Chapter 4
A Two-Stage Approach for Solving Assignment and Routing Problems in Home Health Care Services

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Abstract Human resource planning in Home Health Care (HHC) services is a critical activity that may also affect the quality of the delivered care. The assignment of the patient to operators together with their routing in the served territory are relevant problems that service providers have to deal with on a daily frequency. These problems can be either solved with a two-stage approach or with a simultaneous approach. The simultaneous approach enables to hold both assignment and routing decisions at the same time, however solving this problem is computationally difficult. The two-stage approach is the easier way of solving the assignment and routing problems, but an estimation of travel times is required to properly decompose the simultaneous approach into the two stages. This paper presents a new method to estimate operator travel times based on the Kernel Regression technique. Estimation is made on the basis of the operator travel times observed from previous periods. Numerical results based on realistic problem instances show that the proposed estimation method performs better than the classical Average Value method and that the whole approach is promising to construct realistic schedules.

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4.1 Introduction

Home Health Care (HHC) service is an alternative to the conventional hospitalization and consists of delivering medical, paramedical and social services to patients at their homes. The development of the HHC concept can be attributed to ageing of populations, social changes in families, increase in the number of people with chronical diseases, improvements in medical technologies, advent of new drugs and governmental pressures to contain health care costs [8]. The goal is to help patients to improve or keep their best clinical, social and psychological conditions.

Human resource planning in HHC services is a critical activity which the quality of the provided care depends on. From the admission of the patient, the service provider has to decide which operators will follow the patient during his stay as well as the detailed care delivery plan.

The resource assignment problem refers to the decision of which operators will take care of which patients. The operator routing problem specifies the sequence in which the patients are visited on a daily basis. To obtain the routes for operators, the assignment lists of operators and therefore the travel times between assigned patients should be known. The routing decision can either be held simultaneously with the assignment decision or it can be done just after the assignment procedure. In other words, the assignment and routing problems can be solved with two main approaches. The first one is solving them independently by a two-stage procedure where the output of the assignment problem is integrated as an input to the routing problem of each individual operator (Traveling Salesman Problem, TSP). The second approach aims at solving them simultaneously in a single model (Vehicle Routing Problem, VRP).

The literature available on the assignment and routing problems in HHC services has been enriched by recent works [6, 11]. Here we present some of the existing works. Akjiratikarl et al. [1] generate daily schedules by using the VRP with time windows. They focus on the determination of routes for each operator while minimizing the total distance traveled. Hertz and Lahrichi [5] propose two mixed integer programming models for assigning operators to patients. The objective is to balance the operators workloads. Trautsamwieser et al. [10] develop a model for the daily planning of the HHC services. The goal of the work is securing the HHC services in times of natural disasters. They develop the daily scheduling model as a VRP with state-dependent breaks. The objective of the model is minimizing the sum of travel times and waiting times, and also the dissatisfaction levels of the patients and health care operators. Lanzarone et al. [7] develop different assignment models to balance the operators' workloads considering several peculiarities of HHC services like the operators skills, the geographical areas of patients and operators, and the stochastic patient requests. Yalcindag et al. [12] propose a two–stage approach for assignment and routing decisions in HHC organizations. Their main goal is to analyze the interaction between the assignment and routing processes where travel times between patients are estimated based on average values in the assignment phase.

Current literature mainly focuses on the simultaneous decisions of the assignment and routing problems. Although the simultaneous approach is theoretically the best alternative, it falls into the category of the NP-Hard problems. Due to this complexity, in the existing works either a heuristic solution method is adopted or very small instance sets are used to solve the developed models. Actually, heuristics are the only way to manage complexity in real applications where hundreds of patients receive the care service delivered by a single organisation.

The simultaneous approach is mainly based on the geographical locations of patients and aims to minimize the total traveling times of operators. However, in the HHC services there are other patient attributes that should be considered while trying to minimize travel times of operators such as patients' skill requirements, care profiles, special service requests etc. In these cases, the simultaneous approach may not be able to take into account such patient attributes or it could be computationally harder. Furthermore, each professional can construct the routing based on his (her) specific skills. These operator specific criteria can be hardly modeled in a mathematical programming model.

In order to cope with the problem complexity and special structure of the HHC services, this paper proposes a two-stage procedure for short-term planning of human resources. With this procedure, first the assignment problem needs to be solved and then, with the obtained patients lists and travel times between patients, the routes for each individual operator needs to be constructed. In this procedure, since the routing process is held independently and exact distances between patients are not available at assignment level, estimation of operator travel times is required to be able to solve the assignment problem. In the work of Yalcindag et al. [12], travel times are estimated based on average values. Although this is a intuitive approach, more accurate travel time estimation method is necessary to obtain results close to the ones the simultaneous approach provides. In particular, inaccurate estimations may create infeasibilities between the two stages (e.g., operator availability constraints in the routing problem) in addition to workload unbalancing and high travel times. Estimation is made on the basis of the operator travel times observed from previous periods in order to try capturing the specific operator behaviour. This paper partially addresses the stated problem by considering travel time minimization as the only criterion to construct the routes for the operators. The proposed estimator is assessed on a set of numerical cases.

The rest of the paper is organized as follows. The assignment and routing models are described in Sect. 4.2. In Sect. 4.3, the two-stage approach and travel time estimation methods are presented. In Sect. 4.4, the simultaneous approach is presented. Computational experiments are reported in Sect. 4.5. Finally, concluding remarks and future research directions are presented in Sect. 4.6.

4.2 Problem Definition

The assignment problem of the HHC services is used to determine which operators will provide the service to which patients, whereas the routing problem is used to decide the visiting sequence of patients for each operator. The problem can be defined on a complete directed network $G = (N,A)$, having n nodes where each node i corresponds to a patient.

In this work, we assume that the assignment and routing processes are held within a single category of operators (nurse or doctor) with same professional capabilities. In practice, operators are usually divided into several districts (as groups) based on their main skills and geographical areas to serve. A single district for a single planning period (e.g. day or week) is assumed.

Models are proposed under continuity of care where the newly admitted patient has to be assigned to only one principal operator in the set Ω of all operators. Each operator k, with $k \in \Omega = \{1,\ldots,K\}$, has one main skill that is used to handle a set of patients. The main skill refers to the patients for which the operator is best suited to care. For sake of simplicity, operators have no patient allocated from previous periods. Each operator k is assumed to have a deterministic capacity a_k, which is the maximum amount of time that the operator can accomplish according to his (her) working contract. In particular, it is also assumed that operators can handle excess load with respect to their capacities (i.e., overtime is allowed).

In the following sections, we present the details of the two-stage and simultaneous approaches to solve the assignment and routing problems.

4.3 Two-Stage Approach

In this section we provide details about the decomposed assignment and routing problems and also the travel time estimation methods.

4.3.1 Assignment Model

The considered assignment problem consists in matching operators with patients in a way that the utilization rates of operators (defined as the ratio between the actual workload of the operator and his (her) capacity) are balanced and the total traveling time of operators is minimized.

Each patient i (with $i = 1,\ldots,n$) has deterministic demand λ_i (expressed in amount of time) which denotes the total amount of the care volume needed by the patient. The demand of patient i is calculated as follows:

$$\lambda_i = (\tau_i + s_i) f_i \tag{4.1}$$

where s_i is the service time required by the patient, τ_i is the estimated travel time to reach the patient and f_i is the frequency of visits required by patient i.

The assignment problem is formulated as follows:

$$\min \quad h+\gamma\sum_{k=1}^{K} y_k \tag{4.2}$$

$$\text{s.t.} \sum_{k=1}^{K} x_{ik} = 1 \quad \forall i \tag{4.3}$$

$$y_k = \sum_{i=1}^{n} \tau_i x_{ik} \quad \forall k \tag{4.4}$$

$$w_k = \sum_{i=1}^{n} \lambda_i x_{ik} \quad \forall k \tag{4.5}$$

$$h \geq \frac{w_k}{a_k} \quad \forall k \tag{4.6}$$

$$x_{ik} \in \{0,1\} \quad \forall i,k \tag{4.7}$$

$$w_k \geq 0 \quad \forall k \tag{4.8}$$

$$y_k \geq 0 \quad \forall k \tag{4.9}$$

where variable x_{ik} takes the value 1 if the patient i is assigned to the operator k and 0 otherwise. The decision variable w_k is a continuous variable and is used to calculate the total workload of operator k. The decision variable y_k denotes the total travel time of operator k and γ is a parameter between 0 and 1. The auxiliary variable, h, is used to estimate the maximum utilization rate of the operators from above.

Equation (4.3) implies that all newly admitted patients must be assigned to only one operator. Equation (4.4) calculates the total travel time of each operator k. Equation (4.5) defines the total workload of each operator k. Inequality (4.6) expresses the maximum utilization rate h, which is minimized in the objective function (4.2) together with the penalized sum of travel times.

4.3.2 Travel Time Estimation Methods

Since in the two-stage approach the routing problem is solved after the assignment problem, at the time of the assignment decision the visiting sequences of patients are not known. In this section we provide details on how to build the travel time functions. We adopt a non parametric method to estimate travel times from real data observations. The reason is due to the distribution-free property of non parametric methods and the asymptotic convergence of some estimators. In particular, Kernel Regression (KR) is used to estimate the travel time functions. Remind that, in this paper, we only consider the geographical locations of patients without taking into account their other attributes.

In the literature, only Average Values (AV) are used to estimate travel times. Thus, in the following section, in addition to the proposed method based on KR, we also describe the existing AV method.

4.3.2.1 Average Value Approach

The estimate of the travel time related to a patient is calculated as the weighted average travel time to reach his (her) home from all other patients, including also the common health care center. In such a case, the weights can be assumed to be proportional to the care volume required by each patients (frequency of required visits). Thus, the following estimator $\bar{\tau}_i$ is used:

$$\bar{\tau}_i = \frac{\sum\limits_{j \neq i} w_j t_{ij}}{\sum\limits_{j \neq i} w_j} \tag{4.10}$$

where t_{ij} denotes the traveling time from patient i to j, $(i, j) \in A$ and w_j is the weight related to the patient j.

Since average values are used to calculate the time to reach a patient, this can result in high travel times in comparison with the optimal travel times that are obtained with the simultaneous approach.

4.3.2.2 Kernel Regression Technique

KR is a non-parametric regression technique that does not require a predetermined (e.g. linear) form as the predictor is built with the information derived from the existing data [13]. KR exploits the correlations existing among the observations by assuming a radial basis function explaining the data. Since HHC patients have spacial relationship between each other (i.e., locations, skill requirements, etc.), KR can be adopted to estimate the travel time to visit a set of patients located in a geographical area.

KR technique estimates the expectation of the outcome variable Y (i.e., total travel time of operator) conditional on the random variable X (i.e., patient locations, care profiles), $E(Y|X)$. Than main reason for using KR is that it imposes few restrictions on the functional relationship between the covariates X and the outcome variable Y. This relationship can be shown with the following simple model:

$$Y = \tau(X) + \varepsilon \tag{4.11}$$

where τ is an unknown function and ε is the error term which is independent and identically distributed with $[0, \sigma^2(X)]$.

For our analysis we focus on the Multivariate Kernel Regression since our response variable Y depends on a vector of exogenous variables X. Thus, we try to estimate the following conditional expectation:

$$E(Y|X) = E(Y|x_1, \dots, x_d) = \tau(X), \tag{4.12}$$

where $X = (x_1, \dots, x_d)^T$ and d is the dimension of the covariate X.

To estimate the unknown function we use the Nadaraya-Watson estimator [13]:

$$\hat{\tau}(x) = \frac{\sum_{p=1}^{m} K\left(\frac{X_p - x}{h}\right) Y_p}{\sum_{p=1}^{m} K\left(\frac{X_p - x}{h}\right)}, \tag{4.13}$$

where $K(.)$ is a d dimensional kernel function and h is the bandwidth array. With this approach, the function τ is estimated with a locally weighted average by using the kernel as a weighting function. The selection of the bandwith value is relevant as it affects the smoothness of the predictor. Several methods are available in the literature to select an optimal value for h.

The kernel function, $K(.)$, is chosen as the widely applied Gaussian Kernel,

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-(1/2\theta)x^2}, \tag{4.14}$$

where θ represents the correlation coefficient.

In our context, $\hat{\tau}$ is indicating the estimation of the total travel time function of any operator k and in the remainder of this work it is denoted as $\hat{\tau}_k$. In particular, X_k is used to denote the attributes (in this study only geographical locations) of the patients assigned to the operator k. The outcome variable Y_k is used to express the total travel time of operator k to reach the assigned patients. X_k and Y_k values are used to estimate the total travel time function, $\hat{\tau}_k$.

To test the accuracy of the proposed KR technique, we first run an experiment to compare the predictor in Eq. (4.13) with the observed total travel times. In the experiment, we randomly generate five patients in a geographical area and the TSP model is used to calculate the optimal route to visit them accordingly to the travel time minimization criterion. This total travel time represents one (out of m) observation on which the predictor is constructed. To do this, we use different sizes of historical data (i.e, $m = 25, 35, 50, 100, \dots$) to study the behavior of the predictor as the number of observations increases. At each generation, the five patients are randomly sampled with a triangular distribution between 0 and 100 and the mode equal to 40.

For each data set we calculate $\hat{\tau}$ on the basis of the m observations. Then the predictor is used to estimate the travel times for 100 new data sets randomly generated *out-of-sample*. For these new data sets the TSP model is used to obtain the optimal total travel times. These last are used as benchmark to study the accuracy of the estimator. The error between the estimated values and the optimal TSP values are

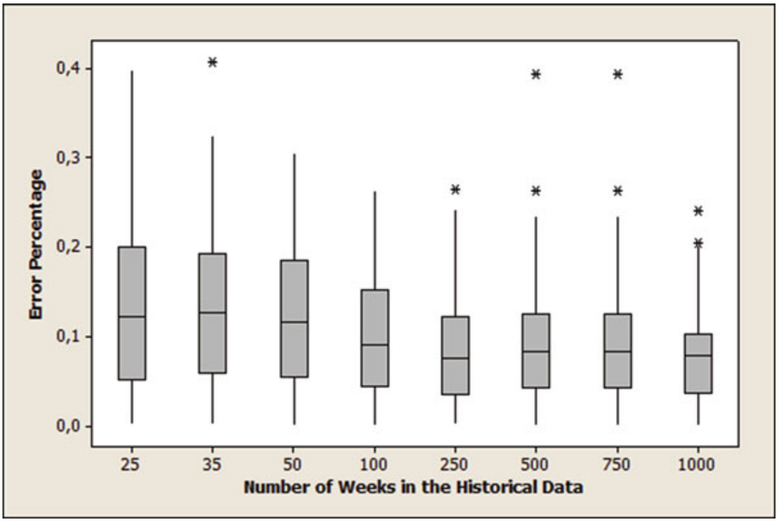

Fig. 4.1 Box-plot for the error between of the estimated and optimal travel times (100 samples)

shown on the box-plot in Fig. 4.1. As it can be seen, as the number of observations in the history increases, the predictor provides better estimates. Similar results were obtained by repeating the experiment with 6, 7 and 8 patients visited in the route. Obviously, the predictor performance deteriorates as the number of patients in the route increases.

The following section provides details on how the two travel time estimation alternatives can be considered in the assignment phase.

4.3.3 Use of Travel Time Estimators in the Assignment Problem

One of the most important point while solving the assignment problem is how to incorporate estimated travel times into the mathematical model. As far as the AV approach, it can be done simply by calculating the average travel times over all patients with Eq. (4.10) and plugging this value into Eq. (4.4) where the total travel time of each operator is calculated.

For the KR estimate, since the regression function is fitted to calculate directly the total travel time of an operator, it is more complex than the AV approach. To incorporate this into the current setting, two different approaches can be followed. A proper approach is to enumerate all possible assignment combinations for all operators and to estimate the related travel times using the KR functions. This can be done off-line, i.e., before the assignment problem is solved. Since the procedure may not be easy in practice, an heuristic approach can be applied as alternative to solve the assignment problem. Indeed, it is very practical to embed the KR function in an heuristic approach such as genetic algorithm, tabu search, etc. In this way, first the heuristic selects (with some specific rules) assignments and then the KR function is executed to get the travel time estimate from which the objective function is calculated. This is repeated for several iterations until an exit condition is satisfied.

In this paper, a genetic algorithm is adopted to solve the assignment problem using KR for the estimation of travel times. The implemented heuristic solves the same assignment problem formulated in Eqs. (4.2)–(4.9).

4.3.4 Routing Model

At routing phase, a TSP model is used to create the routes for all operators in the considered planning period. With the patients lists obtained from the assignment phase, K independent TSP models are solved and the visiting sequences for all operators are determined. In other words, the output of the assignment phase is incorporated into the routing phase and the routes of all operators are obtained from the solution of the TSP models.

As the TSP model, we use the conventional formulation proposed by Dantzig et al. [4] with the objective of minimizing the total traveling time of each operator.

4.4 Simultaneous Approach

To be consistent with the modeled assignment problem, we need to formulate the VRP with the same objective function that balances the trade-off existing between workload balancing and total travel times. The problem has been formulated using the models proposed in [3, 9]. Two consecutive VRP models are solved to balance the total travel times of operators. In the first model, we find an upper bound on the maximum tour length. With the solution from this model, we solve a second VRP problem where the objective is minimizing the total travel times of all operators. As a result, the routes are constructed in a way that the total travel times of the operators are minimized according to the balancing purposes.

Balancing the total travel times of all operators can be considered as the balancing the total workloads of all operators when the service times required from each patient are assumed to be equal.

4.5 Computational Study

In this section we analyze and compare the proposed travel time estimation method with the AV approach. The travel time estimation alternatives are tested on three different instance groups, A, B, C. In the first instance group (A), locations of 15

Table 4.1 Results with instances from groups A and B (15 patients)

Group	Number	T(AV)	T(KR_2)	T(VRP)	$\%\triangle_{AV}$	$\%\triangle_{KR_2}$
A	1	639.14	604.14	601.73	6.2	0.4
	2	630.45	601.49	593.73	6.2	1.3
	3	662.00	619.06	614,58	7.7	0.7
	4	696.48	669.99	668.40	4.2	0.2
	5	666.86	637.02	609.88	9.3	4.5
B	1	882.73	715.62	703.97	25.4	1.7
	2	860.82	784.83	737.32	16.8	6.4
	3	847.01	769.86	718.74	17.6	7.1
	4	873.38	855.82	734.01	19.0	16.6
	5	876.83	792.34	739.71	18.6	7.1

Table 4.2 Results with instances from group C (56 patients)

Group	Number	T(AV)	T(KR_2)	T(KR_1)	$\%\triangle_{AV-KR_2}$
C	1[a]	139.04	105.58	128.69	31.7
	2	141.46	108.96	127.62	29.8
	3	139.47	94.49	129.65	47.6
	4	151.31	100.08	130.04	51.2
	5	147.90	105.14	127.77	40.7
	6	147.62	112.09	127.51	31.7
	7	135.81	109.18	127.55	24.4
	8	138.21	113.82	124.62	21.4

[a]The original real instance

patients are randomly sampled from a triangular distribution between 0 and 100 and the mode equal to 40. In the second instance group (B), patients are generated based on the grouping (clustering) structure. Here, 3 subsets of 15 patients (5 patient for each subset) are used. Each subset is located in a different geographical area and within each subset patients are located closely to each other. In the third group (C) we generate instances with 56 patients based on real data provided by an Italian HHC provider.

All of the presented results are obtained for a single planing period (e.g., day) for a single district. Small sized instances (A and B) are executed with three identical operators whereas the instances based on real setting (C) are solved with seven identical operators.

In all the experiments the historical data are randomly generated according to the instance type and the TSP is used to calculate the optimal travel times for building the KR predictor. In particular, bandwidth values, h, are used as the optimal values [2].

Small instances (A and B) are executed on both assignment and routing methods (two-stage and simultaneous (VRP) approach) whereas due to computational difficulties larger instances (C) are only solved for the two-stage approach. All of the results obtained with three instance groups are presented in Tables 4.1 and 4.2.

In the tables, the total travel time of all operators obtained in the two-stage approach with the AV and KR methods are shown with T(AV) and T(KR_2) notations, respectively. At the same way, the total travel time in the simultaneous approach is denoted with T(VRP). T(AV) and T(KR_2) values are obtained by solving several (as the number of operators) independent TSP models with the outputs obtained from the assignment stage and summing the results of each TSP models. Since we use a genetic algorithm for solving the assignment problem, T(KR_2) values are the average values resulting from five replications of the algorithm.

The percentage differences in Table 4.1 between the VRP approach and the two-stage approach with the two estimation methods are denoted with $\triangle_{AV}$ and $\triangle_{KR_2}$ calculated as follows:

$$\triangle_{.} = \frac{|T(.) - T(VRP)|}{T(VRP)} \tag{4.15}$$

The results in Table 4.1 show that, if the patients are randomly scattered in the region (instance type A), the slight difference between AV and KR methods does not seem to justify the proposed approach. In particular, the two-stage approach has similar performance as the simultaneous approach. When the KR is used the differences with the VRP are quite small except for the instance 4-B.

In the other instance group (B) where patients are concentrated on specific locations, the two-stage approach with KR method is able to provide better solutions than the AV method. Thus, it seems from the reported numerical results that the KR technique performs better when the patients are located close to each other in some specific areas as it happens in the real case. To support this idea we test another instance set based on real data (C).

In the group C, one instance is directly generated from the real data with 56 patients distributed over 7 cities. By using the same patients, other seven instances are generated where, in each instance, the patients are randomly spread over the cities. The results of these instances are presented in Table 4.2.

The percentage differences on the total travel times between the two-stage approach with KR and AV methods are shown as $\triangle_{AV-KR_2}$ and calculated with Eq. (4.15) by replacing T(VRP) value with T(KR_2) value. As it can be seen from Table 4.2, the two-stage method with KR approach provides up to 51.2 % lower total travel times with respect to the AV approach.

The table also reports KR_1 representing the total travel times estimated by the KR method from the solution of the assignment problem. T(KR_1) values are used to test the accuracy of the proposed predictor with respect to the value obtained by the TSP approach, T(KR_2). Since we use the historical data with only 100 weeks to estimate the regression function, the observed differences between the KR_1 and KR_2 are slightly high. But, according to the considerations made in relation with Fig. 4.1, these differences can be reduced with the use of a larger number of historical data. Indeed, if one data corresponds to 1 day the KR can be successfully applied with hundreds of historical observations.

4.6 Conclusions

In this work, we propose a new travel time estimation method and we analyze the performance of this estimator with respect to the existing method. The results show how the proposed estimation method is used in a two-stage approach to decompose a complex problem.

We conclude that the proposed travel time estimator is performing good enough when patients are distributed in a special way (clustered). In particular, we also observe that even with a scattered distribution of patients our approach is providing lower total travel times in comparison to the existing approach.

We also compare the results of the two-stage approach with the simultaneous approach (VRP) and observe that, for the tested instances with few patients, the two-stage approach is able to provide very similar total travel times as the VRP approach provides.

The results reported in this paper suffer of a limited experimentation, thus they have to be confirmed on a larger design of experiments.

An on-going activity is to analyze the decomposition process of the assignment and routing problems in more details and try to compare the solutions with the VRP approach for larger instances according to the real framework. Another on-going activity is the improvement of the proposed travel time estimator to handle with more complex cases where more patient attributes are considered.

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