Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

A Dynamic Patient Assignment System for Home Care Physiotherapy and Rehabilitation

Seda Baş Güre

seda.bas@isikun.edu.tr

Işık University

Tankut Atan

Bahçeşehir University

Emine Özkarlıklı

Research Article

Keywords: Dynamic Patient Assignment, Physiotherapy and Rehabilitation, Continuity of Care, Workload Balance, Integer Linear Model, Rolling Horizon

Posted Date: October 12th, 2025

DOI: https://doi.org/10.21203/rs.3.rs-7570969/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

A Dynamic Patient Assignment System for Home Care Physiotherapy and Rehabilitation

Seda Baş Güre[1][0000−0002−2603−5653], Tankut Atan[2,3][0000−0002−3241−4617], and Emine Özkarlıklı[3]

[1] Işık University, İstanbul, Turkey seda.bas@isikun.edu.tr
[2] Bahçeşehir University, İstanbul, Turkey sabritankut.atan@bau.edu.tr
[3] Işık University, İstanbul, Turkey

Abstract. Home care is the face-to-face delivery of medical care in the patients' homes. In recent years, home health care has been growing rapidly due to an increase in the elderly population, and due to people who have chronic illnesses, or are underprivileged. In order to obtain sustainability of health, it is important to use home care resources efficiently, but the dynamic nature of hospital operations such as limited available personnel, high no-shows and cancellation rates of treatments reduce the productivity and efficiency of hospitals. To overcome difficulties arising due to continuously changing operational conditions, we propose a dynamic patient assignment system for home care physiotherapy and rehabilitation hospital operations. The proposed framework is a rolling-horizon algorithm that iteratively solves an integer linear model for assigning home care physiotherapy patients to operators. Our objectives are ensuring the continuity of care and balancing operator workloads while keeping patient waiting times low. Based on historical data from one of the largest rehabilitation hospitals in İstanbul, the resulting dynamic patient assignment framework was tested under several simulated scenarios. The results show the effectiveness of the proposed system, especially in terms of decreased waiting times.

Keywords: Dynamic Patient Assignment · Physiotherapy and Rehabilitation · Continuity of Care · Workload Balance · Integer Linear Model · Rolling Horizon

1 Introduction

Operational cost increase and limitations related to customers or service operators constrain the service industry to minimize costs while providing better service quality. This challenge is crucially important, especially for mobile services that allow patients to receive personal care at home, called Home Care (HC). Home Health Care (HHC) is one of the most rapidly growing mobile services around the world and covers a wide range of services. In this paper, we will directly focus on HC for physiotherapy and specifically assigning rehabilitation patients to operators. There are three key stakeholders in Home

Health Care Systems (HHCS), each with specific requirements: patients, operators, and health care service providers. While health care service providers in physiotherapy and rehabilitation put requirements related to planning period, service territory, given service type, continuity of care, patients have requirements on frequency of visit, visit date, and personal preferences. For operators, requirements about working hours, workloads, skills, and territory preferences may exist. Considering these requirements concurrently increases the complexity of the assignment problem. Assignment and routing solutions have been successfully applied in many research areas other than HHCS, and thus they constitute a viable approach to solve HHCS problems as well, albeit with customizations to handle specific requirements of HHCS. Moreover, continuity of care constraints present in physiotherapy treatments pose a different HHCS problem compared to the rest of the literature. Continuity of care means that HC provider assigns only one operator to each patient and keeps the operator same during the treatment process. While it limits the flexibility of the provided service to a certain degree, it is crucial in physiotherapy HHCS, since giving care to patients with the same operator is helpful for establishing good patient-operator communication, and rapport between the patient and the operator, and avoiding information loss among operators. Studies that have been carried out in Norway showed that continuity of care not only increases patient satisfaction but also saves time by accumulating a medical history of patients for operators [1].

Due to a large increase in demand recently, HHC service providers have faced several operational issues, and management problems that attracted the attention of many researchers. Therefore, the number of research publications about HHCS increased considerably, especially within the last two decades. Existing research generally focuses on two kinds of problems: tactical problems (e.g. assigning HHC operators to geographic service districts), and operational problems (e.g. routing and scheduling HHC operators) [2]. Recent detailed literature reviews are presented by Di Mascolo *et al.* [3], Grieco *et al.* [4], Cissé *et al.* [5], Fikar and Hirsch [6], and Sahin and Matta [7]. The studies addressing routing and scheduling applications in the HHC industry in the last years make use of several objectives such as minimizing travel time, cost, travel distance, overtime and waiting time [8]. In our literature review, we focused on works about assignments in HHC. HHC assignment problem is studied by considering continuity of care in [9]-[17]; workload balance in [18]-[26]; and both of them in [29]-[36].

Wirnitzer *et al.* [9] developed five mixed integer programming models for a monthly home care nurse rostering problem that considers the assignment of nurses to the required patients. This planning task is under-controlled for a monthly basis in order to see the impact on continuity of care. They claimed that continuity of care is overcome by the decomposition of the current problem to a single nurse problem in the literature but in that case one nurse is not able to cover all shifts of a day for a specified district. That's why they planned a monthly nurse roster where nurses are assigned to master tours with respect to nurse availability, daily and monthly working time restrictions, and patient-nurse compatibilities. Güven *et al.* [10] solved the problem using an integer program-

ming approach and a variant of the petal heuristic method. Their objectives were to maintain continuity of care by minimizing daily deviations from the current schedule and to ensure some consistency in caregiver assignments. Cappanera and Scutellà [11] used a mathematical model and a pattern-based algorithmic framework derived from decomposition where their objectives were to optimize assignment, scheduling, and routing decisions over multiple days while ensuring arrival time consistency, person-oriented consistency, and robustness against demand uncertainty. Algendi *et al.* [12] solved the problem using a mixed-integer linear programming (MILP) model, which was further enhanced with two sets of valid inequalities. Their objectives were to minimize the number of extra shifts for caregivers, maximize the allocation of caregivers to emergencies, and minimize the total route durations over the planning horizon. Hewitt *et al.* [13] carried out a different study in terms of the planning horizon length, instead of analyzing a week or a shorter planning horizon, they examined the long planning horizon length as two to three months considering continuity of care and demonstrated that a long planning horizon is superior to short planning horizon in terms of transportation cost and staffing levels savings. Gamst and Jensen [14] proposed a branch-and-price algorithm in HHC scheduling problem. In this study, first a one-day plan is generated for each employee then all the generated daily plans are merged into a master schedule considering regularity constraints. They mentioned continuity of care as employee regularity in their study and their objective is that all visits of a patient are conducted by the same medical staff and minimized the sum of the visits of a citizen by the number of different employees on the objective function for providing employee regularity. Nickel *et al.* [15] proposed a two-stage approach, in the first stage they used a constraint programming heuristic to find a good feasible solution to the master plan for nurse to patient assignment and in the second stage they applied an adaptive large neighborhood search to overcome local optima. They defined continuity of care as the patient-nurse loyalty which means visits of patients during the planning horizon is delivered by the same nurse and they minimized patient-nurse loyalty to provide continuity of care. Bachouch *et al.* [16] proposed an integer linear program to minimize the travelled distance for the routing problem in HHC and also they decide nurse to patient assignment during the planning horizon while considering the continuity of care. Carello and Lanzarone [17] developed a cardinality-constrained robust assignment model in order to solve the nurse-to-patient assignment problem under continuity of care. They divided patients into five subsets as who require hard continuity of care, who require partial continuity of care and who do not require continuity of care.

Bachouch *et al.* [18] proposed a model for assignment of nurses in a French HHC office. They provided workload balance among health care workers in their study by minimizing the difference between the upper bound of the workload of each nurse and the lower bound of the workload of each nurse. Torres *et al.* [19] used a MILP model within an ϵ-constraint multi-objective optimization framework. Their objectives were to accommodate nurses' scheduling preferences (including days off), and to achieve a balanced workload distribution among nurses,

thereby increasing nurse satisfaction and reducing job dissatisfaction. Blais *et al.* [20] have studied workload balancing among nurses for the Côtedes-Neiges CLSC in Montreal by health care districting problem with the tabu search heuristic algorithm. The difference of this problem from literature is that they measured workload not only by the time spent with patients but also they included the time spent travelling between visiting locations. Cappanera and Scutella [21] proposed an integer linear programming model to maximize the minimum operator utilization factor and minimize the maximum operator utilization factor in order to address assignment, scheduling, and routing decisions while limiting the number of operators that can be assigned to each patient for the weekly plan. Thus, they reduce the loss of information among operators and increase service quality. Errarhout *et al.* [22] proposed a two-stage stochastic model with the uncertainty of the time required for the cares in order to balance the workload of the nurses considering nurses' skill, travel load and capacity. Hertz and Lahrichi [23] proposed a mixed integer programming model and solved with a tabu search algorithm. Their aim is to balance the workload of the nurses and at the same time to avoide long travels while visiting the patients. Nasir *et al.* [24] worked on a flexible HHC planning problem and proposed a mixed integer linear programming model to minimize the total distance travelled, cost to hire nurses, cost for idle time and workload difference, and the costs associated with waiting patients. They suggested using two heuristic methods to solve the model by exploiting the variable neighborhood search algorithm considering compatibility, time restrictions, contract durations, idle time and workload balance. Benzarti *et al.* [25] formulated the HHC districting problem as a mixed-integer programming model by considering locations where patients live, compactness, workload balance between human resources and compatibility. Lahrichi *et al.* [26] analyzed a territorial approach to deliver nursing HC services to a territory public health based on a historical data. With respect to the historical data analysis, they suggested that it is better to use a more dynamic assignment system for the patients not only considering patients' geographic locations but also considering each nurse's workload and case load. They underlined the importance of the workload balance among nurses.

There are some studies in the literature for HHC problem that consider continuity of care and workload balance at the same time. Fathollahi-Fard *et al.* [27] addressed a complex optimization problem using efficient heuristic and advanced nature-inspired metaheuristic methods. The main objectives were to optimize the total cost of logistics activities, minimize the total idle time of caregivers, and ensure continuity of care. Zhao and Bard [28] used a two-stage approach with two new MILP models. The first MILP is used for weekly patient-therapist assignments, while the second determines daily routes. Their objectives include minimizing the number of unscheduled visits and the total travel and service costs, while considering care continuity, workload balance, time windows, overtime, and mileage costs. Bowers *et al.* [29] studied the assignment and routing problem of midwives using multiple travelling salesmen problem algorithm with the objective of minimizing total travel time while considering the relative

workloads. Their aim is to perform care for each mother by the same midwife to achieve a better relationship between mothers and midwives. Borsani *et al.* [30] proposed a linear integer scheduling model to decide which human resource should be used and when to execute the service during the planning horizon, in order to satisfy the care plan for each patient served by the HC providers considering continuity of care of patients and workload balance of the nurses. Hiermann *et al.* [31] presented a general framework for solving a HHC scheduling problem from a major Austrian HHC provider, they proposed a two-stage approach. In the first stage they generated initial solutions by constraint programming techniques or by a random procedure while in the second stage the initial solution is improved by variable neighborhood search, a memetic algorithm, scatter search and a simulated annealing hyper-heuristic. Cappanera *et al.* [32] studied HC problem under demand uncertainy over a multiple-day time horizon and used a cardinality-constrained robust approach to balance the caregiver workload under continuity of care with skill constraints. Carello *et al.* [33] proposed a set of mathematical models for the nurse to patient assignment problem in HC under continuity of care. They tested these models on real life instances with deterministic and uncertain patient demands balancing the workload of nurses. Lanzarone and Matta [34] developed analytical policies to assign patients while balancing the workload among the operators and respecting the continuity of care. They penalize the overtime of operators by minimizing the expected value of a cost function. Lanzarone *et al.* [35] developed mixed integer mathematical models to balance the workload of the operators considering several properties of HHCS such as the continuity of care, operator's skill, and geographical areas while examining single district and multiple district cases in their study. Lastly, Lanzarone *et al.* [36] proposed a stochastic model to represent the workload planning and distribution among the operators while preserving the continuity of care.

Research efforts with respect to assignment of physiotherapy patients in HHC are rare in literature compared to other health care problems. Ogulata *et al.* [37] proposed a hierarchical mathematical model for a highly demanded hospital in physiotherapy to generate weekly staff scheduling. In the first hierarchical stage the patients are selected, and in the second stage the assignment of patients to the staff are provided, and in the last stage these patients are scheduled throughout a day considering only the workload balance. Schimmelpfeng *et al.* [38] developed a decision support system for rehabilitation hospital scheduling using a mixed-integer linear program where they determined patient appointments while maximizing the number of treatments scheduled for all patients without considering the workload balance and continuity of care. Podgorelec and Kokol [39] developed a scheduling method based on a heuristic (genetic) algorithm and machine learning methods taking into account the different physical therapy needs for a limited number of therapeutic devices and therapists without considering the workload balance and continuity of care. Chien *et al.* [40] proposed a genetic algorithm to obtain near-optimal solutions in order to schedule rehabilitation patients so that patient waiting times are reduced and

therapy equipment utilization is increased to result in increased service quality and operation efficiency. They also did not examine the workload balance and continuity of care criteria. Although the number of publications and journals devoted to health care has shown a significant increase recently, to the best of our knowledge, assignment of physiotherapy patients to operators considering workload balance and continuity of care simultaneously has not been applied in physiotherapy for home care patients so far.

In this research, we develop a general and conceptual integer programming framework for the problem of assigning HC physiotherapy patients to operators. In order to overcome assignment problems occurring due to continuously changing operational conditions, we implement a rolling horizon algorithm that iteratively solves an integer linear model for an effective management of this dynamic environment rather than considering a prior knowledge of future incoming patients contrary to the rest of the studies in the literature. Furthermore, we analyze a real case using data from the HHC department of a large physiotherapy and rehabilitation Hospital in İstanbul, referred as Hospital X. Hospital X provides neurological rehabilitation services at home to patients who have cerebral palsy, spinal cord injury, hemiplegia, paraplegia, parkinson, etc. HHC department of Hospital X faces many problems such as low patient satisfaction due to long waiting times to receive medical service, non-continuous care provided by different operators in each visit, and also low operator satisfaction due to lack of workload balance among operators. The proposed model handles these issues with a combination of objective functions through a rolling horizon algorithm while keeping patient waiting times low.

The paper is structured as follows: The mathematical model and rolling horizon algorithm are described in Section 2 whereas the computational experiments performed on the realistic cases are reported in Section 3. Section 4 ends the article with a conclusion and discussion on future work.

2 The Mathematical Model and Rolling Horizon Algorithm

In this section, we provide an integer linear model for the studied patient assignment problem. First, a static model is described. However, we solve this static model daily, each time for the next seven days, using a rolling horizon. The use of the model in this manner suits the dynamic nature of hospital operations as there are frequent changes to the available personnel, and cancellations of treatments due to several reasons which may make a static assignment plan for an extended period not applicable. It is foreseen that, in practice, only the first day's recommendations by the model will be implemented each time after the optimization is run. However, a look-ahead optimization policy using a longer optimization period such as a week and all of the then-available information would help with obtaining more stable daily assignments. Our rolling horizon algorithm's pseudocode and algorithm's explanation follow the description of the static model.

2.1 Integer Linear Model

The mathematical model uses the following notation. I, J and K refer to the set of patients, operators and days in the planning period, respectively. Set G is the set of districts where patients live and operators serve. The operator set includes a dummy operator j^d with infinite capacity. Untreated patients are assigned to the dummy operator, i.e. their treatments are being delayed. x_{ijk} are the main decision variables (binary) specifying whether patient i has been assigned to operator j on day k. b_{ij} are indicator variables set to 1 if patient i is ever assigned to operator j during the planning period. Finally, f_k are positive decision variables stating the minimum number of patients served by all real operators working on day k. First, we make the assumption that patient treatment times are equal. The extension of the model where this assumption is relaxed will be given later. Let d_{ik} be parameters indicating whether patient i requires care on day k. Daily treatment capacity of each operator j on day k expressed as number of patients is denoted by a_{jk}. When set to 1, m_{jg} parameters show that operator j can serve district g whereas c_{ig} parameters are set to 1 if patient i lives in district g. $card(K)$ refers to the cardinality of the set K. The mathematical formulation is provided next.

$$\min \{-10Z_1 + 10Z_2 + 1000Z_3 + Z_4 + Z_5\} \tag{1}$$

$$Z_1 = \sum_{k \in K} f_k$$

$$Z_2 = \sum_{i \in I} \sum_{j \in J, j \neq j^d} b_{ij}$$

$$Z_3 = \sum_{i \in I} \sum_{j = j^d} \sum_{k \in K} x_{ijk}$$

$$Z_4 = \sum_{i \in I} \sum_{j \in J, j \neq j^d} \sum_{k \in K} w_i^1 \cdot x_{ijk}$$

$$Z_5 = \sum_{i \in I} \sum_{j \in J, j \neq j^d} \sum_{k \in K} w_{ij}^2 \cdot x_{ijk}$$

subject to

$$\sum_{j \in J} x_{ijk} = d_{ik} \qquad \forall i \in I, k \in K \tag{2}$$

$$\sum_{j \in J, j \neq j^d} x_{ijk} \leq d_{ik} \qquad \forall i \in I, k \in K \tag{3}$$

$$\sum_{i \in I} d_{ik} \cdot x_{ijk} \leq a_{jk} \qquad \forall j \in J, k \in K \tag{4}$$

$$x_{ijk} \leq \sum_{g \in G} m_{jg} \cdot c_{ig} \qquad \forall i \in I, j \in J, k \in K \tag{5}$$

$$\sum_{i \in I} x_{ijk} \geq f_k \qquad \forall j \in J \setminus \left\{j^d\right\}, k \in K \tag{6}$$

$$\sum_{k \in K} x_{ijk} \leq card(K) \cdot b_{ij} \qquad \forall i \in I, j \in J \setminus \left\{j^d\right\} \tag{7}$$

$$f_k \geq 0 \qquad \forall k \in K \tag{8}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall i \in I, j \in J, k \in K \tag{9}$$

$$b_{ij} \in \{0, 1\} \qquad \forall i \in I, j \in J \tag{10}$$

In planning the assignments, several issues need to be considered, most importantly continuity of care, and operator workload balance. Our model has a weighted objective function to handle this multi-objective problem. Z_1 helps with balancing the workload of operators over the planning period. The balanced workload objective is achieved by linearizing a nonlinear objective function where the daily minimum of the number of assigned patients to each operator on day k is maximized. The linearization is accomplished by Constraints 6 and Z_1. Recall that the decision variables f_k refer to the minimum number of patients served by real operators on day k. By maximizing (note the negative sign for Z_1 in the objective function) the sum of these minima, the operator workload is being balanced. Minimizing the number of assigned real operators given by Z_2 helps with fulfilling the continuity of care since assigning a patient to different operators will only increase this sum. Z_3 equals the number of patients assigned to the dummy operator, and minimizing this sum will increase the number of patients receiving care. Z_4 and Z_5 prioritize certain assignments with the help of respective weights. The smaller w_i^1 in Z_4, the more important is assigning patient i to an operator. On the other hand, smaller w_{ij}^2 in Z_5 make assigning patients to certain operators more desired. How w_i^1 and w_{ij}^2 are calculated will be explained when the rolling horizon algorithm is detailed. In general, the values of the weights in a weighted objective function such as ours is subjective in nature, and they reflect the importance given to individual issues by the decision-maker. In other words, the different objectives can be prioritized by using weights that reflect the decision-maker's choices.

Constraints 2 make sure that all patients are cared for every day. Observe that an assignment to the dummy operator is possible. However, the number of these assignments is going to be kept to a minimum since the sum of these

assignments is being minimized in the objective function with Z_3. Constraints 3 guarantee that each patient will be assigned to at most one operator on each day. Constraints 4 do not allow the daily capacity of the operators to be exceeded. Constraints 5 prohibit assigning a patient to an operator if the operator cannot serve the district where the patient lives in. Constraints 6 state that all real operators should care for more patients daily than the minimum number of patients served on each day. Constraints 7 capture the information on whether a patient is ever assigned to an operator over the planning period. Constraints 8 through 10 specify the types of the decision variables.

The model can slightly be changed to deal with cases where the treatment times for patients are not equal. Let d_{ik} give the treatment time in minutes for each patient i on day k. Also, let a_{jk} denote the availability of operator j on day k in minutes. Then, Constraints 2, 3, and 4 can be changed as follows assuming that each patient will still be served by one operator.

$$\sum_{j \in J} x_{ijk} = 1 \qquad \forall i \in I, k \in K \tag{11}$$

$$\sum_{j \in J, j \neq j^d} x_{ijk} \leq d_{ik} \qquad \forall i \in I, k \in K \tag{12}$$

$$\sum_{i \in I} d_{ik} \cdot x_{ijk} \leq a_{jk} \qquad \forall j \in J, k \in K \tag{13}$$

The modified constraints are interpreted a bit differently with unequal treatment times. Constraints 11 say that each patient should be assigned to an operator on each day. As before, this assigned operator can be the dummy operator if necessary. Constraints 12 make sure that a patient does not get assigned to a real operator if s/he does not need to be treated that day. Finally, Constraints 13 are there so that the daily available working time in minutes of each operator does not get exceeded.

2.2 Rolling Horizon Algorithm

Every day, new patient registrations are made to the HHCS system, or patients with completed treatments leave the HHCS system. Thus, parameters in the model are required to be updated daily. Therefore, solving the linear integer model once and fixing the treatment plan for the near future may not be feasible beyond one day. To handle the dynamic nature of the hospital operations, we propose the static model to be solved every day in a rolling horizon manner. We opted for solving the model for the next seven days on each day as it is important to know about the work schedules, albeit approximately, for the near future. For new patients, w_i^1 and w_{ij}^2 are assigned high values. Initially, a new patient has not been delayed, and has not been assigned to any operator. Input data is updated before each optimization. At each day's optimization, patient-operator assignments are (optionally) kept the same as in the previous day's optimization. These fixed assignments ensure continuity of care. However, the model has other

mechanisms to motivate assigning the same operator to a patient throughout the patient's treatment, namely, Z_2 and the use of w_{ij}^2 in Z_5. Once a solution is obtained, we update several values. If a patient did not receive treatment although one was due (detected by an assignment to the dummy operator), the waiting time for that patient ($waitedPat_i$) is increased. Furthermore, an additional treatment session is added to the end of that patient's existing treatment plan to account for the unrealized treatment. If a patient is assigned to a real operator, then the number of times that patient is assigned to that operator ($nPatOp_{ij}$) is increased by 1. $waitedPat_i$ are used to update w_i^1, and $nPatOp_{ij}$ are used to update w_{ij}^2. The more patient i waits, the smaller w_i^1 becomes. Similarly, the more times patient i is assigned to operator j, the smaller w_{ij}^2 becomes. Since we are solving a minimization problem, smaller weights in the next optimization push the assignments towards prioritizing longer waiting patients, and keeping the same patient-operator assignments as in the previous optimizations. In other words, at each iteration of the rolling horizon algorithm, weights w_i^1 are fine-tuned depending on how long patients have waited, and weights w_{ij}^2 are fine-tuned based on how many times patients have been assigned to the operators. The steps of the rolling horizon algorithm are summarized in Algorithm 1.

Algorithm 1 Pseudocode of the rolling horizon algorithm

$w_i^1 \leftarrow 10$
$w_{ij}^2 \leftarrow 10$
$waitedPat_i \leftarrow 0$
$nPatOp_{ij} \leftarrow 0$
for $k' = 1, \cdots$ **do**
    Get the updated patient, treatment and operator information
    Optional: Assign previously treated patients to their existing operators for day k'
    $x_{ijk}^* \leftarrow$ Solve the integer linear model for the 7 days starting with k'
    Implement the resulting optimal policy for k'
    $waitedPat_i \leftarrow waitedPat_i + 1$ if patient i is assigned to the dummy operator
    Add a session to the end of the treatment plans of the untreated patients on day k'
    $nPatOp_{ij} \leftarrow nPatOp_{ij} + 1$ if patient i is assigned to a real operator j on day k'
    $w_i^1 \leftarrow 1/waitedPat_i$ for $waitedPat_i \neq 0$
    $w_{ij}^2 \leftarrow 1/nPatOp_{ij}$ for $nPatOp_{ij} \neq 0$

3 Computational Experiments

To test the proposed algorithm's performance, we conducted simulations based on the real data obtained from Hospital *X*. Hospital *X* currently attends to pa-

tients from 12 districts. The treatment times are about 50 minutes since patients served in Hospital X are of the same type. Hence, we assumed the daily operator capacity to be 8 patients. The number of operators in the simulations were taken as 25 equaling the number of operators in the data. The patient distribution across districts is not uniform. Thus, we used the percentages calculated from real data for generating patient data from each district. We considered different scenarios where an operator served one, two or three preassigned districts. Operators currently visit patients from two districts. Also, the daily patient to operator ratio was a parameter in the simulations. We tested different values of this ratio ranging from 2 to 10 in multiples of 2. Currently, the patient to operator ratio is somewhere around 6 to 8 in the Hospital X data. 100 different instances were generated for each patient to operator ratio. Each instance comprised of simulated data for a month. To generate the month-long simulation data, we first picked a longer time horizon, 100 days. The number of treatments required for each patient was 30 meaning that once started each patient's treatment took 30 business days. Given a patient to operator ratio, the total number of expected patients over the picked time horizon would be time horizon divided by the treatment duration multiplied with the number of operators and the patient operator ratio. For example, for a patient operator ratio of 8, a time horizon 100 days and a treatment duration of 30 days with 25 operators, the expected number of total patients in 100 days would be $100/30 \cdot 25 \cdot 8$. The arrivals of the patients to the system were assumed to be uniform across the time horizon. Since the rolling horizon algorithm was tested for a month of data, we picked a 36 day interval (corresponding to 30 optimizations for the next 7 days) from the middle of the generated data to allow for some warm-up period so that the patient numbers in the generated data would reach the density levels corresponding to the set ratio. The districts where the patients originated in the generated data were based on the real percentages in the data for each district. Daily optimizations were run as described in the rolling horizon algorithm. We also distinguished between fixing and not fixing the already assigned patient-operator pairs for the first day of the next day's weekly optimization. Fixing the assignments, i.e. assigning the patients to their already assigned operators (possibly until their treatments are over), is in line with the hospital's current practice. This practice helps observing continuity of care. The reported numbers in Table 1 and Table 2 are the averages of the 100 instances. Table 1 shows a summary of the results for the scenario where each operator serves one district only (the least flexible scenario), and the patient-operator assignments are not fixed after daily optimizations (continuity of care not guaranteed). When operators serve more districts (not reported here), the results are improved as one would expect. In addition, when assignments are fixed after daily optimizations (in Table 2 we only report some fixed results with cancellations for the patient-operator ratio of 8), continuity of care reaches 100% but observe that they are already very close to 100% even without fixing.

When the patient to operator ratio increases, balancing the workload is less of an issue since the operators start reaching their maximum capacity. When the

Table 1: Simulation results without fixing the assignments, one district only

Daily Pat/Op Ratio	Daily # of Pat	Waiting Days to First Care	Same Op (%)
6	6.12	0.62	99.29
8	36.87	2.81	99.16
10	108.42	6.59	99.64

hospital first started its home care operations, the number of patients were low but it has been increasing since then. It seems that earlier low patient densities can only be encountered again if the number of operators is increased at some point. The average wait time before a patient gets her first treatment in the simulations is seven days which is very good compared to the current delay of 30 days. It should be noted that limiting the districts operators serve increases patient waiting times since an operator cannot attend patients from other districts even when available.

We also tested the impacts of treatment cancellations by patients. While the cancellation rates of the hospital are not very high, currently running around 2%, they make some of the assignment planning obsolete, and manually dealing with abrupt changes is difficult. In fact, all such sudden changes are difficult to respond to quickly and efficiently with a manual process. Another example causing the hospital administrators difficulty occurs when operators call in sick requiring immediate changes to the treatment plans. The results for cancellation simulations with the same data can be seen in Table 2 where the patient to operator ratio was taken to be 8. In the reported results, operators were responsible of one district only. To simulate cancellations, each patient in the generated data was assumed to cancel with a probability equaling the cancellation rate. Mimicking how the hospital operates, the experiments were run by fixing the assignments of the first day of treatment to those already made by the previous optimization when a new optimization was run. However, if a treatment was cancelled, those assignments were relaxed. As the cancellation rate increases, the average waiting times to first care decrease since the openings resulting from cancellations can be used to treat waiting patients. Observe that average waiting times to receive first care are already very low even without cancellations. However, continuity of care gets negatively affected by cancellations since the responsible operators are assigned to other patients for the cancelled slots, and these new assignments might slightly change operators' assignments in the future. However, since most assignments are fixed between optimizations, continuity of care percentages still stay quite high also when there are cancellations.

Overall, the simulations verified that the suggested rolling horizon algorithm can adequately handle the assignment process which is currently dealt with manually.

Table 2: Simulation results with cancellations, fixed assignments, daily patient/operator ratio is 8

Cancellation rate (%)	Daily # of Pat	Waiting Days to First Care	Same Op (%)
0	27.94	2.27	100.00
2	26.12	2.12	98.99
5	22.97	1.86	98.19

4 Conclusion and Future Work

In this research, we considered the problem of assigning home care physiotherapy patients to operators. To deal with continuously changing operational conditions, we implemented a rolling horizon algorithm that repetitively solved an integer linear model. The main concerns of the algorithm were achieving the continuity of care and balancing the operator workload while keeping patient waiting times low. Our algorithm was shown to perform well using simulations for several scenarios which were based on real data obtained from the hospital we worked with.

Routing of the operators is left to the operators at the moment. If the number of districts served by each operator increases, routing may pose another challenging problem to be solved. In the current practice, some operators do their visits by walking from one patient to another while some operators use automobiles. The routing problem may also need to consider differences between operators on foot and with vehicles. Operators with vehicles are more likely to visit several districts covering a larger area, and their routing may become more critical with increased numbers of patients per operator. Currently, an MS Excel-based application is under development for the use of the hospital administrator in charge of the home care treatment planning. This decision support tool will make it much easier to respond to changes in the patient and operator information that occur very often. It is expected to save much time in dealing with these changes, and at the same time, to provide enhanced treatment plans that were not possible before.

Bibliography

[1] Hjortdahl, Per and Laerum, Even, Continuity of care in general practice: effect on patient satisfaction. *British Medical Journal*, 304(6837), 1287–1290, 1992.

[2] Milburn, Ashlea Bennett, Operations research applications in home healthcare. *Springer: Handbook of Healthcare System Scheduling*, 281–302, 2012.

[3] Di Mascolo, Maria and Martinez, Clea and Espinouse, Marie-Laure, Routing and scheduling in home health care: A literature survey and bibliometric analysis. *Computers and Industrial Engineering*, 158, 107255, 2021.

[4] Grieco, Luca and Utley, Martin and Crowe, Sonya, Operational research applied to decisions in home health care: A systematic literature review. *Journal of the Operational Research Society*, 1–32, 2020.

[5] Cissé, Mohamed and Yalçındağ, Semih and Kergosien, Yannick and Şahin, Evren and Lenté, Christophe and Matta, Andrea, OR problems related to Home Health Care: A review of relevant routing and scheduling problems. *Operations Research for Health Care*, 13, 1–22, 2017.

[6] Fikar, Christian and Hirsch, Patrick, Home health care routing and scheduling: A review. *Computers and Operations Research*, 77, 86–95, 2017.

[7] Sahin, Evren and Matta, Andrea, A contribution to operations management-related issues and models for home care structures. *International Journal of Logistics Research and Applications*, 18(4), 355–385, 2015.

[8] Cinar, Ahmet and Salman, F Sibel and Bozkaya, Burcin, Prioritized single nurse routing and scheduling for home healthcare services. *European Journal of Operational Research*, 2019.

[9] Wirnitzer, Jacqueline and Heckmann, Iris and Meyer, Anne and Nickel, Stefan, Patient-based nurse rostering in home care. *Operations Research for Health Care*, 8, 91–102, 2016.

[10] Güven-Koçak, Şeyma, Heching, Aliza, Keskinocak, Pınar, and Toriello, Alejandro, Continuity of care in home health care scheduling: a rolling horizon approach. *Journal of Scheduling*, 27(4), 375–392, 2024.

[11] Cappanera, Paola, and Scutellà, Maria Grazia, Addressing consistency and demand uncertainty in the home care planning problem. *Flexible Services and Manufacturing Journal*, 34(1), 1–39, 2022.

[12] Algendi, Abdalrahman and Urrutia, Sebastián and Hvattum, Lars Magnus and Helgheim, Berit Irene, Home Healthcare Staffing, Routing, and Scheduling Problem With Multiple Shifts and Emergency Considerations. *Networks*, 85(2), 223–242, 2025.

[13] Hewitt, Mike and Nowak, Maciek and Nataraj, Nisha, Planning strategies for home health care delivery. *Asia-Pacific Journal of Operational Research*, 33(5), 1650041, 2016.

[14] Gamst, Mette and Jensen, T Sejr, A branch-and-price algorithm for the long-term home care scheduling problem. *Operations Research Proceedings 2011*, 483–488, 2012.

[15] Nickel, Stefan and Schröder, Michael and Steeg, Jörg, Mid-term and short-term planning support for home health care services. *European Journal of Operational Research*, 219(3), 574–587, 2012.

[16] Bachouch, Rym Ben and Guinet, Alain and Hajri-Gabouj, Sonia, A decision-making tool for home health care nurses' planning. *Supply Chain Forum: an International Journal*, 12(1), 14–20, 2011.

[17] Carello, Giuliana and Lanzarone, Ettore, A cardinality-constrained robust model for the assignment problem in home care services. *European Journal of Operational Research*, 236(2), 748–762, 2014.

[18] Bachouch, Rym Ben and Guinet, Alain and Hajri-Gabouj, Sonia, An optimization model for task assignment in home health care. *2010 IEEE Workshop on Health Care Management (WHCM)*, 1–6, 2010.

[19] Torres Ramos, Andrés Felipe and Castaño, Fabián and Velasco, Nubia and Montoya, Carlos, A Multi-Objective Approach for the Nurse Scheduling Problem. A Home Health Care Delivery Case Study. *A Home Health Care Delivery Case Study*, 2025.

[20] Blais, Marko and Lapierre, Sophie D and Laporte, Gilbert, Solving a home-care districting problem in an urban setting. *Journal of the Operational Research Society*, 54(11), 1141–1147, 2003.

[21] Cappanera, Paola and Scutellà, Maria Grazia, Joint assignment, scheduling, and routing models to home care optimization: a pattern-based approach. *Transportation Science*, 49(4), 830–852, 2015.

[22] Errarhout, A and Kharraja, S and Corbier, C, Two-stage stochastic assignment problem in the home health care. *IFAC-PapersOnLine*, 49(12), 1152–1157, 2016.

[23] Hertz, Alain and Lahrichi, Nadia, A patient assignment algorithm for home care services. *Journal of the Operational Research Society*, 60(4), 481–495, 2009.

[24] Nasir, Jamal Abdul and Hussain, Shahid and Dang, Chuangyin, Solving a more flexible home health care scheduling and routing problem with joint patient and nursing staff selection. *Sustainability*, 10(1), 148, 2018.

[25] Benzarti, Emna and Sahin, Evren and Dallery, Yves, Operations management applied to home care services: Analysis of the districting problem. *Decision Support Systems*, 55(2), 587–598, 2013.

[26] Lahrichi, Nadia and Lapierre, Sophie D and Hertz, Alain and Talib, A and Bouvier, Lorraine, Analysis of a territorial approach to the delivery of nursing home care services based on historical data. *Journal of Medical Systems*, 30(4), 283–291, 2006.

[27] Fathollahi-Fard, Amir M and Ahmadi, Abbas and Karimi, Behrooz, Multi-objective optimization of home healthcare with working-time balancing and care continuity. *Sustainability*, 13(22), 12431, 2021.

[28] Zhao, Ai and Bard, Jonathan F., Weekly home healthcare routing and scheduling with overlapping patient clusters. *Health Systems*, 14(2), 145–165, 2025.

[29] Bowers, John and Cheyne, Helen and Mould, Gillian and Page, Miranda, Continuity of care in community midwifery. *Health Care Management Science*, 18(2), 195–204, 2015.

[30] Borsani, Valeria and Matta, Andrea and Beschi, Giacomo and Sommaruga, Francesco, A home care scheduling model for human resources. *International Conference on Service Systems and Service Management, IEEE*, 1, 449–454, 2006.

[31] Hiermann, Gerhard and Prandtstetter, Matthias and Rendl, Andrea and Puchinger, Jakob and Raidl, Günther R, Metaheuristics for solving a multimodal home-healthcare scheduling problem. *Central European Journal of Operations Research*, 23(1), 89–113, 2015.

[32] Cappanera, Paola and Scutellà, Maria Grazia and Nervi, Federico and Galli, Laura, Andrea and Puchinger, Jakob and Raidl, Günther R, Demand uncertainty in robust Home Care optimization. *Omega*, 80, 95–110, 2018.

[33] Carello, Giuliana and Lanzarone, Ettore and Mattia, Sara, Trade-off between stakeholders' goals in the home care nurse-to-patient assignment problem. *Operations Research for Health Care*, 16, 29–40, 2018.

[34] Lanzarone, Ettore and Matta, Andrea, A cost assignment policy for home care patients. *Flexible Services and Manufacturing Journal*, 24(4), 465–495, 2012.

[35] Lanzarone, Ettore and Matta, Andrea and Sahin, Evren, 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(6), 1346–1363, 2012.

[36] Lanzarone, Ettore and Matta, Andrea and Scaccabarozzi, Gianlorenzo, A patient stochastic model to support human resource planning in home care. *Production Planning and Control*, 21(1), 3–25, 2010.

[37] Ogulata, S Noyan and Koyuncu, Melik and Karakas, Esra, Personnel and patient scheduling in the high demanded hospital services: a case study in the physiotherapy service. *Journal of Medical Systems*, 32(3), 221–228, 2008.

[38] Schimmelpfeng, Katja and Helber, Stefan and Kasper, Steffen, Decision support for rehabilitation hospital scheduling. *OR spectrum*, 34, 461–489, 2012.

[39] Podgorelec, Vili and Kokol, Peter, Genetic algorithm based system for patient scheduling in highly constrained situations. *Journal of Medical Systems*, 21(6), 417–427, 1997.

[40] Chien, Chen-Fu and Huang, Yi-Chao and Hu, Chih-Han, A hybrid approach of data mining and genetic algorithms for rehabilitation scheduling. *International Journal of Manufacturing Technology and Management*, 16(1-2), 76–100, 2009.