to-patient assignment problems. The combination of two problems under continuity of care and patterns for visits is of general validity in HHC. However, to specify the characteristics of the problems and to model them, we must refer to a specific class of HHC providers. To this end, we focus on the class and the features described in the previous published works where Problem I and Problem II are described, i.e., [25] and [17], respectively.

The problems consist of assigning a set \( P \) of patients to a set \( O \) of operators. The time horizon is divided into a set \( W \) of weeks, and the first week is further divided into a set \( D \) of days. In particular, the working week consists of six days (\(|D| = 6\)).

Each patient \( p \in P \) is characterized by a weekly number \( v_{pw} \) of required visits at each week \( w \in W \), whose service time for each visit is denoted by \( s_p \). The service time \( s_p \) is assumed to be the same for all visits to the same patient \( p \in P \), while it may vary from patient to patient. The numbers of visits \( v_{pw} \) represent the expected values that are used to plan the service in a deterministic setting.

Operators can be considered homogeneous, as the problems deal with the assignment of one type of operators (e.g., nurses). Moreover, in the considered provider class, operators usually have several skills to be able to take care of all types of patients. Thus, it is assumed that each patient \( p \in P \) can be potentially assigned to each operator \( o \in O \). Moreover, each operator \( o \in O \) has a fixed weekly capacity \( a_o \), which refers to a maximum working time per week, including both service and travel times, and is assumed to be constant over the weeks \( w \in W \).

Operators are assigned to patients with continuity of care, i.e., only one reference operator \( o \in O \) is assigned to each patient \( p \in P \). As the working week consists of six days, the seventh day is the day off of all operators together. Moreover, providers working under continuity of care include additional substitute operators who replace the reference ones in case of their unavailability, holidays or illness. In this way, there is no need to reschedule, but simply a substitute operator replaces the reference one for the required number of days.

Three problems are considered in this setting:

- **Problem I**: operator-to-patient assignment and scheduling problem for the days \( d \in D \) of the first week \( w = 1 \). The schedule is defined considering the set of possible patterns \( \Pi \) and that each patient \( j \in J \) can receive at most one visit per day. Indeed, \( \Pi \) includes the list of alternative patterns for each possible number of visits \( v_{p1} \) required by any patient \( p \in P \) at week \( w = 1 \), and only one of the patterns \( \pi \in \Pi \) with number of visits \( n_{\pi} \) equal to \( v_{p1} \) can be selected while scheduling the visits of patient \( p \in P \). Then, each pattern \( \pi \in \Pi \) includes the list of days \( d \in D \) in which a visit is performed by means of the parameters \( m_{\pi,d} \), which are equal to 1 if pattern \( \pi \in \Pi \) includes a visit at day \( d \in D \), and 0 otherwise; obviously, \( \sum_{d \in D} m_{\pi,d} = n_{\pi} \). Continuity of care is pursued within the week, and estimations of the travel times \( r_p \) to reach each patient \( p \in P \) are taken into account while computing the daily workloads of operators. Estimations are required as real travel times are available only when assignment and routing decisions are made at the same time, and here routing is not included. Finally, the daily capacity of each operator, which is defined as the ratio between \( a_o \) and the cardinality \( |D| \) of \( D \), cannot be exceeded.
• **Problem II**: operator-to-patient assignments over the weeks \( w \in W \). Assignments are provided considering the continuity of care over the weeks and the overall workloads of the operators at each week, which are determined based on \( v_{pw} \) and \( s_p \). Moreover, the maximum workload of each operator \( o \in O \) at week \( w \in W \) cannot exceed \( a_o \). Scheduling decisions and selection of patterns are not considered.

• **Problem III**: combination of Problem I and Problem II including the decisions of both problems. In particular, this problem provides the detailed schedule for week \( w = 1 \), as in Problem I, and consider the overall weekly workloads for the weeks with \( w > 1 \), as in Problem II.

| Sets | Model I | Model II | Model III |
|------|---------|----------|-----------|
| \( O \) | ✓ | ✓ | ✓ |
| \( P \) | ✓ | ✓ | ✓ |
| \( W \) | ✓ | ✓ | • |
| \( D \) | ✓ | ✓ | ✓ |
| \( \Pi \) | ✓ | ✓ | ✓ |

| Parameters | Model I | Model II | Model III |
|------------|---------|----------|-----------|
| \( v_{pw} \) | ○ | ✓ | ✓ |
| \( s_p \) | ✓ | ✓ | ✓ |
| \( n_\pi \) | ✓ | ✓ | ✓ |
| \( m_{\pi d} \) | 0 | ✓ | ✓ |
| \( r_p \) | ✓ | ✓ | ✓ |
| \( a_o \) | ✓ | ✓ | ✓ |
| \( \alpha_w \) | ✓ | ✓ | ✓ |

| Decision variables | Model I | Model II | Model III |
|--------------------|---------|----------|-----------|
| \( \lambda_{od} \) | ✓ | ✓ | ✓ |
| \( \omega_{ow} \) | ✓ | ✓ | • |
| \( h_w \) | ✓ | ✓ | ✓ |
| \( z_{p\pi} \) | 0 | ✓ | ✓ |
| \( u_{op} \) | ✓ | ✓ | ✓ |
| \( v_{op} \) | ✓ | ✓ | ✓ |
| \( m_{dop} \) | 0 | ✓ | ✓ |

**Table 1.** Sets, parameters and decision variables for the three models. Symbol ✓ means that the set, parameter of variable is included in the model, symbol ○ that it is included only for \( w = 1 \), and symbol • that it is included only for \( w > 1 \).
4. Mathematical models. Each problem described in Section 3 is solved through a Mixed Integer Linear Programming (MILP) model, which is denoted with the number of the corresponding problem (e.g. Model I solves Problem I).

Model I and Model II are directly inspired by our previous works, while the combined Model III is here proposed to analyze the trade-offs between the short-term planning with patterns and continuity of care and the long-term operator-to-patient assignments with continuity of care. As mentioned, Model I is taken from [25], while Model II is taken from [17]. All models are detailed below while sets, parameters and decision variables are summarized in Table 1.

4.1. Assignment and scheduling model for the first week (Model I). Model I provides a detailed scheduling for the first week respecting patterns, continuity of care within the week, and maximum daily workloads of operators.

The model is as follows:

\[
\text{min } \{ h_1 \} \quad (1)
\]

subject to

\[
\lambda_{od} = \sum_{p \in P} (r_p + s_p) \mu_{op}^d \quad \forall o \in O, d \in D \quad (2)
\]

\[
\lambda_{od} \leq \frac{a_o}{|D|} \quad \forall o \in O, d \in D \quad (3)
\]

\[
\sum_{d \in D} \frac{\lambda_{od}}{a_o} \leq h_1 \quad \forall o \in O \quad (4)
\]

\[
\sum_{\pi \in \Pi} z_{p\pi} = 1 \quad \forall p \in P \quad (5)
\]

\[
\mu_{op}^d \leq u_{op} \quad \forall o \in O, p \in P, d \in D \quad (6)
\]

\[
\sum_{o \in O} u_{op} = 1 \quad \forall p \in P \quad (7)
\]

\[
\sum_{o \in O} \mu_{op}^d = \sum_{\pi \in \Pi: m_{x}d = 1} z_{p\pi} \quad \forall p \in P, d \in D \quad (8)
\]

\[
\sum_{\pi \in \Pi} z_{p\pi} n_{\pi} = v_{p1} \quad \forall p \in P \quad (9)
\]

\[
\sum_{o \in O \ d \in D} u_{op}^d = v_{p1} \quad \forall p \in P \quad (10)
\]

\[
\mu_{op}^d \in \{0, 1\} \quad \forall o \in O, p \in P, d \in D \quad (11)
\]

\[
u_{op} \in \{0, 1\} \quad \forall o \in O, p \in P \quad (12)
\]

\[
z_{p\pi} \in \{0, 1\} \quad \forall p \in P, \pi \in \Pi \quad (13)
\]

Constraints (2) compute the workload of operator \( o \in O \) on day \( d \in D \) as the summation of service times and travel times over the patients visited in the day. Constraints (3) limit the daily workload based on the daily capacity. Constraints (4) compute the maximum utilization rate \( h_1 \) for the first week, which is then minimized in the objective function. Constraints (5) impose that exactly one pattern \( \pi \in \Pi \) can be assigned to each patient \( p \in P \). Constraints (6) and (7) model the continuity of care: constraints (6) impose an operator \( o \in O \) can visit a patient \( p \in P \) on a day \( d \in D \) only if he/she is the reference operator assigned to that patient, and constraints (7) that only one operator is assigned as reference operator to that
patient. Constraints (8) impose that an operator can visit patient $p \in P$ only if and only if the visit is planned by the selected pattern, i.e., if and only if $m_{\pi dp} = 1$. Constraints (9) and (10) impose that the number of scheduled visits is equal the demand for each patient $p \in P$.

4.2. Operator-to-patient assignment model over the weeks (Model II). Model II considers the operator-to-patient assignments over the weeks without any scheduling detail. Only the overall workloads of the operators at each week are considered and limited.

The model is as follows:

$$\min \left\{ \sum_{w \in W} \alpha_w h_w \right\}$$  \hspace{1cm} (14)

subject to

$$\omega_{ow} = \sum_{p \in P} (r_p + s_p) v_{pw} u_{op} \quad \forall o \in O, w \in W$$  \hspace{1cm} (15)

$$\omega_{ow} \leq a_o \quad \forall o \in O, w \in W$$  \hspace{1cm} (16)

$$\frac{\omega_{ow}}{a_o} \leq h_w \quad \forall o \in O, w \in W$$  \hspace{1cm} (17)

Coefficients $\alpha_w$ are the weights associated with the different weeks $w \in W$ in the objective function. Constraints (15) impose that the workload of each operator $o \in O$ at week $w \in W$ is equal to summation of service times and travel times for each visit of the assigned patients at the same week. Constraints (16) limit the workloads up to the capacity. Constraints (17) compute the maximum utilization rates $h_w$ at each week, which are minimized in the objective function. Finally, the constraints dealing with the continuity of care (last line) are the same as in Model I.

4.3. Combined model (Model III). This model combines the features of Model I and Model II, merging the constraints from the two models together with their objective functions. Thus, the model is as follows:

$$\min \left\{ \sum_{w \in W} \alpha_w h_w \right\}$$  \hspace{1cm} (18)

subject to

$$\omega_{ow} = \sum_{p \in P} (r_p + s_p) v_{pw} u_{op} \quad \forall o \in O, w \in W$$  \hspace{1cm} (15)

$$\omega_{ow} \leq a_o \quad \forall o \in O, w \in W$$  \hspace{1cm} (16)

$$\frac{\omega_{ow}}{a_o} \leq h_w \quad \forall o \in O, w \in W$$  \hspace{1cm} (17)

The objective function is the same as in Model II, even if $h_1$ is here the result of the detailed scheduling. The first group of constraints (first line) is taken exactly from Model I. The second group of constraints (second line) is taken from Model II but repeated $\forall w \in W \setminus \{1\}$ rather than $\forall w \in W$. The third group of constraints (third line) already appears in both Model I and Model II, and is here repeated.

Variables $\tilde{\omega}_{ow}$ are not computed by Model III; however, they can be derived from the solution as $\sum_{d \in D} \lambda_{od}$. 
5. **Computational experiments.** This section describes the experiments conducted to analyze the trade-offs between the models in function of two factors: the flexibility of patterns and the variability of patients’ demands. The flexibility of patterns concerns the number of possible patterns associated with a given weekly number of visits, as more possible patterns allows for easier scheduling and vice versa. The variability of the demands is in terms of the variation in the number of visits for a patient between consecutive weeks.

Two sets of realistic instances have been generated while varying these factors, as described in Section 5.1; the former analyzes different combinations for the factors, while the latter consider bigger instances and variable service times $s_p$ among the operators.

All models have been applied to the instances, and the results are presented in Section 5.2.

5.1. **Instances and experimental design.** Instances have been generated considering the real case of one of the largest Italian HHC providers, which was already taken as a general example in previous works [17, 14, 16, 5, 6]. This provider usually takes care of long-stay patients with chronic diseases or of palliative patients who require a high number of visits for a short period, up to death. It works mainly with nurses and pursues the continuity of care. From the management viewpoint, it first addresses the nurse-to-patient assignments under continuity of care over a period of 4 to 8 weeks, as this is the key problem with continuity of care and long-stay patients, and then defines the schedules based on the decided assignments. The routing problem is marginally considered as this HHC provider deals with short distances between patients within the covered territory.

Based on this case, we consider that patients are classified in several Care Profiles (CPs) and that each CP is associated with a range for the number of visits $v_{uw}$ required in a week. Patients also evolve over time, and both the value in the range or the CP may change [18, 1, 2].

Moreover, based on both the experience of several other providers and the scheduling mechanism of the considered provider, we include patterns among the features of the instances [4, 25].

We generate a set of simulated instances that respect the above features and differ from each other based on the level selected for each of the two factors, so as to describe a wide range of possible applicative contexts and find out the trade-offs between models based on such context.

- **Flexibility of patterns**
  The number of patterns $|\Pi|$ is considered either flexible by including $|\Pi| = 21$ patterns or rigid by limiting to $|\Pi| = 7$ patterns. The overall list for the flexible alternative, reported in Table 2, ensures that there is at least one pattern for every possible number of visits $n_\pi$. Each reduced list for the rigid alternative is randomly extracted from that with 22 patterns while keeping the condition of at least one pattern for every possible number of visits $n_\pi$.

- **Variability of patients’ demands**
  Each number of visits $v_{uw}$ for patient $p \in P$ at week $w \in W$ is generated according to a random process. The demand at the first week $w = 1$ is generated by assuming that patients randomly belong to 3 different CPs. Patients in the first CP require $v_{p1} \in \{1, 2\}$, those in the second CP require $v_{p1} \in \{3, 4\}$, and those in the third CP require $v_{p1} \in \{5, 6\}$. Each patient
\( p \in P \) is randomly assigned to a CP with equal probabilities; then, \( v_{p1} \) is sampled from the two values of the selected CP giving probability 0.5 to each of them. Then, the demands \( v_{pw} \) for the following weeks are generated by means of the following truncated autoregressive model with Gaussian error:

\[
\begin{align*}
\bar{v}_{p1} &= v_{p1} & \forall p \in P \\
\bar{v}_{pw} &= \bar{v}_{pw} - 1 + \kappa_{p} + \sigma_{p} \varepsilon_{pw} & \forall p \in P, w \in W \setminus \{1\} \\
\hat{v}_{pw} &= \begin{cases} 
0 & \bar{v}_{pw} < 0 \\
\bar{v}_{pw} & 0 \leq \bar{v}_{pw} \leq 6 \\
6 & \bar{v}_{pw} > 6
\end{cases} & \forall p \in P, w \in W \setminus \{1\} \\
v_{pw} &= \lfloor \hat{v}_{pw} \rfloor & \forall p \in P, w \in W \setminus \{1\}
\end{align*}
\]

where \( \varepsilon_{pw} \) are independent Gaussian noises with null mean and unitary standard deviation, and the symbol “\( \lfloor \cdot \rfloor \)” in (22) denotes rounding. The two regression parameters \( \kappa_{p} \) and \( \sigma_{p} \) are stochastic:

\[
\begin{align*}
\kappa_{p} &\sim U(m_{\kappa}, M_{\kappa}) \\
\sigma_{p} &\sim U(0, M_{\sigma})
\end{align*}
\]

where \( U \) denotes a Uniform density whose parameters represent the minimum and maximum values of the density. Thus, the properties of the instance are in terms of the values assigned to the hyperparameters \( m_{\kappa}, M_{\kappa} \) and \( M_{\sigma} \); the former two parameters determine the increasing or decreasing average trend of patients’ demands, while the latter determines their variability. The considered combinations used to generate low variability or high variability instances are reported in Table 3; in each instance half of the patients have a decreasing trend and half an increasing trend, and all patients have the same variability in terms of \( M_{\sigma} \).

A first set of instances includes 4 operators (\(|O| = 4\)), 50 patients (\(|P| = 50\)), and 4 weeks (\(|W| = 4\)) for \textit{Model II} and \textit{Model III}. Each combination of levels (flexible with \(|\Pi| = 21\) patterns vs rigid with \(|\Pi| = 7\) patterns, and low variability vs high variability according to Table 3) has been tested, thus giving 4 alternatives. Each alternative combination has been considered to randomly generate 3 replications, thus giving a total of 12 tested instances. As for the rigid instances with \(|\Pi| = 7\) patterns, the random generation also includes the selection of a subset of patterns among the 21.

The service time \( s_{p} \) required for a visit is assumed to be equal to 45 minutes for all patients. To obtain the travel time \( r_{p} \) for each patient \( p \in P \), we have randomly generated the locations of the patients, while taking into account that the territory is composed of 7 urban zones (whose geographical coordinates are known) with higher density. Thus, for the random generation, each patient is first associated with one of the urban zones and his/her exact location in the selected zone is randomly generated at a distance from the zone center equal to \( 1 \pm 0.5 \text{ km} \) (mean and standard deviation, respectively, adopting a normal distribution); see [24] for more details. Given the randomly generated positions, each travel time \( r_{p} \) is calculated as the average traveling time to reach patient \( p \) from all other patients and from the HHC provider (the depot). The weekly capacity \( a_{o} \) of the operators is assumed equal to 3000 minutes for all operators \( o \in O \) (50 hours corresponding to 8 hours and 20 minutes in all days).
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\[ \pi_d (\text{visit at day } d) \]

\begin{array}{cccccc}
\pi & d = 1 & d = 2 & d = 3 & d = 4 & d = 5 & d = 6 \\
1 & 0 & 1 & 0 & 0 & 0 & 0 \\
2 & 0 & 0 & 1 & 0 & 0 & 0 \\
3 & 0 & 0 & 0 & 1 & 0 & 0 \\
4 & 0 & 0 & 0 & 0 & 1 & 0 \\
5 & 1 & 0 & 1 & 0 & 0 & 0 \\
6 & 1 & 0 & 0 & 1 & 0 & 0 \\
7 & 1 & 0 & 0 & 0 & 1 & 0 \\
8 & 0 & 1 & 0 & 0 & 1 & 0 \\
9 & 0 & 0 & 1 & 0 & 1 & 0 \\
10 & 0 & 0 & 0 & 1 & 0 & 1 \\
11 & 1 & 0 & 1 & 0 & 1 & 0 \\
12 & 1 & 0 & 0 & 1 & 0 & 1 \\
13 & 1 & 1 & 0 & 1 & 0 & 1 \\
14 & 1 & 0 & 0 & 1 & 0 & 1 \\
15 & 1 & 1 & 0 & 0 & 1 & 0 \\
16 & 1 & 1 & 1 & 0 & 1 & 0 \\
17 & 0 & 0 & 1 & 1 & 0 & 1 \\
18 & 0 & 1 & 1 & 0 & 1 & 1 \\
19 & 1 & 1 & 1 & 0 & 1 & 1 \\
20 & 1 & 1 & 0 & 1 & 1 & 1 \\
21 & 1 & 1 & 1 & 1 & 1 & 1 \\
\end{array}

\text{Table 2.} List of patterns for the flexible alternative, with at least one pattern for each \( n_\pi \). The list for the rigid alternative is randomly extracted while keeping the condition of at least one pattern for each \( n_\pi \).

\begin{array}{cccc}
\text{Instance} & \text{Percentage of patients} & \text{Variability} & \text{Trend} \\
& & M_M & M_\kappa \\
Low variability & 50\% & -0.5 & 0 & 0.5 \\
High variability & 50\% & 0 & 0.5 & 0.5 \\
\end{array}

\text{Table 3.} Combinations of hyperparameters used to generate low variability and high variability instances.

The second set consists of four instances: the first includes a higher number of patients and operators (\(|P| = 150\) and \(|O| = 10\)); the second a longer time horizon (\(|W| = 8\)); the third includes both a higher number of patients and operators, and a longer time horizon (\(|P| = 150\) and \(|O| = 10\), \(|W| = 8\)); the fourth instance extends the third one including variable service times \(s_p\) among patients (denoted by “V”). The instances of this set have been generated with a data augmentation approach, starting from one instance of the first set with flexible set of patterns and low variability of demand. The parameters of the first 50 patients in the first week have been fixed equal to those of the instance selected as starting point. The other parameters are generated with the same mechanism adopted in the first set of
instances. The demands of the added patients at \( w = 1 \) are generated by randomly assigning these patients to the 3 CPs, while the demands for the following weeks by means of the truncated autoregressive model with low variability of demand. As above, also the locations of these patients are generated by first associating an urban zone and then the location in the zone. As for the operators, the same weekly capacity \( a_o \) of 3000 minutes is considered.

In all instances, all weights \( \alpha_w \) are set equal to \( \frac{1}{|W|} \) in both Model II and Model III. This allows us to consider equal weights and easily compare the Objection Function Value (OFV) of Model II and Model III with that of Model I independently of the number of weeks \( |W| \) in the specific problem. Moreover, we have also tested different weights in preliminary experiments, but the results have been not reported here because they led to the same conclusions as with equal weights, and because there is no practical meaning in considering any week more important than the others.

All models are applied to the instances of both sets. Moreover, the solution from each model is also cross executed on the others, to evaluate the impact of the first-week schedule on the other weeks and the impact of long-term assignments on scheduling. Three metrics are considered to evaluate a solution or its cross execution on another model: OFV, \( h_1 \) and the ranges \( \delta_w \) of the utilization rates at the different weeks \( w \in W \). Each \( \delta_w \) is defined as follows:

\[
\delta_w = \max_{o \in O} \left\{ \frac{\omega_{ow}}{a_o} \right\} - \min_{o \in O} \left\{ \frac{\omega_{ow}}{a_o} \right\}
\]

Only \( \delta_1 \) is obviously computed when solving Model I or executing a solution on it; as for Model III, \( \omega_{o1} = \sum_{d \in D} \lambda_{od} \) as mentioned above.

5.2. Results. The models have been run on a Windows machine equipped with CPU Intel Core i7 at 2.20 GHz and 8GB of installed RAM; models have been written in GAMS and solved via CPLEX 12.6. An optimality gap of 1% has been imposed, while no time nor memory limits have been considered.

The results for the first set of experiments are separately presented the four combinations of levels in Tables 4-7, reporting the values of OFV, \( h_1 \) and the ranges \( \delta_w \) for each replication. Both the values directly obtained from a model solution and those from the cross executions are shown.

As for the model solutions themselves, it is evident that all models provide similar OFV, \( h_1 \) and \( \delta_w \) values. Thus, based on these outcomes only, it is not possible to assess which model outperforms the others, and under which combination of levels it is better to employ one model rather than another.

However, this analysis does not consider whether the assignments from Model II guarantee to respect the possible patterns for the different number of visits, nor whether the assignments from Model I prevent unbalanced workloads in the next weeks. This information can be obtained through the cross executions, as worse values of the metrics or infeasibilities while cross executing a solution prove that a model is not able to guarantee the requisites pursued by another. To this end, we consider the executions of the solution from Model II on Model I and on Model III, the execution of the solution from Model I on Model II, and the execution of the solution from Model III on Model II. The execution of Model I on Model III does not provide additional insights with respect to that on Model II, because Model I provides itself the best solution for the first week and Model II evaluates the other weeks in the same way than Model III.
Results from these cross executions show that applying Model II on the other problems always creates infeasibilities when patterns are rigid (Tables 6 and 7). This means that, though the models exhibit a similar behavior in terms of metrics, it is never possible to fix the stand-alone assignment decisions from Model II and append the scheduling decisions at a later time when patterns are rigid. On the other hand, in case of flexible patterns, the solutions provided by Model II are feasible for Model I, at least for the considered experiments (Tables 4 and 5).

| Replication 1 | Model solutions | Executions |
|---------------|-----------------|------------|
|               | Model I | Model II | Model III | Model II on I | Model I on II | Model II on III | Model III on II |
| OFV           | 0.804   | 0.841    | 0.841     | 0.801         | 0.841         | 0.841          |
| $h_1$         | 0.804   | 0.801    | 0.802     | 0.801         | 0.801         | 0.802          |
| $\delta_1$    | 0.010   | 0.006    | 0.007     | 0.006         | INF           | 0.007          | 0.007          |
| $\delta_2$    | –       | 0.018    | 0.016     | –             | 0.016         | 0.016          |
| $\delta_3$    | –       | 0.005    | 0.010     | –             | 0.010         | 0.010          |
| $\delta_4$    | –       | 0.023    | 0.018     | –             | 0.018         | 0.018          |

| Replication 2 | Model solutions | Executions |
|---------------|-----------------|------------|
|               | Model I | Model II | Model III | Model II on I | Model I on II | Model II on III | Model III on II |
| OFV           | 0.850   | 0.805    | 0.806     | 0.853         | 0.879         | 0.805          | 0.806          |
| $h_1$         | 0.850   | 0.853    | 0.851     | 0.853         | 0.850         | 0.853          | 0.851          |
| $\delta_1$    | 0.011   | 0.022    | 0.016     | 0.022         | 0.011         | 0.022          | 0.016          |
| $\delta_2$    | –       | 0.017    | 0.023     | –             | 0.283         | 0.017          | 0.023          |
| $\delta_3$    | –       | 0.039    | 0.039     | –             | 0.228         | 0.039          | 0.039          |
| $\delta_4$    | –       | 0.005    | 0.007     | –             | 0.254         | 0.005          | 0.007          |

| Replication 3 | Model solutions | Executions |
|---------------|-----------------|------------|
|               | Model I | Model II | Model III | Model II on I | Model I on II | Model II on III | Model III on II |
| OFV           | 0.802   | 0.785    | 0.787     | 0.800         | 0.840         | 0.785          | 0.787          |
| $h_1$         | 0.802   | 0.800    | 0.800     | 0.800         | 0.802         | 0.800          | 0.800          |
| $\delta_1$    | 0.013   | 0.015    | 0.018     | 0.015         | 0.013         | 0.015          | 0.018          |
| $\delta_2$    | –       | 0.015    | 0.016     | –             | 0.307         | 0.015          | 0.016          |
| $\delta_3$    | –       | 0.008    | 0.006     | –             | 0.135         | 0.008          | 0.006          |
| $\delta_4$    | –       | 0.015    | 0.025     | –             | 0.135         | 0.015          | 0.025          |

Table 4. Results for the flexible set of patterns and high variability of demands (first set of experiments). INF denotes infeasibility.

The results for the second set of experiments are reported in Table 8, following the same layout of the previous tables. They confirm the findings from the first set, showing the stability of the outcomes with respect to different dimensions of the problems, in terms of higher number of weeks up to $|W| = 8$, higher number of patients up to $|P| = 150$ (with consequently more operators up to $|O| = 10$), and variability of $s_p$ among patients (which follow a uniform distribution between 30 and 60 minutes).

Using Model I or Model III seems to be more appropriate as they include both assignment and scheduling decisions, at least for the first week $w = 1$. Indeed, considering the cross executions of their solutions, we observe that both models are more successful than Model II in finding feasible executions. However, the results show that even Model I does not provide feasible executions in half of the cases with high variability of demands (Tables 4 and 6). In fact, Model I only addresses the first week $w = 1$ and, thus, the solution obtained for this week cannot be used in the following ones when the variability of the demand is high, i.e., when patients have very different demands from week to week.
| Replication | OFV   | $h_1$ | $\delta_1$ | $\delta_2$ | $\delta_3$ | $\delta_4$ | OFV   | $h_1$ | $\delta_1$ | $\delta_2$ | $\delta_3$ | $\delta_4$ |
|-------------|-------|-------|-------------|-------------|-------------|-------------|-------|-------|-------------|-------------|-------------|-------------|
| Replication 1 | 0.849 | 0.822 | 0.821       | 0.013       | 0.013       | 0.028       | 0.011 | 0.013 | 0.011       | 0.013       | 0.026       | 0.013       |
| Replication 2 | 0.776 | 0.764 | 0.764       | 0.013       | 0.012       | 0.020       | 0.011 | 0.013 | 0.012       | 0.036       | 0.080       | 0.012       |
| Replication 3 | 0.748 | 0.726 | 0.726       | 0.003       | 0.012       | 0.014       | 0.004 | 0.004 | 0.003       | 0.013       | 0.013       | 0.004       |

Table 5. Results for the flexible set of patterns and low variability of demands (first set of experiments).

| Replication | OFV   | $h_1$ | $\delta_1$ | $\delta_2$ | $\delta_3$ | $\delta_4$ | OFV   | $h_1$ | $\delta_1$ | $\delta_2$ | $\delta_3$ | $\delta_4$ |
|-------------|-------|-------|-------------|-------------|-------------|-------------|-------|-------|-------------|-------------|-------------|-------------|
| Replication 1 | 0.801 | 0.810 | INF         | INF         | INF         | 0.810       | INF   | INF   | INF         | INF         | INF         | INF         |
| Replication 2 | 0.853 | 0.854 | 0.805       | 0.013       | 0.017       | 0.039       | 0.014 | 0.012 | 0.014       | 0.012       | 0.008       | 0.018       |
| Replication 3 | 0.799 | 0.800 | 0.787       | 0.014       | 0.015       | 0.008       | 0.014 | 0.015 | 0.014       | 0.012       | 0.007       | 0.018       |

Table 6. Results for the rigid set of patterns and high variability of demands (first set of experiments). INF denotes infeasibility.
### Model solutions

| Replication | Model | Model | Model | Model | Model | Model |
|-------------|-------|-------|-------|-------|-------|-------|
|              | I     | II    | III   | I on I| I on II| I on III|
| OFV         | 0.848 | 0.822 | 0.821 | 0.866 | 0.848 | 0.821 |
| $h_1$       | 0.848 | 0.848 | 0.847 | INF   | INF   | INF   |
| $\delta_1$ | 0.012 | 0.013 | 0.010 | INF   | INF   | INF   |
| $\delta_2$ | -     | 0.013 | 0.010 | 0.101 | 0.010 | 0.010 |
| $\delta_3$ | -     | 0.028 | 0.018 | 0.173 | 0.018 | 0.018 |
| $\delta_4$ | -     | 0.018 | 0.019 | 0.173 | 0.019 | 0.019 |

### Executions

| Replication | Model | Model | Model | Model | Model | Model |
|-------------|-------|-------|-------|-------|-------|-------|
|              | I on I| I on II| I on III|       |       |       |
| OFV         | 0.777 | 0.764 | 0.764 | 0.799 | 0.764 | 0.764 |
| $h_1$       | 0.777 | 0.776 | 0.781 | INF   | INF   | INF   |
| $\delta_1$ | 0.017 | 0.010 | 0.018 | INF   | INF   | INF   |
| $\delta_2$ | -     | 0.012 | 0.010 | 0.072 | 0.010 | 0.010 |
| $\delta_3$ | -     | 0.020 | 0.010 | 0.089 | 0.010 | 0.010 |
| $\delta_4$ | -     | 0.027 | 0.010 | 0.196 | 0.010 | 0.010 |

| Replication | Model | Model | Model | Model | Model | Model |
|-------------|-------|-------|-------|-------|-------|-------|
|              | I on I| I on II| I on III|       |       |       |
| OFV         | 0.749 | 0.726 | 0.726 | 0.746 | 0.726 | 0.726 |
| $h_1$       | 0.749 | 0.751 | 0.750 | INF   | INF   | INF   |
| $\delta_1$ | 0.003 | 0.007 | 0.008 | INF   | INF   | INF   |
| $\delta_2$ | -     | 0.017 | 0.016 | 0.033 | 0.016 | 0.016 |
| $\delta_3$ | -     | 0.014 | 0.016 | 0.105 | 0.016 | 0.016 |
| $\delta_4$ | -     | 0.006 | 0.006 | 0.054 | 0.006 | 0.006 |

**Table 7.** Results for the rigid set of patterns and low variability of demands (first set of experiments). INF denotes infeasibility.

Summing up, *Model I* is effective as long as the variability of patients’ demands is limited, and the demand layout of the first week $w = 1$ is representative of the other layouts at the following weeks. *Model II* is effective as long as the patterns are flexible, allowing to first decide the operator-to-patient assignments and then to select the patterns under fixed assignments.

To overcome these drawbacks and build plans in providers with rigid patterns and variable demands, it is thus required to adopt the combined *Model III*. Results show that this model provides solutions with about the same performance of *Model I* and *Model II*, and always provides feasible executions with almost the same performance as the original solution (Tables 4-8). This means that *Model III* is able to select a solution that is good for both *Model I* and *Model II* among the equivalent optimal solutions of both.

From the computational viewpoint, the increased complexity of *Model III* does not represent a limitation for the considered application, as all models have been solved in less than 30 seconds for the first set of experiments, and the computational times have not exceeded 190 seconds in the second set of experiments. Thus, even in large instances, the computational times are short and admissible from the practical viewpoint, even for the most complicated *Model III*.

### 6. Discussion and conclusion

In this work, we have analyzed the trade-offs between two typical problems that arise in planning HHC human resources, i.e., the short-term scheduling problem and the long-term assignment problem. They have been studied in a context with continuity of care and patterns for visits, with reference to a particular class of HHC providers, where these two problems have
contrasting needs and HHC solutions that take only one them into account may create issues for the other problem in terms of bad quality of the plan or even infeasibility. Thus, we have investigated the integration of two separate models to analyze these trade-offs and suggest whether it is valuable to combine them or not in a single integrated model.

Analyses have been conducted on a set of realistic instances that reproduce the real conditions of the addressed HHC provider class, which differ as regards the

| Model solutions | Executions |
|-----------------|------------|
| Model | Model | Model | Model | Model | Model | Model |
| Model I | Model II | Model III | Model I on II | Model on III | Model on II |
| OFV | 0.887 | 0.888 | 0.889 | 0.890 | 0.888 | 0.889 |
| h_1 | 0.887 | 0.890 | 0.889 | 0.890 | 0.890 | 0.889 |
| δ_1 | 0.019 | 0.036 | 0.039 | 0.036 | INF | 0.036 |
| δ_2 | 0.035 | 0.038 | – | – | 0.035 | 0.038 |
| δ_3 | 0.027 | 0.025 | – | – | 0.027 | 0.025 |
| δ_4 | 0.015 | 0.021 | – | – | 0.015 | 0.021 |
| OFV | 0.776 | 0.744 | 0.744 | 0.780 | 0.744 | 0.744 |
| h_1 | 0.776 | 0.780 | 0.779 | 0.780 | 0.776 | 0.780 |
| δ_1 | 0.010 | 0.036 | 0.018 | 0.036 | 0.010 | 0.036 |
| δ_2 | 0.001 | 0.003 | – | – | 0.001 | 0.003 |
| δ_3 | 0.018 | 0.018 | – | – | 0.018 | 0.018 |
| δ_4 | 0.018 | 0.018 | – | – | 0.018 | 0.018 |
| δ_5 | 0.011 | 0.020 | – | – | 0.011 | 0.020 |
| δ_6 | 0.017 | 0.017 | – | – | 0.017 | 0.017 |
| δ_7 | 0.002 | 0.002 | – | – | 0.002 | 0.002 |
| δ_8 | 0.001 | 0.003 | – | – | 0.001 | 0.003 |

Table 8. Results for the larger instances (second set of experiments). INF denotes infeasibility.
two critical factors that may affect the applicability of a solution: the variability of patients’ demands, as highly variable demands require not to be limited to a short planning horizon to guarantee the continuity of care, and the flexibility of patterns, as too rigid pattern schemes may prevent the continuity of care.

The obtained results show the trade-offs in applying different modeling alternatives, which lead to the same conclusions independent of the size of the instance. First of all, we have found that the combined and more general Model III is needed when the provider faces critical situations in terms of limited patterns and high variability of patients’ demands. Moreover, in the tested instances, we have found that the solutions from Model III do not cause additional costs to the solution, and it is always worthy of using them. This seems to suggest that Model III selects among the equivalent of solutions of Model I and Model II those that are common to both. In other instances, where there might be a cost to pay in terms of worse performance to ensure feasibility, a trade-off analysis could be considered to find a good compromise by giving different weights $\alpha_w$ to the weeks in Model III.

From the computational viewpoint, the additional effort for Model III is always negligible in the considered instances; thus, it is always convenient to employ such a model.

From the practical viewpoint, it is generally useless in HHC providers to employ Model I and provide a detailed schedule for several weeks, while anticipating the assignments with continuity of care through Model III is more important and beneficial. Therefore, our work provides useful information to the decision makers of HHC with continuity of care and patterns for visits, who are aware of possible infeasibilities when they focus only on long-term assignments or short-term scheduling. Moreover, it also shows the risk of taking in several patients with highly variable demands and the risk of considering only a limited number of possible patterns to perform the visits.

In the future, we will extend our analysis by adopting stochastic and robust models, especially for the assignment part (following weeks in Model II and Model III), which take care not only of the expected evolution/variability of patient’s demands but also of their randomness, to evaluate the trade-offs in a setting where there may be a bias when executing a solution, due to the gap between expectations and values actually occurred. Moreover, we will include new arrivals of patients in the framework, which can be modeled by including patients characterized by a null demand $v_{pw}$ in the first weeks and a positive demand starting from the week in which they arrive to the system. In this case, the combination of the different time horizons could be more critical in terms of infeasibilities if the weekly capacities $a_0$ are too strict to consider new arrivals.

REFERENCES

[1] R. Argiento, A. Guglielmi, E. Lanzarone and I. Nawajah, A Bayesian framework for describing and predicting the stochastic demand of home care patients, Flexible Services and Manufacturing Journal, 28 (2016), 254–279.

[2] R. Argiento, A. Guglielmi, E. Lanzarone and I. Nawajah, Bayesian joint modelling of the health profile and demand of home care patients, IMA Journal of Management Mathematics, 28 (2016), 531–552.

[3] P. Cappanera, M. G. Scutellà, F. Nervi and L. Galli, Demand uncertainty in robust home care optimization, Omega (United Kingdom), 80 (2018), 95–110.

[4] P. Cappanera and M. G. Scutellà, Joint assignment, scheduling, and routing models to home care optimization: A pattern-based approach, Transportation Science, 49 (2015), 830–852.
[5] G. Carello and E. Lanzarone, A cardinality-constrained robust model for the assignment problem in home care services, *European Journal of Operational Research*, 236 (2014), 748–762.

[6] G. Carello, E. Lanzarone and S. Mattia, Trade-off between stakeholders’ goals in the home care nurse-to-patient assignment problem, *Operations Research for Health Care*, 16 (2018), 29–40.

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

[8] A. Errarhout, S. Kharraja and I. Zorkani, Caregivers’ assignment problem in home health care structures, in *Proceedings of 2013 International Conference on Industrial Engineering and Systems Management (IESM)*, IEEE, 2013, 1–8.

[9] P. Eveborn, P. Flisberg and M. Rönqvist, Laps Care—an operational system for staff planning of home care, *European Journal of Operational Research*, 171 (2006), 962–976.

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

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

[12] L. Grieco, M. Utley and S. Crowe, Operational research applied to decisions in home health care: A systematic literature review, *Journal of the Operational Research Society*, 22 (2020), 1–32.

[13] A. Hertz and N. Lahrichi, A patient assignment algorithm for home care services, *Journal of the Operational Research Society*, 60 (2009), 481–495.

[14] E. Lanzarone and A. Matta, A cost assignment policy for home care patients, *Flexible Services and Manufacturing Journal*, 24 (2012), 465–495.

[15] E. Lanzarone and A. Matta, The nurse-to-patient assignment problem in home care services, in *Advanced Decision Making Methods Applied to Health Care*, Springer, 2012, 121–139.

[16] E. Lanzarone and A. Matta, Robust nurse-to-patient assignment in home care services to minimize overtimes under continuity of care, *Operations Research for Health Care*, 3 (2014), 48–58.

[17] E. Lanzarone, A. Matta and E. Şahin, Operations management applied to home care services: the problem of assigning human resources to patients, *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 42 (2012), 1346–1363.

[18] E. Lanzarone, A. Matta and G. Scaccabarozzi, A patient stochastic model to support human resource planning in home care, *Production Planning and Control*, 21 (2010), 3–25.

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

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

[21] S. Nickel, M. Schroder and J. Steegb, Mid-term and short-term planning support for home health care services, *European Journal of Operational Research*, 219 (2012), 574–587.

[22] M. I. Restrepo, L.-M. Rousseau and J. Valle, Home healthcare integrated staffing and scheduling, *Omega (United Kingdom)*, 95 (2020), 102057.

[23] J. Wirnitzer, I. Heckmann, A. Meyer and S. Nickel, Patient-based nurse rostering in home care, *Operations Research for Health Care*, 8 (2016), 91–102.

[24] S. Yałçindağ, A. Matta, E. Şahin and J. G. Shanthikumar, The patient assignment problem in home health care: Using a data-driven method to estimate the travel times of care givers, *Flexible Services and Manufacturing Journal*, 28 (2016), 304–335.

[25] S. Yałçindağ, P. Cappanera, M. G. Scutellà, E. Şahin and A. Matta, Pattern-based decompositions for human resource planning in home health care services, *Computers & Operations Research*, 73 (2016), 12–26.

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E-mail address: semih.yalcindag@yeditepe.edu.tr
E-mail address: ettore.lanzarone@unibg.it