[213010] Home Health Care Routing and Scheduling Problem: A preventive approach

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Abstract

Due to several challenges in hospital service caused by the increasing demand for hospitalization, Home Health Care Service (HHCS) has become the best alternative for hospitals to provide a delivery service system that allows patients to be cared at their place of residence. The HHCS offers benefits because it helps hospitals to reduce costs, prevent contagious infections and give some emotional and psychological benefits to the patients. In this paper, a tactical and operational solution is proposed to the Home Health Care Routing and Scheduling Problem (HHCRSP) applied in the study case presented by Instituto Roosevelt (IR). IR manually defines the daily routes, and it generates the monthly staffing and workforce scheduling based on the HHCS head's experience. This causes additional workload and human errors in routing assignments, staffing, and demand forecasting. This project integrates a single-objective Mixed Integer Linear Programming (MILP) model to tackle the monthly staffing and scheduling decisions, and a multi-objective MILP model to the scheduling and routing problem. The aim is to minimize the tactical costs associated with doctor's hiring and monthly assignment, and to minimize the operative costs and the gap differences between the maximum and minimum workload of the doctor's routes assignment. Due to the high computation times of the routing MILP, a Non-dominated Sorting Genetic Algorithm (NSGA II) metaheuristic is applied. The final objective of the project is to design a tool that builds the daily route and the monthly staffing and workforce scheduling of the HHCS offered by the Instituto Roosevelt. Additionally, the tool will consider different stochastic parameters (demand and travel time) with a series of constraints associated with the Instituto Roosevelt's case study. The methodology to deal with the stochastic parameters is through simulation and a Genetic Algorithm sim-heuristic that hybridizes the NSGA II with Monte Carlo Simulation. These methodologies and the MLPI's proposed are carried out on a set of instances and their efficiencies are compared to test their performance. In the deterministic routing solution, the GA shows a competitive result by giving an average difference of 16% of the optimal costs and 0.4% on the optimal workload balance. In the stochastic routing component, it is evident that the results obtained by deterministic metaheuristic with NSGA II are good, since approximately 100% of the time they obtain better results than the Institute's proposal. According to the literature review, the combined tactical and operational decisions with stochastic parameters have been little applied and discussed on HHCRSP (Home Health Care Routing and Scheduling Problem). That is the added value of this work.

Key words: HHCRSP, Routing , Home Health Care, Preventive, Mathematic Model, Deterministic, Stochastic, Simulation, Optimization, Multi-objective, NSGA II.

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1. Justification and Problem Statement

Home Health Care Service (HHCS) is a service modality that allows patients with different clinical conditions to be cared for at their place of residence. It requires medical and paramedical services to be delivered to patients at home (En-Nahli et al., 2015). It has been argued that HHCS reduces the disadvantages if long hospitalization: increased access barriers, saturation of emergency rooms and increased costs, among other (Ceballos-Acevedo et al., 2014). Therefore, HHCS has become an alternative that improves efficiency of the system, improves quality of care, reduces maintenance costs and increases capacity (A.G. Srinivasan, 2020; En-Nahli et al., 2015). Additionally, from the patient's point of view, HHCS enables healthcare workersto come into direct contact with the patient's environment and identify both protective and risk factors (A.G. Srinivasan, 2020), reduces psychological stress related to prolonged or repetitive hospitalizations (Landers et al., 2016) and reduces the risk of contagion of other diseases (A.G. Srinivasan, 2020; Landers et al., 2016).

Several authors have studied the levels of planning and decision making related to HHCS design and they have proposed different frameworks to understand these decisions (Matta et al., 2014; Nickel et al., 2012; Valentina Gutiérrez & Julio Vidal, 2013). Broadly, these decisions can be categorized into three main levels: Strategic, Tactical and Operational. The first one (Strategic), focuses on defining the mission of the service, the geographic coverage, the partners selection, and the selection of districts to be served. The second decision level (Tactical) focuses on resource sizing, patient admission, shift assignment, staff dimensioning, staff competency management and coordination with partners. The third one (Operational), focuses on staff distribution, scheduling of routes and medical activities. According to Matta et al. (2014) there are many studies related to each of these levels. Most of them focus on the study of operational decisions and leave aside important aspects related to human resource allocation (tactical decisions) and medical supplies (A.G. Srinivasan, 2020; Grieco et al., 2021).

In this context, the Home Health Care Routing Problem and Scheduling Problem (HHCRSP) deals with the assignment, scheduling, and routing decisions to meet the patient demand in different geographical locations. Traditionally, the HHCRSP has been classified into three major problems: i) the problem of geographical partitioning into districts or zones, ii) the allocation of resources for the development of the service and iii) the scheduling of routes (Hassen et al., 2019). At the operational level, HHCRSP requires a combination of vehicle routing and scheduling decisions, leading to complex optimization models (Hassen et al., 2019). This problem is often divided through literature in a single-period (problem settings where a single working day is assumed as the planning horizon) or multi-period (more than one day) scheduling and routing approach (Fikar & Hirsch, 2017). These also can integrate solutions that include multimodality in transport, stochastic methods for dealing with uncertainty andothers (A.G. Srinivasan, 2020; R. Liu et al., 2019; Yong Shi et al., 2017a). Moreover, it has been argued that themost common constraints for HHCSRP include time windows, skill requirements, working time regulations, synchronization constraints, the consideration of breaks, various preferences of clients and nurses, workload, and continuity of care measures (Fikar & Hirsch, 2017; Li et al., 2021).

Different solution approaches have led to a classification of the HHCRSP into two categories: Static and Stochastic. First, the Static (or preventive) approach handles the routes with a deterministic number of patients and their requirements. Usually, the patients must be visited only once in each route plan. Additionally, the travel and service times are known and the relevant data for the route planning does not changeafter the routes have been executed (A.G. Srinivasan, 2020). Then, the Stochastic approach (a priori optimization) considers the uncertainty of one or more parameters to model a phenomenon that cannot be precisely predicted such as travel or service times. Although including the stochastic features of the problem could be a better representation of the real operational conditions of the service, those models have been little researched in the literature (A.G. Srinivasan, 2020; Fikar & Hirsch, 2017).

This project is aimed at developing a tool to support the workforce scheduling (tactical) and routing (operational) decisions for the Home Health Care Service of the Institute Roosevelt (IR). IR is located in Bogotá, and it provides Home Health Care Service for children. Currently, the service manager makes the scheduling decisions based on her own criteria and experience with Bogotá's and Soacha's traffic conditions. First, according to the admissions of a given day, the list of patients that must be visited on the next day is updated. Then is assigned to an available doctor, following a geographic proximity criterion (helped with Google Maps). Additionally, doctors are required to visit specific hospitals to conduct admissions tasks for the new HHCS patients who are hospitalized. Therefore, the doctor assigned to the hospital assessment evaluates whether the patients fulfill the conditions to be admitted or not. Those newly admitted patients will be included on the list and need to be visited for the next working day. Likewise, it was stated by the administrative coordinator of HHCS that there is an interest in reducing transportation and labor costs to ensure a positive profit for the HHCS provided by the Institute.

The current manual routing generates additional workload for the doctor in charge of planning, which in turn causes human errors with the daily scheduling and routing solutions. For example, in some cases a patient is scheduled to different doctors on the same day, or a doctor´s route has duplicated patients, among others. Therefore, program managers have identified a need to improve decision to reduce transportation and labor costs while ensuring good service levels.

Our tool will support two decision levels: Tactical and Operational. Figure 1 describes the solution structure based on the preventive approaches addressed on both decision levels. The solution will consider the effect of certain stochastic parameters such as demand (nodes to be visited) and travel time. In summary, to obtain a preventive workforce definition (monthly staffing and scheduling), the solution will first contemplate an initial estimation of the nodes that should be visited during a planning horizon (demand forecast). After defining the workforce for a given planning horizon, a preventive route scheduling will be obtained for each day, considering stochastic travel times, estimated from the simulation of probabilistic distributions. The proposed solution will minimize the costs associated with the workforce scheduling and routing. As constraints, the tool will consider the flexibility of doctors in their available time windows, the periodic visit of doctors, the continuity of care in the monthly planning horizon and the fair workload.

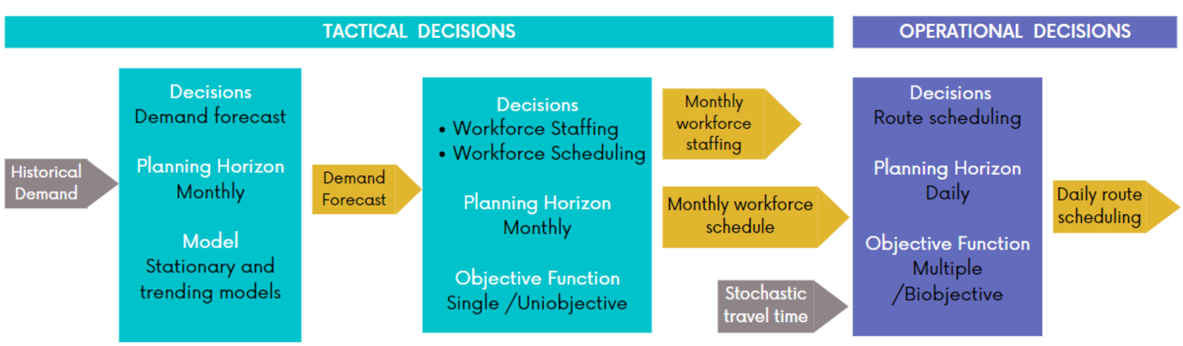

Figure 1. Tactical and operational decisions for the proposed solution.

2. Background

Two recent literature reviews have concluded that more research on the stochastic version of the problem is needed (A.G. Srinivasan, 2020; Fikar & Hirsch, 2017). Fikar & Hirsch (2017) provide overview of the current work on HHC scheduling and routing field by comparing different objectives and constraints and considering the problem settings. Consequently, the review divides all the included articles in two groups: single-period and multi-period planning problem. The review states that most work focused on static single-modal, single-period problems, modelling the problem as an extension of the Vehicle Routing Problem (VRP), where travel is the focus. (Fikar & Hirsch, 2017) The authors then concluded by highlighting promising future research directions in stochastic routing and scheduling, integrated multi-stage (Strategic, Tactical and Operational) multi-period planning approaches, multimodality and mode of transport choices, sustainability considerations and acceptance of HHC optimization. Additionally, A.G. Srinivasan (2020) analyzed works from 2006-2020 of the routing problems in HHCS and it classified the problems into three categories: static, dynamic, and stochastic. The review concludes that very few studies have included constraints such as continuity of care, break times for doctors, priority-based visits, the flexibility of doctors, periodic visits of doctors, and strategic planning horizon.

More recently (Grieco et al., 2021) conducted a systematic review of operational research approaches to HHC which identified some paper that integrate decisions at different planning levels (strategic, tactical, operational). The systematic review selected 77 papers where their focus was on solutions for operational planning level (staff- to-patient allocation, visit scheduling and staff routing). The authors state that there are few studies that deal with tactical decisions such as team size and composition or strategic decisions of districting. Moreover, the paper claims that there is insufficient literature to provide a coherent set of tools for strategic, tactical, and operational decision-making in HHCS. It concludes that the reviewed literature does not provide guidance for coherent decisions across planning levels on HHCS. Similar conclusions have been previously reached in other reviews (Valentina Gutiérrez & Julio Vidal, 2013).

Some attempts that deal with tactical decisions on staff planning have tried to explore the effects of the patients' priority and continuity of care on the patient/operator assignment problem in the HHCS context (Lin et al., 2016). An additional Lanzarone et al. (2010) deal with workload planning in HHCS. It proposes an approach to develop a stochastic model for studying the changes in clinical, functional, and social conditions for patients receiving an HHC service. The study balances the workload based on the future expected number of visits by a stochastic model to predict the number of patients followed up in the course of time. Another tactical decision approach is from Restrepo et al. (2017) which formulates a discontinuous multi-activity tour scheduling problem under demand uncertainty as a two-stage stochastic program. The first stage decisions correspond to the assignment of employees on weekly tours and the article claims that the use of the stochastic model helps to reduce understaffing and overstaffing costs (Restrepo et al., 2017). It has been argued that most of the time, the workforce problem (staff dimensioning) in HHCRSP is modeled as a Markov decision process system (Koeleman et al., 2012). This is justified because the predicted/forecasted/simulated variables provide information about the future workload of each operator that becomes a useful support tool for human resource planning in the medium and short terms (Lanzarone et al., 2010).

In HHCSRP, several methodologies have been developed, (Ouertani et al., 2019) proposes a HGA (Hypermutation Genetic Algorithm) to minimize the travel costs by considering route changes from new requests in real time (dynamic approach). Also, there is the case of (Bazirha et al., 2020) that proposes Stochastic Programming with Recourse (SPR) to address HHCSRP with stochastic travel and service times. (Bazirha et al., 2020) minimizes the transportation costs of caregivers and they model the expected value of number of patients by a Monte Carlo simulation. In addition, (Y Shi et al., 2017) use a hybrid genetic algorithm integrated with stochastic simulation to solve HHCSRP with a diffuse drug demand. The article first carries out a demand simulation from a triangular distribution and a computational comparison is made until a specific constraint is met. Then, the model is simulated with the new estimated demands and the expected value of the distances are estimated after all the computational experiments. (Borchani et al., 2019) focus on a variant problem of the vehicle routing problem with time windows and synchronized visits to home caregivers and the sequence of visits execution. They propose a heuristic dedicated to minimizing the difference in service time between different vehicles to optimize the workload balance, they provide Genetic Algorithm (GA) and Hybrid Genetic Algorithm with Variable Neighborhood Descent search called (GA-VND).

Other more recent articles are included in the summary table 1 below. From there, there are some papers that address a multicriteria objective function and provide a solution by metaheuristic models (Li et al., 2021; W. Liu et al., 2021; Nikzad et al., 2021). A robust metaheuristic to address the multicriteria objective problems is the Nondominated Sorting Genetic Algorithm (NSGA II), which builds a Pareto Front to obtain a set of non-dominated optimal solutions (Gutiérrez-Antonio & Briones-Ramírez, 2009; Hernández et al., 2016). According to (Deb et al., 2002), NSGA II presents superior performance as it can find better dispersion of solutions and better convergence near the true Pareto-optimal Front compared to Pareto-Archived Evolution and Pareto-Force EA-two. Additionally, some studies mention some advantages related with NSGA II, such as reduced computational complexity and increased diversification by combined pairing of parent and child populations to select the best solutions (Deb et al., 2002; J. Liu & Chen, 2019; Nisperuza et al., 2019).

Additional articles to those in the table have shown that in HHCS both travel and service times may vary from what was initially planned due to factors over which there is no control. Those factors are influenced by conditions outside the development of the operation such as road conditions or specific situations that may occur during patient care and could generate some kinds of delays. This is the case of (Yong Shi et al., 2017a), who proposed to address this problem through Stochastic Programming with Recourse (SPR). They use Hybrid Genetic Algorithm (HGA) and a stochastic simulation method, and they integrate a simulation that defines travel and attention times from a normal distribution. Then, the expected time values are obtained for the route solutions. In this way, the solution model is divided into two stages: the first one is route planning with the information that is initially available; and the second one, the random generation of travel and service times (Yong Shi et al., 2017a). To have a more realistic approximation of what happens in practical life, the second stage models randomness through a penalty for delays on the provision of the services (Yong Shi et al., 2017).

Table 1. References Comparison and background. Own Construction.

Article´s Reference	**Operational Routing Horizon approach**		**Tactical Scheduling Horizon approach**		**Objective Function**		**Constraints**							**Methodology**
	PD	PE	PD	PE	S	M	CC	TW	WTR	WB	P	F	SR	
This Paper	x	x	x	x	x		x	x	x	x	x	x		
(Demirbilek et al., 2021)					x		x						x	SBAM
(Nikzad et al., 2021)		x	X			x	x			x			x	Multi-phase matheuristic algorithm
(Li et al., 2021)	x		x			x		x	x	x			x	HGA
(Doulabi et al., 2020)	x	x		x	x			x						L-Shaped; Branch & Cut
(Leeftink & Hans, 2021)	x		x		x					x				Greedy Heuristic;ALNS
(Hassen et al., 2019)		x			x			x				x		MAS - CSA
(Zheng et al., 2021)	x	x		x	x			x						SGBNA
(W. Liu et al., 2021)	x					x	x	x	x	x				ALNS
(Goodarzian et al., 2021)	x					x		x		x				ISEO
(Cappanera et al., 2020)	x				x			x					x	MILP
(Yong Shi et al., 2017b)	x	x		x		x		x						HGA Stochastic simulation
(Yong Shi et al., 2017a)	x	x	x	x	x									HGA Stochastic simulation
(Ouertani et al., 2019)		x		x			x							HGA
(Bazirha et al., 2020)	x		x	x									x	Monte Carlo simulation/GA

(Rodriguez et al., 2015)		x		x		x	x	x		x		x	x	Stochastic Programming Monte Carlo Simulation
(Restrepo et al., 2017)	x			x	x		x			x				Stochastic Programming Monte Carlo Simulation Multi-cut L-shaped method
(Restrepo et al., 2020)	x			x		x	x	x				x	x	Facebook Prophet; Monte Carlo Simulation
(J A Nasir & Dang, 2018)	x		x			x		x		x		x		MILP

Notes: PD=Preventive-Deterministic, PS=Preventive and Stochastic, S=Single objective, M=Multiple Objectives, CC= Continuity of Care, TW=Time Windows, WTR= Working Time Regulations, WB=Workload Balance, P= Periodicity, DF= Doctor's Flexibility, SR=Skill Requirements, SGBNA= Super gradient-based nested decomposition Algorithm, ISEO=Improved Social Engineering Optimizer, MILP=Mixed Integer Linear Programming, SBAM= Scenario based approach for multiple nurses, HGA=Hybrid Genetic Algorithm, ALNS= Adaptative Large Neighborhood, MAS= Multi-Agent System, CSA= Clonal selection algorithm, GA= Genetic Algorithm, NSGA II: Nondominated Sorting Genetic Algorithm.

One of the different articles, that might be the closest to our work, formulated a flexible mixed-integer linear programming (MILP) model by incorporating the dynamic arrival and departure of patients along with the selection of new patients and nursing staff (Jamal Abdul Nasir & Dang, 2018). The paper considers the assignment, scheduling, and routing decisions along with staff hiring and patient selection decisions. They formulate a model that is flexible enough to handle the existing and new patients simultaneously so that the existing routes are optimized again on the inclusion of new patients in the daily planning system (Jamal Abdul Nasir & Dang, 2018). In addition, when the routes of existing nurses and patients are again optimized, it gives effective and efficient routes in fluctuating health care demands (Jamal Abdul Nasir & Dang, 2018).

Finally, from the table it can be concluded that, even in most recent articles, they do not address joint tactical and operational scheduling approaches to routing. This leads to the fact that a differentiating factor in this work is to address tactical workforce scheduling with a preventive approach and operational scheduling and routing with a preventive approach. Moreover, few articles consider constraints as periodicity and doctor's flexibility that will be considered on the development of this work.

3. Objectives

To design a decision support tool for the workforce scheduling and routing problem of the HHCS offered by the Instituto Roosevelt, using a preventive solution that includes stochastic and deterministic parameters.

a) To design a mixed integer programming model to tackle the deterministic version of the HHCRSP, considering the specific features of Instituto Roosevelt.
b) To develop a solution approach for the deterministic version of the HHCRSP, considering the specific features of Instituto Roosevelt.
c) To design a solution technique that combines optimization and simulation for the stochastic version of the problem.
d) To design an interface for the proposed solution technique.
e) To quantify the impact of the proposed solution approach by comparing the results of the operating costs and total service times with the ones obtained with the current strategy applied by Instituto Roosevelt.

4. Methodology

a. Data collection for problem solution

Within the current problem, different parameters are considered necessary for the development of the proposed solutions:

a) Problem's parametrization:

i) Type of Doctors: Currently, IR carries out two types of service provision contracts for HHCS: Weekend doctors (Saturday-Sundays and Holidays) and Weekday doctors (Monday-Friday).
ii) Flexible Availability: Because each doctor is a service provider contract, they choose their availability for each day monthly. It is notified in advance if they are available for each day of the month to be chosen or not.
iii) Service Time Windows: It is related to the type of doctors' employment contract and their flexible availability. They can choose every day if they work part-time or full-time each day. The difference is the total time that each doctor can (and decide to) work during the day. Although service time windows may vary on different days for each doctor, they are usually the same average times. There are cases in which doctors notify in advance of a different working time limit than usual due to external commitments. Therefore, it is necessary to respect the time available for the day of assignment of routes to the doctors.
iv) Demand: From the historical data obtained from IR, it is observed that the demand is made up of two factors: previous day's admissions and days of stay within the system. Daily patient admissions are modeled with stationery and trending models according to the month that will be forecasted. Then, the errors are modeled by bootstrap and the days of stay are modeled by means of an empirical probability distribution.
v) Attention Time: It is the estimated time that lasts the entire care of a patient. This time is independent of the different services packages offered by IR. The attention time is 20 minutes for each patient and 60 minutes to review hospital admissions.

b) General information parametrization:

i) Doctors' cost: Doctors' contract is for the provision of services. The total cost to be paid to each doctor is given by the total time worked.

ii) Vehicle rental cost: Currently, IR rents vehicles from its supplier to transport the doctors for the next day's assigned routes.
iii) Average monthly speed: The average speed parameter in Bogota is extracted from the information provided by the observatory of long, medium, and short distance freight movement (*Observatorio - Cámara de Comercio de Bogotá*, n.d.).

On the other hand, to estimate travel times on the planned routes, the following parameters are considered:

i) Nodes' location: Upon receiving as input the addresses of the patients to be seen the next day, it is used an open-source repository that connects to a free API from Microsoft Bing Maps (Ortiz-Rubio, 2021). The patients' addresses are translated into specific geographic location coordinates (latitude and longitude) that are stored in the database.
ii) Distance between nodes: As mentioned above, the open-source repository and the different nodes' location allow us to use a special function to find the geodesic distances between two points.
iii) Vehicle speed: The speed at which vehicles travel along the city's road corridors does not remain constant throughout the day. It is directly influenced by several factors, such as roadworks, accidents, and protests. These factors generate variations in the travel times used to move between different points along a route. Therefore, it is important to analyze the effect generated by the variability of speeds, modeling their uncertainty through Monte Carlo simulation from the Lognormal distribution, which is suitable for modeling positive random variables such as speed (Guimarans et al., 2016). This probability density function is used to generate the speeds, using as parameters the average speed recorded in the observatory of long, medium and short distance freight movement (*Observatorio - Cámara de Comercio de Bogotá*, n.d.), and a deviation of 20% of the average speed proposed, which represents medium variability according to (Hollander & Liu, 2008), in order to evaluate the behavior in the stochastic approach.
iv) Travel time between nodes: By estimating the geodesic distance from two locations and the vehicle speed, it is possible to estimate the arrival time from an origin to a destination.

b. Mixed Integer Linear programming model for the deterministic version of the HHCRSP

a) Tactical Scheduling and Staffing Problem

The problem is initially proposed with the monthly staffing and scheduling over the days to meet the forecasted demand. The main decision corresponds to quantifying the number of doctors needed for the forecasted demand and their respective assignments in the monthly schedule. The objective is to minimize tactical costs corresponding to hiring and doctor's average monthly allowance costs. Additionally, IR wanted to ensure a minimum workload balance on the total days allocated in the planning month for each doctor hired. Currently, IR hires doctors by service provision, which implies that there are no fixed schedules, and the scheduling must consider whether the doctor is hired on weekdays, weekends, or the whole week. Also, it needs to consider the available and flexible days that the doctors reserve for personal matters and the daily time windows. Because many times the doctors work in other entities or perform external activities that prevent them from working at certain specific times throughout the month. This information is shared at the beginning of each month with the hired doctors. Below are presented the sets, parameters, variables, and constraints of the MILP model proposed, inspired by (W. Liu et al., 2021; Jamal Abdul Nasir & Dang, 2018; Yong Shi et al., 2017a, 2017b).

Sets	
D	Planning horizon days
M	List of doctors
Parameters	
$\boldsymbol{disp_{md}}$	Availability of the doctor $m \in M$ on the day d $\in D$
$\boldsymbol{dem_d}$	Daily demand on day d $\in D$
$\boldsymbol{R_m}$	Attention ratio of the doctor $m \in M$
$\boldsymbol{cont_m}$	Binary parameter: 1, if the doctor $m \in M$ was hired in the previous month; 0 otherwise
$\boldsymbol{CA}$	Cost of assignment of the day over the doctor
$\boldsymbol{Ch}$	Hire cost
$\boldsymbol{CM}$	Maximum workload level (20%)
Decision Variables	
$\boldsymbol{X_{md}}$	Binary decision variable: 1, if the doctor $m \in M$ is assigned on day d $\in D$; 0, otherwise
$\boldsymbol{Z_m}$	Binary decision variable: 1, if the doctor $m \in M$ is hired in the current month; 0, otherwise
$\boldsymbol{monthDays_m}$	Total days assigned in the planning on doctor $m \in M$
$\boldsymbol{Dmax}$	Maximum days assigned to a doctor
$\boldsymbol{Dmin}$	Minimum days assigned to a doctor
Objective Function	
(1) $\boldsymbol{Min\ Costs = \sum_{m\forall M;d\forall D} X_{md} * CA * R_m + Ch * \sum_{m\forall M} Z_m - cont_m}$	
Model constraints	
(2) $\boldsymbol{\sum_{m\forall M} X_{md} * R_m \geq dem_d}$	$\boldsymbol{\forall d \in D}$
(3) $\boldsymbol{X_{md} \leq Z_m}$	$\boldsymbol{\forall m \in M}$
(4) $\boldsymbol{Z_m \geq cont_m}$	$\boldsymbol{\forall m \in M}$
(5) $\boldsymbol{X_{md} \leq disp_{md}}$	$\boldsymbol{\forall m \in M\ ;\ \forall d \in D}$
(6) $\boldsymbol{\sum_{w=0}^{6} X_{m(d+w)} \leq 6}$	$\boldsymbol{\forall m \in M\ ;\ \forall d < (30-6) \in D}$
(7) $\boldsymbol{\sum_{d\forall D} X_{md} = monthDays_m * \sum_{m\forall M} disp_{md}}$	$\boldsymbol{\forall m \in M}$
(8) $\boldsymbol{Dmax \geq monthDays_m - NM * (1 - Z_m)}$	$\boldsymbol{\forall m \in M}$
(9) $\boldsymbol{Dmin \leq monthDays_m + NM * (1 - Z_m)}$	$\boldsymbol{\forall m \in M}$
(10) $\boldsymbol{Dmax - Dmin \leq CM}$	

The objective function (1) overseed minimizing of assignment and recruitment monthly costs. The problem considers the cost per hour of a doctor in relation to the available hours of the assigned doctor on that specific day. In the case of hiring cost, this applies only to doctors who were not hired the previous month and who are required for this month's demand. Hire cost is evaluated by the administrative costs involved in the hiring process (human resources time in managing the documentation, contract's legalization, resumes reviewing, interviewing, and doctor's selection.

Constraint (2) ensures the necessary staffing to meet the projected demand in the month to be scheduled. Constraint (3) defines the doctor's status, whether the doctor is hired/required for that month in planning. Constraint (4) prioritizes continuing to hire doctors who were already hired in the previous month. Constraint (5) assigns the doctors by their availability on the days. Constraint (6) prevents the doctors' staff from working more than six days in a row without rest. The set of constraints (7-10) helps balance the workload by reducing the gap between the maximum and minimum planned allocation between different doctors hired in the scheduled month. CM is defined as a maximum workload percentage difference between doctor's schedules allowed by IR.

The solution of MILP scheduling model provides a solution in optimal computational times for the real instances handled by the IR, the mathematical model is used as the solution methodology for both deterministic and stochastic comparisons. The execution time did not exceed 1.2 seconds for the real instances to the current problem in IR and deterministic version. The solution provided is better than the current assignment. These comparisons are demonstrated below (5.4. Performance tests).

b) Operational Scheduling and Routing Problem

The following MILP model is inspired by (Jamal Abdul Nasir & Dang, 2018; Restrepo et al., 2017, 2020) and defines the routes assigned to each doctor who was assigned to work that day. The problem solution proposes the best sequence of nodes to complete the visit of all patients. In this case, IR addresses a multicriteria objective function by minimizing the routes operation costs and minimizing the workload balance gap on the doctors' routes. The model considers the different working time windows of each doctor. Below are presented the sets, deterministic parameters, variables, and constraints of the MILP model proposed.

Sets	
D	List of patients (New and returning)
M	List of doctors
Q	Nodes
Subsets	
$\boldsymbol{Q^o}$	Origin nodes
$\boldsymbol{Q^d}$	Destination nodes
Parameters	
$\boldsymbol{LTW_m}$	Minimum available time of doctor $m \in M$
$\boldsymbol{HTW_m}$	Maximum available time of doctor $m \in M$
$\boldsymbol{t_{ij}}$	Travel time to go from node $i \in \boldsymbol{Q^o}$ to node $j \in \boldsymbol{Q^d}$
$\boldsymbol{ta_j}$	Attention patient time j $\in P$
$\boldsymbol{Cv}$	Cost per minute of vehicle rental
$\boldsymbol{Cm}$	Cost per minute of doctor
NM	Very large number
Decision Variables	
$\boldsymbol{X_{mij}}$	Binary decision variable: 1, if the doctor $m \in M$ is assigned on the route from node $i \in \boldsymbol{Q^o}$ to node $j \in \boldsymbol{Q^d}$; 0, otherwise
$\boldsymbol{q_{mi}}$	Continuous decision variable of the arrival time of the doctor $m \in M$ to the node $i \in Q$
$\boldsymbol{O_m}$	Working time assigned percentage to doctor $m \in M$ regarding his available time on that day of routing assignment
O$\boldsymbol{max}$	Percentage of maximum labor utilization assigned to a doctor
O$\boldsymbol{min}$	Percentage of minimum labor utilization assigned to a doctor
Objective Function	
(1) $\boldsymbol{Min\ Costs} = \sum_{m\forall M; i\forall Q^o; j\forall Q^d} \boldsymbol{X_{mij}} * \left(\boldsymbol{ta_j} + \boldsymbol{t_{ij}}\right) * (\boldsymbol{Cm} + \boldsymbol{Cv})$	
(2) $\boldsymbol{Min\ Balance} = \boldsymbol{Omax} - \boldsymbol{Omin}$	
Model constraints	

$$(3)\ \sum_{m\forall M}\sum_{i\forall Q^o} X_{mij} = 1 \qquad \forall j \in P$$
$$(4)\ \sum_{j\forall Q^d} X_{mOj} = 1 \qquad \forall m \in M; O = IRo$$
$$(5)\ \sum_{i\forall Q^o} X_{miF} = 1 \qquad \forall m \in M; F = IRf$$
$$(6)\ \sum_{i\forall Q^o(j\neq h)} X_{mjh} = \sum_{k\forall Q^d(k\neq h)} X_{mhk} \qquad \forall m \in M;\ \forall h \in P$$
$$(7)\ q_{mO} = LTW_m \qquad \forall m \in M;\ O = IRo$$
$$(8)\ q_{mj} \geq (LTW_m + t_{Oj}) * X_{mOj} \qquad \forall m \in M; \forall j \in P; O = IRo$$
$$(9)\ q_{mh} + \left(ta_h + t_{hj}\right) * X_{mhj} \leq q_{mj} + NM * (1 - X_{mhj}) \qquad \forall m \in M; \forall j \in Q^d; \forall h \in P$$
$$(10)\quad q_{mj} + \left(ta_h + t_{hj}\right) * X_{mjF} \leq HTW_m \qquad \forall m \in M; \forall j \in P; F = IRf$$
$$(11)\quad \sum_{i\forall Q^o}\sum_{j\forall Q^d} X_{mij} * \left(ta_h + t_{hj}\right) = q_{mF} - q_{mO} \qquad \forall m \in M;\ F = IRf;\ O = IRo$$
$$(12)\quad q_{mF} - q_{mO} = O_m * (HTW_m - LTW_m) \qquad \forall m \in M;\ F = IRf;\ O = IRo$$
$$(13)\quad Omin \leq O_m \qquad \forall m \in M$$
$$(14)\quad Omax \geq O_m \qquad \forall m \in M$$

Two objective functions were considered to solve the problem described above. The first objective (1) oversees minimizing the operative costs associated with the routing operation (the hourly cost of each doctor and the transportation costs). The second objective function (2) minimizes the gap differences between the maximum workload of the doctor’s assignment and the minimum. The balance is worked out as a percentage regarding the total time assigned to the route of each doctor and its available time for that day. Constraint (3) ensures that the patient is seen only once by a single doctor. Constraint (4) and (5) indicate that all doctors’ routes must start from IR and end in IR. Constraint (6) preserves the route flow, it ensures that if an arc between nodes (j,h) is performed by a doctor m (i.e. $X_{mjh} = 1$), the arrival to h and its next destination (i.e. $X_{mhk} = 1$) Will be by the same doctor m. Constraint (7) indicates the route start time. Constraint (8) indicates the arrival time for the first patient to each doctor, it is the travel time from IR to the first patient on the route. Constraint (9) indicates the arrival time for the rest of the patients, which considers the travel time and the care time for each patient assigned to each doctor’s route. Constraint (10) ensures the time limit of each route, it is important to consider the maximum time window the doctor has available to see patients. Constraint (11) relates the final and initial arrival times as the total route time of each doctor. The set of constraints (12-14) identify the maximum and minimum percentage time assigned with respect to each doctor's available time to reduce this gap in objective (2).

c. Solution technique for the deterministic version of the HHCRSP

I. Genetic Algorithm

Genetic Algorithm (GA) metaheuristic allows good solutions, to larger instances, in a shorter computational time compared to MILP models. For the current instance of the IR and the number of daily patients to schedule, the mathematical model did not provide opportune computational times. For this reason, this project decided to use a robust alternative found in the literature: the NSGA-II algorithm within the genetic algorithm in order to solve the current multi-objective routing problem.

a). Chromosome definition: Based on chromosome proposals for Multiple Traveling Salesperson Problem (MTSP) in genetic algorithms (Carter & Ragsdale, 2006), the following chromosome design is chosen:

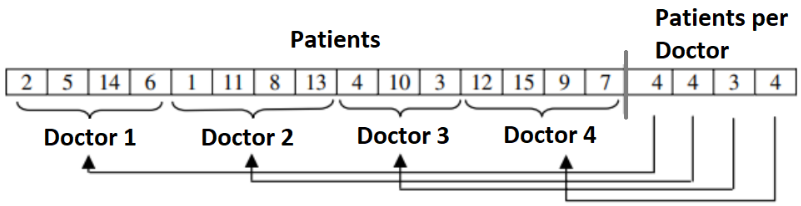

Figure 2: Example of the two-part chromosome representation. Inspired by (Carter & Ragsdale, 2006)

b). Solution Representation: Initially, the chromosome will be filled by generating random numbers without repeated values, which will represent the patient to be attended. Then, 100% of the first population are selected and their chromosomes are adjusted by the Balance Methodology, then are adjusted with the Nearest Neighborhood algorithm starting from the first random node. The solution described below:

- Balance Methodology: This is an own authorship algorithm created to better balance the number of patients between doctors' routes. In this, the methodology defined a balance constant, which is the ratio between the number of patients over the number of available doctors (the final number will be a positive integer). This is the ideal number of patients to be seen by each doctor. However, this number of patients is met if the doctor is unable to see any more patients, the assignment to that doctor is stopped until the last possible patient is to be seen within the available time.

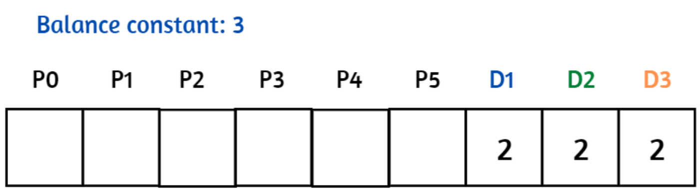

Figure 3: Example of the balance methodology representation.

- Nearest neighborhood: The chromosome is sorted by the nearest neighbor algorithm starting from the first random patient. Then, a few consecutive patients from the chromosome are assigned to each doctor's route until the doctor attends the number of the patients defined by Balance constant or the total route time does not exceed the maximum doctor's time window. This patient's allocation maximizes the doctor´s utilization.

c). Crossover operator: The selected operator is Order Crossover (OX), which has shown superior performance in the context of traveling salesman problem (TSP) when compared experimentally with six other operators (Uniform Crossover Operator, Cycle Crossover, Partially Mapped Crossover, Uniform Partially Mapped Crossover, and Non-Wrapping Ordered Crossover), obtaining better results, according to (Otman, 2011)**.** The OX consists of creating two children from two parents, from which two random points are selected. Then, the patients between those points of parent 1 are copied in the same positions to child 1. Then, the empty positions, which are before and after the randomly generated points, are copied in the same order in which they appear in parent 2 by evaluating that there are no repeated values in the chromosome. To obtain the second child, the same procedure must be done, exchanging parent 1 with parent 2 (Kumar G et al., 2017).

The following is a graphical representation as an example of the use of Order Crossover (OX) for the creation of child 1:

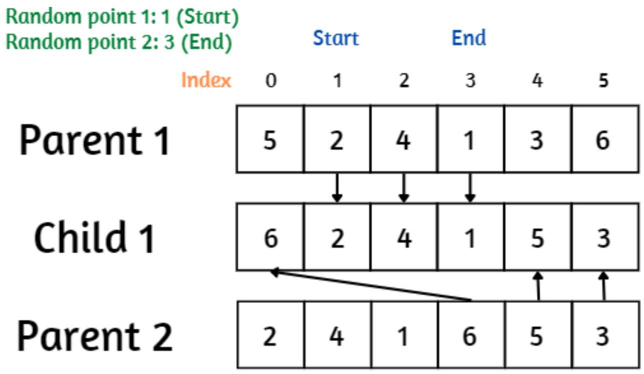

Figure 4: Example of the Order Crossover representation. Inspired by (Kumar G et al., 2017).

According to the graph above, the first random point generated is 1 and the second point is 3. In this way, the patients in the range between 1 and 3 from parent 1 will be copied to child 1 at those same positions or indexes. Then, the indexes before the first random point generated (i.e., 0), and those after the second random point (i.e., 4 and 5) of parent 2 will be evaluated, by analyzing if these values are not already immersed in child 1. In case the values are repeated, the next position is evaluated until no values are repeated and the vector is filled.

d). Mutation operator: The selected mutation operator is the Reverse Sequence Mutation (RSM), which has shown to have better results and performance when it is used with the ordered crossover operator (Abdoun et al., n.d.). This operator needs two random points in the chromosome, which are going to be the break points. The values between the break points are going to be reversed to obtain the muted chromosome. The following is a graphical representation as an example of the use of Reverse Sequence Mutation (RSM), for the creation of a child:

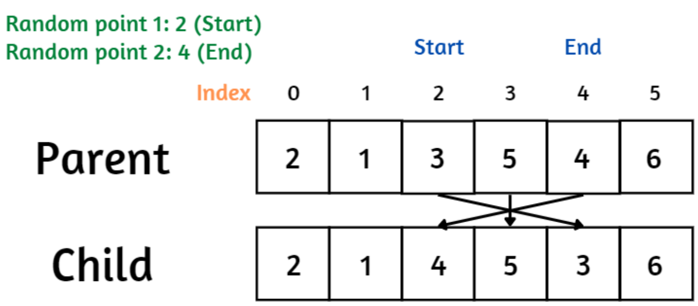

Figure 5: Example of the Reverse Sequence Mutation representation. Inspired by (Otman, 2011)

In this, the first random generated point is 2 (start), and the second random point is 4 (end). The values comprised in this range of the parent will be reversed and inserted in the same indexes in the child. The values before the start point and after the end point are inserted in the same positions in which they were originally found in the parent.

II. NSGA II Approach within the Genetic Algorithm

e*). Selection and replacement:* Once the initial population Pt has been generated and new offspring have arisen by crossing and mutation (Qt), this new Rt conjunct will be evaluated and ranked under the criterion of non-dominated sorting. The non-dominated sorting process classifies the individuals on different fronts regarding their domination criterion. The best front is called “Pareto Front”, which is composed of individuals who are not being dominated with respect to other individuals on the two objective functions. An individual is not dominated if it is the best in both objective functions with respect to another. The non-dominated sorting process classifies the individuals on different fronts with respect to the number of individuals that dominate them (figure 6 - 1° selection). Once ranked by group, the individuals corresponding to the first fronts are selected until the size of individuals of the first population is reached. In the moment when a front of individuals cannot be completely selected, a second ranking is carried out to determine the best individuals of the group (figure 6 - 2° selection). This second ranking is called “crowding sorting distances”, which prioritizes the most distant individuals regarding the others belonging to the same front. This is under the aim of generating diversification in the algorithm and it is how the new population for the next generation is obtained (Deb et al., 2002; J. Liu & Chen, 2019; Nisperuza et al., 2019).

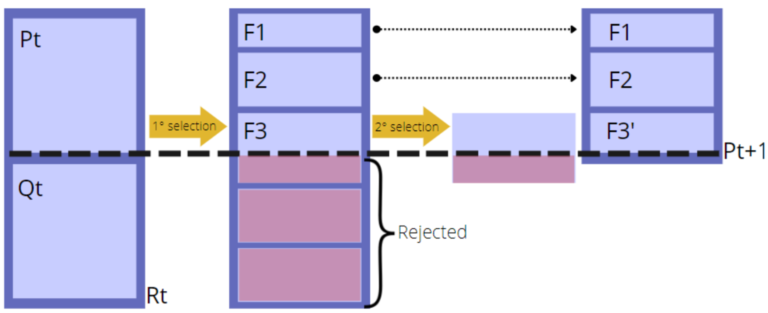

Figure 6. NSGA II Method. Inspired by (Deb et al., 2002)

d. *Solution technique for the stochastic version of the HHCRSP*

In this project, two stochastic parameters are considered: stochastic demand and stochastic travel times. The stochastic demand is an input parameter for the tactical staffing and scheduling monthly decisions and the stochastic travel times are an input parameter for the operational scheduling and routing problem. In this way, the following sections explain in detail how stochastic solutions are approached.

I. *Stochastic demand*

IR’s demand forecasting consists of two parts: the daily patient admissions forecast and the estimation of the length of each patient's stay in the system (days of stay). In this way, a forecast of daily admissions is made, and errors are simulated with time series models to adjust it. After that, for each forecasted admission, a value of an empirical distribution is simulated in order to calculate the days of stay of a patient in the system. By combining the forecasted admissions with the simulation of the days of stay, the daily number of patients to be attended per day, of the month under consideration, is obtained. This stochastic demand obtained is an input parameter for the tactical staffing and scheduling monthly decisions. In detail, there are eight steps to build the demand forecast. The first six steps refer to the estimation of patient admissions over a month by means of time series models. The last 2 steps refer to the simulation of days of stay for each patient admitted. The 8 steps are:

STEP 1: Select the training and test windows from the historical input data.

STEP 2: Select the best fit forecast model for the first and second training window.
STEP 3: Forecast the test window with the first forecasting model selected in step 2.
STEP 4: Calculate the forecast errors (residuals) regarding the test window.
STEP 5: Forecast the month under consideration with the second selected forecast model.
STEP 6: Simulate the errors (residuals) from step 4 to adjust the forecast patient admissions model of step.
STEP 7: Simulate the number of days of stay for each forecast patient admission.
STEP 8: Evaluate the days of stay of each patient to count how many patients there are per day of month.

The first step is to select two training windows and one test window. The test window is the month prior to the month under consideration. The first training window is the month of the test window one year earlier and the second training window is the month under consideration one year earlier. Then both training windows are tested with the SES, Holt and ARIMA time series models, to define which forecast model has a better fit with the data set. Once the time series model with optimal parameters for each training window are defined, the first selected model (the one of the first training window) is forecasted by comparing it with the test window, in order to calculate the forecast errors (residuals). Then, the revenue admissions forecast is performed with the second selected model as shown in (Figure 7).

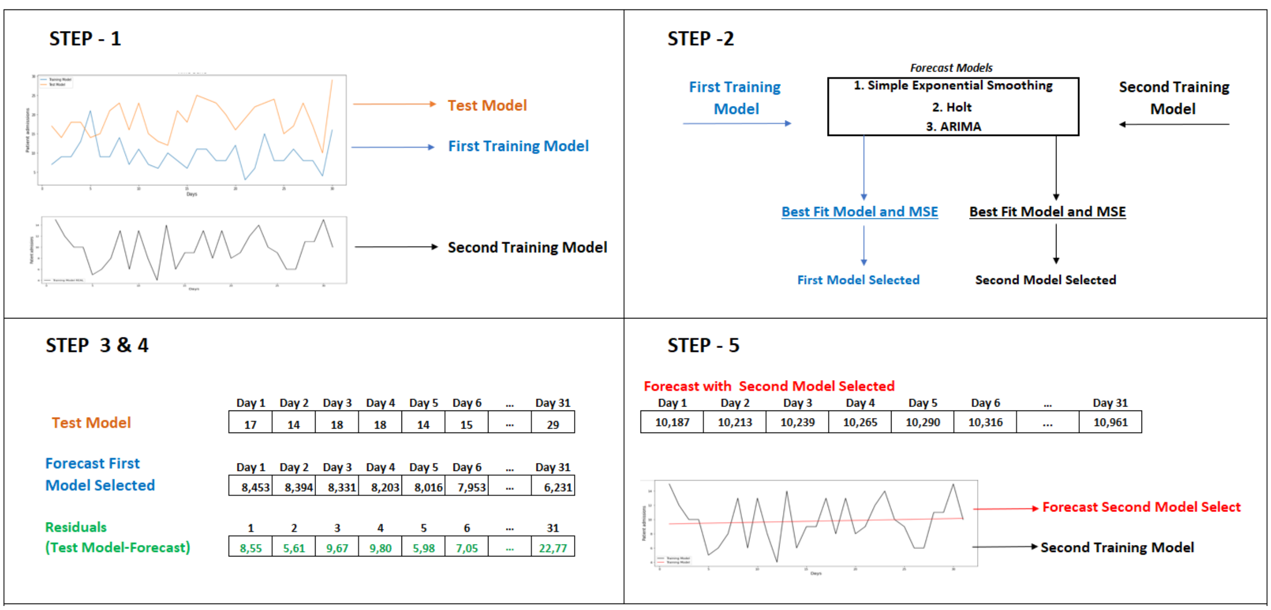

Figure 7. Step 1 to Step 5 forecast estimation methodology

The sixth step consists of choosing a random residual among those calculated previously and adding it to each daily forecast with the second forecast model. Once each randomly calculated error is added to each forecast value, the forecast of patient admissions can be adjusted with a correct mean of the forecasted year, as shown in the image (Figure 8). The error simulation performed allows to adjust the mean for the predicted month since it is assumed that the errors between months remain the same. So, the residuals generated by the comparison of the first training model and the test window represent the mean gap between one year and another.

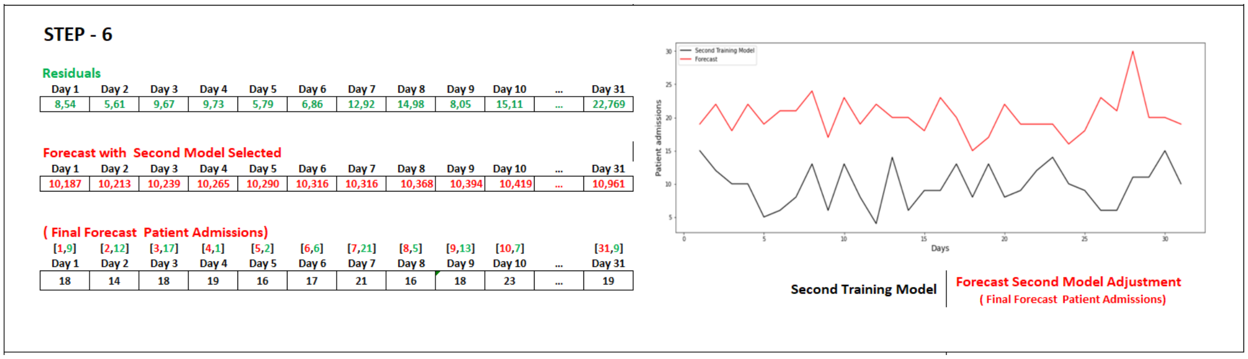

Figure 8. Step 6 Forecast estimation methodology

To build the final demand vector, the days of stay of each patient admitted to the system must be simulated. The patients admitted in a day and their days of stay simulated with the empirical probability function are evaluated. The demand of a day will be the patients admitted on the previous day, together with the patients who stay in the system on the day evaluated, as shown in the image (Figure 9).

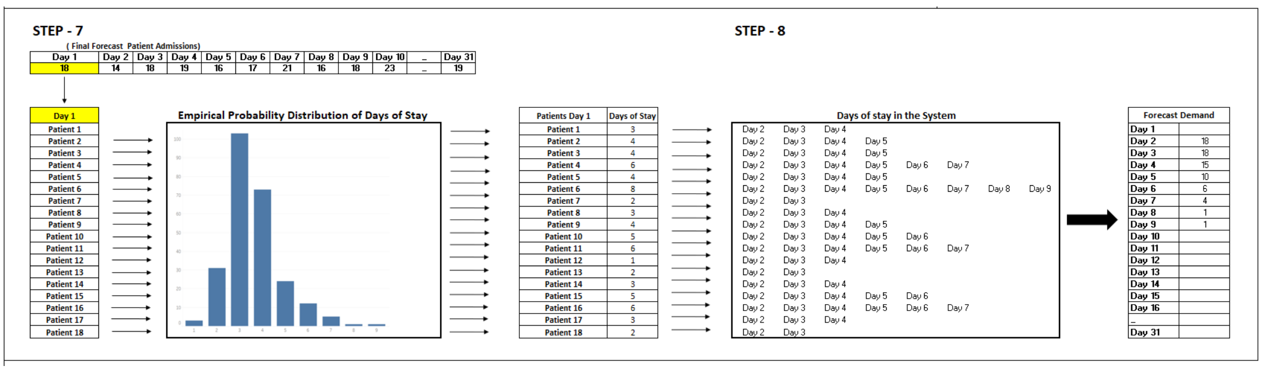

Figure 9. Step 7 to Step 8 Forecast estimation methodology

II. Stochastic staffing and scheduling approach

The stochastic staffing and scheduling approach is based on the demand forecasting model explained above. This forecasting model generates different demand scenarios, which are simulated and evaluated within the staffing and scheduling MILP. This simulates multiple staffing and scheduling solutions for each demand scenario. After converging on a mean cost with confidence intervals of less than 2.5%, the mode of the number of doctors needed per month is obtained. Then, the number of doctors given by the mode, and the doctors with the highest frequency in the previous scheduling assignments, are simulated 100 times until obtaining the number of doctors required with the least cost in demand shortages. Each simulation evaluates the statistic's performance (cost confidence intervals) of the number of doctors needed in the month and their respective assignments in the monthly schedule for each demand scenario.

III. *Stochastic travel times and routing simheuristic*

The stochastic travel times are an input parameter for the operational scheduling and routing problem. From our literature review, (A. A. Juan et al., 2015) describes a general methodology called "Simheuristics," that allows for extending metaheuristics through simulation to solve stochastic combinatorial optimization problems (COPs). Based on (A. A. Juan et al., 2015), the stochastic solution proposal for the IR´s routing problem is addressed by generating a simulation within the GA. First, the displacement speeds are generated using the Lognormal probability density function with the average monthly speed recorded in the observatory of long, medium, and short distance freight movement (Observatorio - Cámara de Comercio de Bogotá, n.d.). The standard deviation entered as a parameter of the Lognormal distribution is 20% of the average monthly speed based on different articles in the literature (Guimarans et al., 2016; Hollander & Liu, 2008; A. Juan et al., 2011). This, with the objective of simulating the speeds at which the doctors will move to visit the assigned patients. In this approach, 100 different speeds are generated, according to the methodology proposed by (A. A. Juan et al., 2015). Then, the simheuristic consists of replicating each GA´s chromosome sequence with 100 simulations from different speeds for the same individual. After having all replicas, each individual is measured by the average objective functions obtained from its own evaluation of its replicas. The simheuristics algorithm is described in detail in the diagram below.

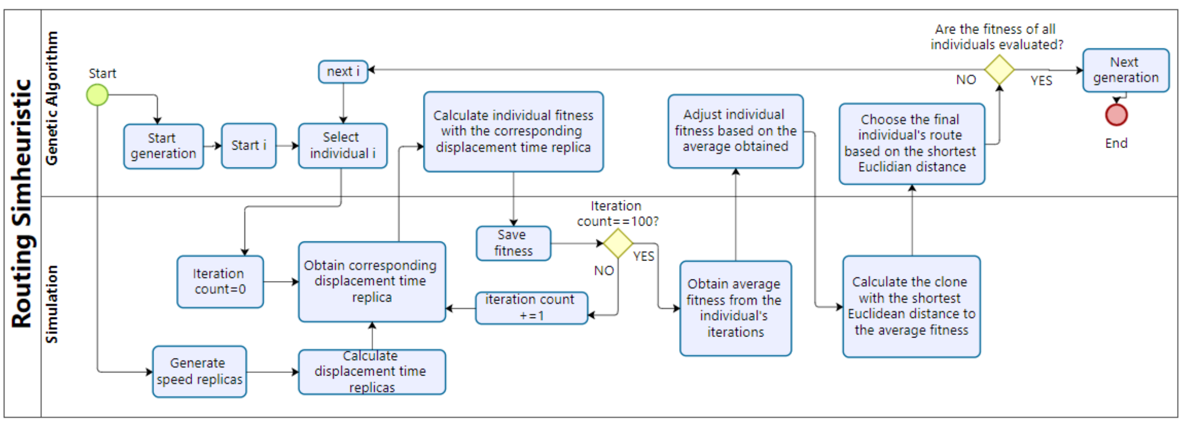

Figure 10. Routing simheuristics algorithm.

For the development of the simheuristic, the execution of the genetic algorithm is carried out, and in the creation of the individuals, each one of them is cloned 100 times. Each clone is evaluated for its feasibility and its objective functions (costs and workload balance) with one speed replica value obtained from the 100 Lognormal simulations. Then, only the feasible clones are kept, and the averages of their objective functions are calculated. Those averages will be the final values for the objective functions of the simulated individual. Also, the individual's route will take the assignation of the clone that has the shortest Euclidean distance to the average because that is the reference to consider both objective functions.

e. *Interface and final design deliverable*

The final deliverable is a tool to define a monthly workforce scheduling and their daily route for the home health care service of a hospital entity, focused on the study of the Home Health Care Routing and Scheduling Problem (HHCRSP). The tool considers both deterministic and stochastic scheduling and routing scenarios to develop a preventive solution. The preventive workforce scheduling contemplates uncertainties in demand forecasting and the preventive daily route scheduling includes stochastic travel times. In addition, the tool considers the series of restrictions associated with Instituto Roosevelt’s case study and the simulation of their different scenarios to minimize the associated costs with the Home Health Care Service provided and generate a workload balance in the monthly schedule and daily doctor's routes assignments.

The proposed tool is developed in two principal phases, the first one makes a forecast of the demand through a stochastic model that allows to estimate the required number of doctors to be recruited for the period under analysis. This first phase is required for the second one because the second one schedules the daily routes for the available resulting doctors from the first phase. The tool displays the resulting values of forecast demand, the number of doctors required monthly and the sequenced nodes for each doctor available for the next day. In that way, this tool makes it possible to reduce the planning time and avoid the excess of workload generated by the manual routes designed for each doctor every day. For access to the tool by IR users, an interface was developed. The tool has an interface through which the user can enter specific data, such as patients to be scheduled and the available doctors with their time windows. Also, relevant information about each patient can be entered, such as name, age, address, date of admission, health insurance company, observations made by the doctor, among other things. “User Manual” (annex 1) shows the visual design of the interface and the functionalities it offers.

f. Performance test and comparative results

I. Factorial design for Genetic Algorithm and NSGA II hyperparameters

A factorial design (DoE) was carried out in order to determine experimentally the values of the hyperparameters for the heuristic and simheuristic model developed for the routes problem. For this factorial design, 3 factors with 3 levels and 3 replications were proposed, in order to analyze possible non-linear behaviors (curvature) in the factors proposed for the design. On the (annex 2), the proposed factors and the corresponding levels for the 3^3 factorial designs are observed. It was determined that the 3 factors are significant, the first factor with high level, the second factor with low level and the third factor with high level, however it was evidenced that the difference of effects of the levels in the context of the problem is not significant, due to the fact that the objective function varies in small costs, for that reason it was decided to work with smaller levels, with the objective of reducing the computational time of the model.

II. Demand Forecast

Below are the results of September 2021, March and April 2022 for the forecast proposal and their performances in error measures (Table 2). It can be observed that the mean absolute percentage error is maintained between the admissions and demand forecasts, so it can be identified that the variation of percentage errors depends mainly on the estimation of patient admissions. On average, there is an estimation error between 10 and 15 patients per day, which represents the use of an additional doctor or the adjustment of loads for the doctors available in the tactical planning system. This is not serious because the scheduling simulation considers the assignment and hiring of contingency doctors.

Table 2. Forecast error measures

Month	Patient Admissions Forecast			Demand Forecast		
	MSE	**MAD**	**MAPE**	**MSE**	**MAD**	**MAPE**
September 2021	47.73	5.26	25.01%	265.23	13.56	25.01%
March 2022	52.00	5.74	25.15%	137.06	10.03	25.15%
April 2022	26.83	4.56	18.57%	280.66	14.80	18.57%

Although maintaining these error measures represents an impact on the tactical decision, the technique that is being used allows to predict the cumulative behavior of the demand due to the days of stay in the system for each patient. Figure 11 shows the forecast of patient admissions in March 2022 with respect to actual admissions. It is evident that the mean of the forecast is very similar to that of the actual admissions, but the difference lies in the predicted peaks and the stationary variation that may exist on some days. Figure 12 shows the comparison between the actual demand in March and the final forecast. This forecast follows the same trend as the demand and presents the cumulative effect of the days of stay of the patients, which is seen as smoothed hills. Being able to estimate the cumulative effect on demand is an indicator that the simulation of days of stay does allow capturing the behavior of patient's demand.

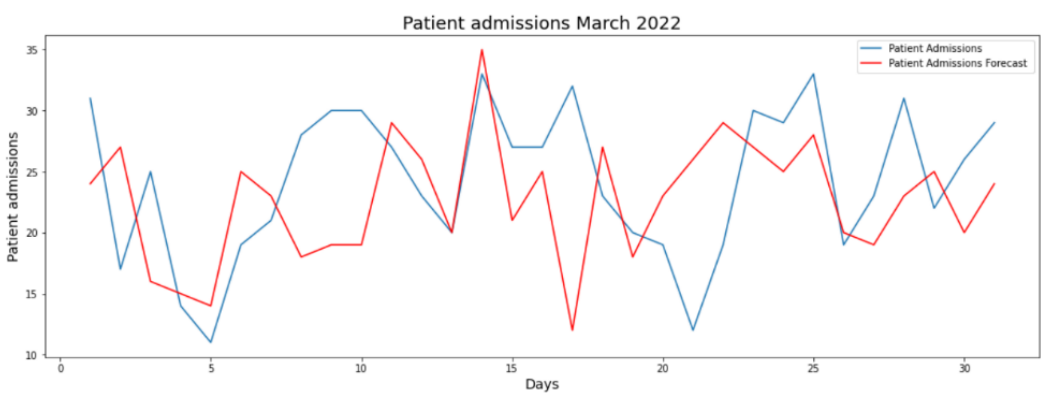

Figure 11. Patient Admissions March 2022 vs Patient Admission Forecast

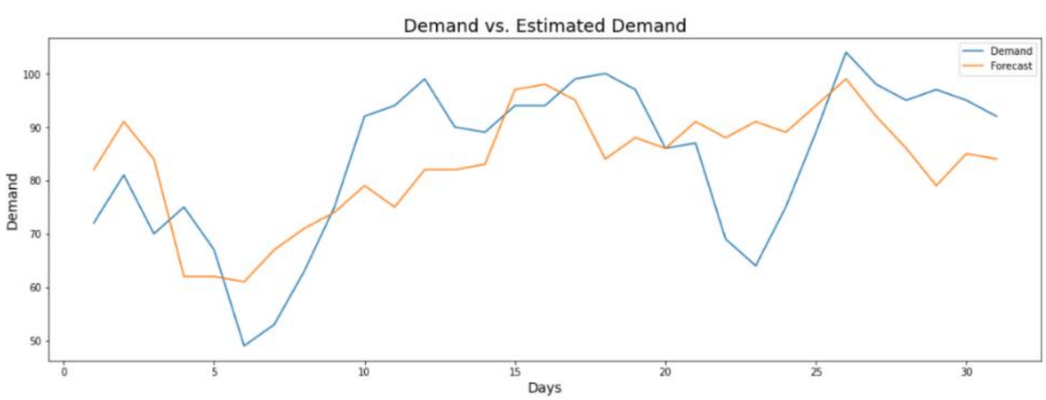

Figure 12. Patient Demand March 2022 vs Patient Demand Forecast

III. Staffing and Scheduling problem

a. Comparison between MILP, staffing and scheduling simulation and current Instituto Roosevelt's results with the real demands.

Below are the objective function results of October 2021 and April 2022 for the actual daily demands by fixing the stochastic solution obtained with the simulations carried out without considering the real demand (A), the deterministic solution obtained with the forecasted demands without knowing the real demand (B), and the currently Instituto Roosevelt's results (C). Table 3 shows the results of Scheduling and hiring costs and Workload balance satisfaction for the three comparative models. In addition, it shows the results of comparative percentage improvements between all instances.

Table 3. Comparative percentage improvements.

	A: Staffing and Scheduling Simulations with real demand				B: MILP with real demand				C: Currently Instituto Roosevelt's results			
Month	Scheduling and hiring costs	Workload balance satisfaction			Scheduling and hiring costs	Workload balance satisfaction			Scheduling and hiring costs	Workload balance satisfaction		
		Max	Min	Gap		Max	Min	Gap		Max	Min	Gap
October 2021	$44,313,082	50.0%	35.0%	15.0%	$44,644,282	57.1%	40.0%	17.1%	$71,870,400	100%	19%	81%
April 2022	$66,802,746	66.7%	47.4%	19.3%	$66,989,046	72.0%	52.4%	19.6%	$87,342,764	100%	100%	0%

According to Table 3, the Staffing and Scheduling Simulations with real demand always have a better performance in scheduling and hiring costs than the current solution that IR has and MILP. As shown in Table 4, the simulation manages to reduce by 38.3% the current costs of the IR for October and by 24% in that for April. That, without considering the reduction in the cost of the time spent by the boss on doing the monthly assignments. Likewise, the MILP evaluated with the actual demand, also improves the costs compared to the current Instituto Roosevelt's results. MILP reduces by 37.9% the current costs incurred by the IR in October and reduces by 23% the costs of the month of April

Table 4. Improvement percentage between comparisons

Month	Comparisons	Percent Improvement	
		Costs	Balance Gap
October 2021	A -B	0.7%	12.5%
	A-C	38.3%	81%
	B-C	37.9%	78.8%
April 2022	A -B	0.28%	2%
	A-C	24%	0%
	B-C	23%	0%

Notes: A: Staffing and Scheduling Simulations with real demand, B: MILP with real demand, C: Current Instituto Roosevelt's results

Taking into consideration now, the workload balance gap results, it is observed that in October both the simulation and the MILP reach an 81% and 78.8% improvement in reducing the workload balance gap, respectively. On the contrary, for April, Instituto Roosevelt manages to assign 100% of the doctors according to their availability. However, it is worth the tradeoff of sacrificing workload balance for the resulting cost benefit that offer both the simulation and the MILP.

IV. Routing problem

i. Performance of deterministic approach

The next table shows the performance of the proposed GA for the deterministic version of our problem. MILPS and GA metaheuristic approach are evaluated in different instances, which vary with respect to the number of patients to be attended and the available doctors. The large instance has 12 patients, because is the maximum number of patients the MILP program can run without taking longer than the time it takes a doctor to run the routes manually. The GAP, the resulting of the compliance of each one of the objectives functions based on the optimal values obtained from MILP shows a competitive result by giving an average difference of 16% of the costs (F1) and 0.4% on the workload balance (F2).

Table 5. Performance of deterministic approach according to MILP´s

GAP						**MILP computational time (s)**		**GA computational time (s)**	
Instance				**GA**					
	#	**Demand**	**Doctors**	**F1**	**F2**	**F1**	**F2**	**F1**	**F2**
Small	1	6	4	15,0215%	0,0000%	5,5222	10,1688	12,6847	16,0422
	2	6	3	15,0215%	0,0000%	1,6480	5,6564	11,9698	13,8345
	3	6	2	15,0215%	0,0000%	0,9844	3,0822	11,1926	13,7396
Medium	4	9	4	15,0859%	0,0000%	220,7317	5674,8519	17,7306	28,3491
	5	9	3	15,0859%	1,1260%	147,6501	1890,6271	16,6347	16,8549
	6	9	2	15,0859%	0,0109%	43,0683	12,2490	16,7323	15,9325
Large	7	12	5	15,5526%	1,7383%	5399,9862	5399,4563	43,7389	35,1515
	8	12	4	19,8472%	0,6421%	2934,2083	6415,9453	30,1620	36,2281
	9	12	3	19,8472%	0,1622%	3931,6528	5400,0000	31,8982	39,0357
Average compliance				**16,1743%**	**0,4088%**				

ii. Stochastic version

a. Comparison between deterministic solution, simheuristic and actual routing assignment in IR

For the stochastic solution, three instances with different levels of patients and hospitals were evaluated. In this, 50 replicas of the program were evaluated for each proposed scenario. The performance results obtained for the deterministic approach (NSGA II), the simheuristic approach (with 20% deviation of the average speed parameter), and the real cost of the routing that was performed by Instituto Roosevelt in each of the instances are presented on the table below.

Table 6. Performance of deterministic and simheuristic approach

	Deterministic approach		Simheuristic approach		Routing assignment IR	
	Balance	Costs	Balance	Costs	Costs	% Savings
Instance 1 **96 patients - 6 hospitals**	0.16	$2,450,382.07	0.16	$2,484,980.51	-	-
Instance 2 **81 patients - 5 hospitals**	0.08	$2,480,186.44	0.09	$2,523,009.79	$4,268,820.00	40.90%
Instance 3 **70 patients - 5 hospitals**	0.32	$2,482,654.14	0.33	$2,467,851.63	$4,105,720.00	39.89%

Outstanding results are obtained in the deterministic approach, since with the NSGA II the solutions obtained 100% of the time are better than the proposal made by Instituto Roosevelt. Also, with this approach, the routes are obtained in less than a minute, compared to the actual time spent by the coordinator of the HHCS, who spent an average of 2 hours a day routing the patients to be visited on the following day, thus generating a time saving of 99%, and allowing specialized medical professionals to focus on other activities of the service.

Additionally, the average costs of the different scenarios in the deterministic approach were $2,450,382.07, $2,480,186.44, and $2,482,654.14, for instances 1, 2 and 3 respectively. When compared it with the costs incurred by the Institute, it generated savings of close to 40% in instances 2 and 3. This reduces operating costs by presenting savings in terms of the effective assignment of doctors to the patients to be attended during the day and achieving a reduction in the number of hours that doctors are contracted.

On the other hand, the simheuristic presents better results than Instituto Roosevelt 100% of the time in all instances, with average costs of $2,484,980.51, $2,523,009.79, and $2,467,851.63, in instances 1, 2 and 3 respectively. In this scenario, simulating different speeds improves the deterministic genetic proposal, by considering the variability of the speed.

5. Limitations, conclusions, and recommendations.

Conclusions

This paper develops a tool to define monthly workforce scheduling and their daily route for the home health care service of a hospital entity, focused on the study of the Home Health Care Routing and Scheduling Problem (HHCRSP). The proposed tool is developed in three principal phases, the first one makes a forecast of the demand through a stochastic model that allows to estimate the number of patients to be assigned for each day's routes. The stochastic demand is the input parameter for the second phase, which estimates the required number of doctors to be recruited for the period under analysis and their monthly schedule. The third phase considers the daily scheduling and routing assignments.

Under the fulfillment of the proposed objectives, the mixed integer programming models to tackle the deterministic version of HHCRSP are presented. Regarding the deterministic solutions, the MILP scheduling model is used because of the optimal computational times for the real instances handled by the IR. However, since this does not happen with the MILP routing problem, its deterministic approach is addressed by implementing an NSGA II within the GA. The stochastic version of the problem is addressed by combining simulation within the optimization approaches (simheuristic). The stochastic staffing and scheduling approach is based on the demand forecasting model, which generates different demand scenarios that are simulated and evaluated within the staffing and scheduling MILP. Then, the stochastic solution proposal for the IR´s routing problem is addressed by generating a simulation within the GA algorithm and the stochastic travel times are the input parameters for it.

Regarding the performance results, it can be concluded that there is an estimation error between 10 and 15 patients per day on demand forecast which is still good because the scheduling simulation considers the assignment and hiring of contingency doctors. In the staffing and scheduling problem, the simulations with real demand and the MILP have better performance in scheduling and hiring costs than the current solution that IR has. That, without considering the reduction in the cost of the time spent by the boss on doing the monthly assignments. In the deterministic routing solution, the GA shows a competitive result by giving an average difference of 16% of the optimal costs and 0.4% on the optimal workload balance. In the stochastic routing component, it is evident that the results obtained by deterministic genetics with NSGA II are good, since 100% of the time they obtain better results than the Institute's proposal.

Limitations

Some limitations, presented during the development of the project, were mainly on the demand forecast because the available historical information on daily patient admissions and days of stay is just from 2018 to May 2022. For the proposed models, only data from 2019, 2021 and 2022 were considered because IR has incorporated over time different agreements with EPS institutions, which generates that 2018's demand is not representative. Additionally, 2020 data is totally atypical due to the pandemic situation presented and it also influences the demand effect in 2021 and 2022. Currently, the HHCS of IR continues to grow in EPS' agreements and it is stabilizing, so the predictability of the current demand scenarios is complex by the situation, the context and the available information. In that way, the demand forecast models have been a particular proposal that could best capture the behavior of the months to forecast, adjusting the annual average or the month considered.

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