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A decision support system for home dialysis visit scheduling and nurse routing

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ABSTRACT

Over the last years home dialysis has become the preferred treatment option for some patients with kidney failure. However, determining efficient and effective daily home-dialysis service plans imposes multiple challenges to hospital administrators, as it is a complex task with a number of interrelated decisions. These decisions are about the number of nurses required for daily visits and their travel itineraries, and involve multiple (often conflicting) objectives.

Working together with physicians and administrators from The Ottawa Hospital (TOH) in Canada, we have developed a system intended to support administrators of nephrology departments in creating daily visit schedules and routes for nurses assisting with dialysis treatment in patients' homes. The decision support system, called Home Dialysis Scheduler System (HDSS), employs a mixed-integer linear programming model to create daily nurse itineraries that minimize the cost of providing home dialysis for a pre-specified group of patients. In developing this model, we also considered nurses' workload balance, overtime work, need for mealtime breaks (lunch or dinner, depending on shift times), restrictions and preferences associated with the time of the visits, and different types of services provided to patients. The model was validated using data provided by the Division of Nephrology at TOH. The interface of the HDSS was developed following the principles of user-centred design and validated with a group of end-users. In the validation stage, daily visit schedules and nurse routes generated by the HDSS were compared to nurse itineraries created manually by hospital administrators. The use of the HDSS resulted in improved workload distribution among nurses, simpler routes, and reduced total distance travelled — which translates into lower costs for the home dialysis program. In this paper, we provide details about the mixed-integer linear programming model, describe the HDSS, and discuss its implementation results and managerial implications.

1. Introduction

Dialysis is a life-sustaining treatment for patients with end-stage kidney disease. There are two basic types of dialysis: hemodialysis and peritoneal dialysis. Hemodialysis involves purifying blood directly through an extracorporeal dialysis machine, whereas peritoneal dialysis involves filling up the peritoneal cavity with sterile fluid and allowing the peritoneal membrane to act as a natural filter. A patient can complete peritoneal dialysis at home while hemodialysis is usually done by trained healthcare professionals in a dialysis centre or hospital. Although clinical outcomes of both types of dialysis are similar, peritoneal dialysis offers the possibility of a more flexible treatment schedule, greater convenience for patients, and represents a more cost-effective option [14, 18, 34] . However, despite its benefits, the broader use of in-home dialysis is limited by the inability of some older and frail patients to perform the treatment independently [3, 15, 36] . For this reason, and with the ultimate goal of expanding the delivery of in-home peritoneal dialysis (hereafter simply called “home dialysis”), many healthcare authorities around the world provide hospitals with additional funding to support regional home-dialysis programs. Patients in these programs receive nursing visits up to twice a day to assist them with the use of the dialysis equipment [7, 21, 22] . This additional financial support has resulted in an increase in the utilization of home dialysis services, for example, in Ontario, Canada. However, recent

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Sets

P	: Set of patients
N	: Set of nurses
V	: Set $P \cup N$

Indices

i, j	: A patient, $i,j \in P$
k	: A nurse (nurse home), $k \in N$
l, m	: A location (patient or nurse home), $l,m \in V$

Input parameters

d_{lm}	: Distance from location $l \in V$ to location $m \in V$[km]
t_{lm}	: Travel time from location $l \in V$ to location $m \in V$[min]
a_i	: Earliest allowed service start time for patient i [min]
b_i	: Latest allowed service start time for patient i [min]
st_i	: Visit duration for patient i [min]
t_k	: Travel time from nurse k's home to the main nephrology clinic [min]
ws_k	: Shift start time of nurse k [min]
we_k	: Shift end time of nurse k [min]
al_k	: Earliest allowed mealtime break start time for nurse k [min]
bl_k	: Latest allowed mealtime break end time for nurse k [min]
R_{ik}	: 1 if nurse k can visit patient i, and 0 otherwise
LB	: Mealtime break duration [min]
KM	: Unit travel cost [dollars/km]
OV	: Unit overtime cost [dollars/min]
M	: A large positive constant (commonly known as big-M)

Decision variables

x_{lmk}	: 1 if nurse k directly visits location $m \in V$ after location $l \in V$, and 0 otherwise
y_{ik}	: 1 if nurse k takes a break right before visiting patient i, and 0 otherwise
y_{ik}'	: 1 if nurse k takes a break right after visiting patient i, and 0 otherwise
s_{ik}	: Service start time for patient i if he/she is visited by nurse k
l_k	: Start time of the mealtime break of nurse k
$over_k$	: Amount of overtime required from nurse k
μ	: Nurse workload balance variable

changes in funding has shifted the responsibility for providing home dialysis visits from regional healthcare authorities to hospitals, thereby increasing the need for decision support tools that help make an efficient use of the resources available at these programs.

Many home dialysis patients receive daily visits from nurses. A nursing visit is required to set up a peritoneal cycler (dialysis machine) and, in some cases, to connect and disconnect the patient from the cycler. Some of these visits are time sensitive as patients need to be connected to the cycler for a specific period of time. Home dialysis patients quickly become familiar with the nurses who visit them at home and, consequently, continuity of care by the same care provider plays an important role in patient satisfaction. If, on top of these considerations, we take into account other aspects of home dialysis delivery such as geographical location, shift times of the nurses, mandatory mealtime breaks (lunch or dinner, depending on the specific shift times), overtime work, and workload balance, then determining an efficient daily home dialysis visit schedule becomes a challenging task that is very difficult and time consuming if done manually.

This paper describes a decision support system, called Home Dialysis Scheduler System (HDSS), designed to help hospital administrators with the scheduling of home dialysis visits and the routing of nurses. This system uses a mixed-integer linear programming (MILP) model to optimize nurse itineraries with an objective function that combines multiple criteria: total distance travelled by all nurses, travel and overtime costs, number of nurses required to visit all patients, and workload balance across nurses. The objective function is minimized and each individual criterion is weighted to reflect its relative importance as requested by hospital administrators. The optimization model also considers patient-nurse compatibility restrictions (e.g., required skill level and case load complexity), nurse availability (i.e., shift times, mealtime breaks, and overtime work), patient preferences for specific visit times, and visit durations. Hospital administrators interact with the HDSS using a spreadsheet-like user interface. To the best of our knowledge, the HDSS is the first-of-its-kind decision support system available to hospital administrators in charge of home dialysis programs.

The remainder of this paper is organized as follows: Section 2 describes home dialysis delivery as implemented by the Division of Nephrology at The Ottawa Hospital (TOH) in Ontario, Canada. Section 3 reviews related relevant work and Section 4 introduces the MILP model that is at the core of the HDSS. Section 5 describes the development of the HDSS and Section 6 discusses the use of the system for visit scheduling and nurse routing in Ottawa, Ontario, Canada. Section 6 also reviews some of the managerial implications associated with the use of the system. Finally, in Section 7, the paper concludes with final remarks.

2. Problem definition

The home dialysis program at TOH is one of the largest dialysis programs in North America. It currently serves more than 220 patients and involves close to 18 full-time nurses. Before the development of the HDSS, visit scheduling and nurse routing decisions were made manually by the home-dialysis clinical care facilitator.

Every day, the care facilitator first needs to prepare a daily schedule for nurses either to provide in-home patient visits or to deliver teaching and clinical support to hemodialysis patients at a nephrology clinic located at one of TOH campuses. After having this information, and for each nurse, the care facilitator schedules the order in which patients are visited by creating routes depending on where the nurse lives and where the homes of the patients to be visited are located. Last minute changes to the schedule are either taken up by an available nurse who is close to the specific patient's home, or by one of the nurses assigned to clinic duties. The schedule for a given day is developed one day in advance and provided to the nurses before they finish their daily shift. Considering that the number of patients that need to be served and the number of available nurses are relatively stable throughout the week, developing a daily schedule instead of weekly or monthly is acceptable at this point of time.

During the set-up of the home dialysis program it was decided that nurses work in pre-defined teams that serve three areas of Ottawa and the National Capital Region: western, eastern, and central areas. Each area has a specific team of nurses providing care to patients that are geographically assigned to the area based on their home address. Nurses are given their schedules and routes depending on the team they are assigned to and work shifts (morning or evening). In the event of an emergency, nurses assigned to work in the home dialysis clinic can be requested to provide in-home service to any patient in any area. These nurses are called “floating nurses” (or hub nurses) and their services are also used to minimize the need for overtime work from the nurses visiting patients at their homes. In addition, there are some nurses working the evening shift who are assigned to a specific team during the daytime, but that can provide service to any patient after the start time of the evening shift. In that sense, these nurses can be considered as a special case of floating nurses. Existence of these three different work practices (overtime work, floating nurse from the clinic, and evening nurse) provides flexibility for the hospital administrator to plan visits to all patients who need to be visited on any given day.

The home dialysis program at TOH considers two main criteria when scheduling visits and routing nurses: balanced workload across the nurses visiting patients' homes, and the shortest possible total distance travelled by these nurses. The rationale for the second criterion is to minimize the program delivery cost by controlling the amount of compensation being paid to each nurse for the distance travelled. Moreover, minimizing the total distance travelled and thus increasing the time available for delivering service has an indirect effect on reducing the need for overtime work. In some circumstances, such as when there is an increased demand at the hemodialysis clinic or limited nurse availability, the program manager might be interested in finding the minimum number of nurses required to perform the daily visits at patients' homes.

Currently, the care facilitator needs to schedule daily visits for about 40-50 patients who are served by about 9 nurses. Considering that the roster of patients and available nurses changes from day to day, this is a very time-consuming task that requires significant skills including knowledge of possible routes, travel times, starting locations of available nurses, and the types of services to be provided to individual patients. This last piece is especially important as some patients may require two daily visits to be connected and disconnected from the cycler, one visit to be either connected or disconnected, or regular maintenance and check-up visits, while others may require teaching with each visit taking a different amount of nursing time.

3. Related work

In general, home health care (HHC) involves visits to patients' homes by different care providers (social workers, physiotherapists, nurses, etc.) and often represents an interesting scheduling and routing problem (SRP). Recent research on SRP in HHC is summarized in Refs. [11], [5], and [6]. These review papers present problem classifications based on solution methodology, planning time horizon, objectives, and constraints.

The SRP is classified as either single-period or multi-period depending on the planning time horizon [11]. While a single-period problem focuses on a single working day, a multi-period problem considers multiple days over a week or a month. Furthermore, SRP solution methodologies can be classified as exact, (meta)heuristic, or hybrid (combination of exact and heuristic methods). The SRP considered in this paper is a single-period problem modelled as a MILP solved using an exact method.

Following Ref. [11], this section systematizes recent work on SRP in HHC according to: (1) general characteristics such as planning time horizon, solution methodology, data used, decision support tool development, and (2) objectives and constraints considered in the problem formulation.

A summary of recent studies in terms of general problem characteristics is presented in Table 1. Most of these studies focus on single-period optimization models solved by (meta)heuristics using data provided by HHC organizations. Only two of them involved the development of a decision support system to facilitate the use of the proposed model in practice [8].

Types of objectives and constraints considered in these recent studies are presented in Table 2. It can be seen that travel time, total cost, travel distance, wait times, overtime and care provider preferences are the most commonly used objectives. Although the number of care providers needed to deliver service is clearly an important cost factor, only a few models in the literature minimize the number of providers assigned to daily service [1, 27, 38] . In terms of constraints, most of the reviewed studies consider service time windows, skill level requirements, and working time regulations. However, other important practical considerations such as timing of mealtime breaks, overtime work, workload balance, start time of first and last visits have received limited attention.

This study deals with all the important aspects of the SRP as summarized in Tables 1 and 2. Moreover, it is unique as it:

- Considers home dialysis as a specific HHC problem. Only Issabakhsh et al. [13] have considered this problem before, but the authors used

Table 1
Classification of recent HHC routing and scheduling literature according to general problem characteristics.

Article	Planning horizon	Solution method	Data	DSS development
[2]	Single-period	Exact	Randomly generated	
[31]	Single-period	Hybrid (Exact/Metaheuristic)	HHC organization	
[32]	Single-period	Hybrid (Exact/Metaheuristic)	HHC organization	
[24]	Single-period	Exact	HHC organization	
[29]	Multi-period	Exact/Metaheuristic	HHC organization	
[1]	Single-period	Hybrid (Exact/Metaheuristic)	Randomly generated	
[16]	Single-period	Exact	HHC organization	
[17]	Single-period	Hybrid (Exact/Metaheuristic)	Randomly generated	
[20]	Single-period	Metaheuristic	Randomly generated	
[33]	Multi-period	Exact/Metaheuristic	HHC organization	
[10]	Single-period	Hybrid (Exact/Metaheuristic)	HHC organization	
[12]	Single-period	Metaheuristic	HHC organization	
[19]	Single-period	Heuristic	HHC organization	
[38]	Single-period	Hybrid (Exact/Metaheuristic)	Literature	
[8]	Multi-period	Hybrid (Exact/Metaheuristic)	HHC organization	✓
[27]	Multi-period	Exact	HHC organization	
[4]	Single-period	Exact/Metaheuristic	HHC organization	
[25]	Single-period	Heuristic	HHC organization	
[26]	Single-period	Metaheuristic	HHC organization	
[37]	Single-period	Hybrid (Exact/Metaheuristic)	HHC organization	
[35]	Multi-period	Exact	HHC organization	
[13]	Multi-period	Exact	Randomly generated	
This study	Single-period	Exact	HHC organization	✓

Table 2
Classification of recent HHC routing and scheduling literature according to objectives and constraints.

	Objectives							Constraints					
	Travel time	Total cost	Travel distance	Wait time	Overtime	Preference	# of nurses	Balance of workload	Time windows	Skill requirements	Work regulations	Breaks	Overtime
[2]			✓						✓	✓	✓	✓	
[31]	✓			✓	✓	✓			✓	✓	✓	✓	
[32]	✓			✓	✓	✓			✓	✓	✓	✓	
[24]		✓				✓			✓	✓			
[29]		✓			✓				✓	✓		✓	✓
[1]							✓		✓	✓			
[16]					✓			✓		✓	✓		✓
[17]		✓						✓	✓	✓			
[20]			✓					✓	✓	✓			
[33]	✓			✓					✓	✓	✓	✓	
[10]	✓			✓					✓	✓	✓	✓	
[12]	✓				✓	✓			✓	✓			✓
[19]	✓			✓	✓	✓			✓	✓	✓		
[38]		✓					✓		✓	✓	✓		
[8]			✓			✓			✓	✓	✓		
[27]							✓			✓	✓		
[4]		✓			✓	✓			✓	✓	✓		✓
[25]	✓			✓					✓				
[26]	✓			✓	✓				✓	✓	✓	✓	
[37]	✓							✓			✓		
[35]						✓				✓	✓		
[13]		✓		✓					✓	✓			
This study		✓	✓		✓		✓	✓	✓	✓	✓	✓	✓

fictitious data and did not develop any decision support tool;

- Describes the development of a decision support tool to facilitate the use of the underlying optimization model in practice. This is similar to Refs. [9] and [8];
- Allows for flexibility in considering multiple optimization criteria through the parametrization of the different components of the objective function; and
- Introduces the notion of a “floating nurse” to allow for cross-area service when needed and to meet emergency requests or changes in daily requirements.

4. Mathematical model

We consider a single-period model that allows us to determine a set of daily nurse itineraries. A nurse itinerary defines when a specific nurse should leave home, visit each patient assigned to him/her, have a mealtime break (if any), and return home. The sets of patients and nurses are denoted by $P = \{1,2,\ldots,p\}$ and $N = \{1,2,\ldots,n\}$, respectively, where p is the total number of patients to be visited on a given day and n is the total number of nurses available that day. The travel distance and the travel time from location l (patient or nurse home) to location m (patient or nurse home), $l \neq m$, are denoted d_{lm} and t_{lm}, respectively. As visits can take place at different times, we assume that travel distances and travel times are fixed during the day and a constant compensation time is utilized to deal with the variations in these parameters due to traffic conditions and delays due to accidents, road works, and weather conditions. The travel cost is of KM dollars per km. The visit to patient $i \in P$ requires st_i minutes and can only occur in the time interval $[a_i,b_i]$, where a_i and b_i are the earliest and the latest service start times for this patient. The initial location of nurse $k \in N$ is his/her home address, which defines the starting and ending location of any possible itinerary assigned to him/her. The interval $[ws_k,we_k]$ defines the time window during which nurse k is available to visit patients. A mealtime break has a duration of LB minutes and nurse k can only take such a break in the time interval $[al_k,bl_k]$. The travel time from nurse k's home to the main nephrology clinic is denoted by t_k. This parameter allows us to consider commute times into the definition of nurse itineraries. For example, a nurse living 20 min away from the clinic ($t_k = 20$) and starting his/her shift at 08:00 cannot visit a patient who lives 30 min away from her/his home at 08:00. This is because this nurse would normally leave home around 07:40 to commute to the nephrology clinic and thus could only arrive at the patient's home around 08:10.

Nurses are organized in teams covering different service areas and can only visit patients who live in their respective areas. The parameter R_{ik} is equal to 1 if nurse k can visit patient i, and 0 otherwise. Since the number of available nurses and their working hours are limited, in some cases, the regular-hour service capacity may not be sufficient to visit all patients. For this reason, nurses are allowed to work overtime at a cost of OV per minute. In addition, floating and evening nurses, as explained in Section 2, help deal with the use of overtime in some situations. The value of parameter R_{ik} for these types of nurses is equal to 1 for all patients. Thus, overtime work and floating and evening nurses are alternate ways of guaranteeing a solution to the optimization problem. The workload of nurse k, denoted by w_k, is defined as the sum of his/her travel times, service times, and mealtime break duration.

Patients requiring two visits a day are modelled as requiring two separate visits with specific earliest and latest service start times, which are defined based on the required time between the connect and disconnect from the cycler tasks. The rationale behind this is that some patients may require to be connected to the cycler in the evening and disconnected the next morning, and our model only deals with one day at a time. Due to shift constraints and/or nurse availability, it is not always possible to assign the same nurse to visit a specific patient. For this reason, we assume that continuity of care is achieved by having a patient be visited only by nurses in the team covering the patient's service area.

Seven types of decision variables are used in the MILP model. The binary routing variable x_{lmk} takes the value of 1 if nurse k directly visits location m after location l, and 0 otherwise. The binary mealtime break variable y_{ik} is equal to 1 if nurse k takes a mealtime break right before visiting patient i, and 0 otherwise. Similarly, the binary mealtime break variable y_{ik}' is equal to 1 if nurse k takes a mealtime break right after visiting patient i, and 0 otherwise. The non-negative variable s_{ik} determines the service start time for patient i if he/she is visited by nurse

k. The non-negative variable l_k is used to determine the start time of the mealtime break of nurse k (if needed). The non-negative variable $over_k$ represents the expected amount of overtime required from nurse k in minutes. Finally, the non-negative auxiliary variable μ is used to ensure a balanced workload across nurses. A summary of the notation described above along with the complete formulation of the home dialysis problem is presented below:

Objective function

We consider an objective function that combines four criteria: the total distance travelled by all the nurses (D), the total travel and overtime cost (C), the number of nurses required to visit all patients (R), and the maximum workload across all the nurses (A). The logic behind the last criterion is to avoid solutions where a few nurses perform a large number of visits due to their proximity to patients while others are less busy. The goal is to minimize the weighted sum of these four criteria according to the weights λ_1 to λ_4 as follows:

$$\min \lambda_1 \times \underbrace{\sum_{k\in N}\sum_{l\in V}\sum_{m\in V} d_{lm}x_{lmk}}_{D} + \lambda_2 \times \underbrace{\left(KM\sum_{k\in N}\sum_{l\in V}\sum_{m\in V} d_{lm}x_{lmk} + OV\sum_{k\in N} over_k\right)}_{C} + \lambda_3 \times \underbrace{\sum_{k\in N}\sum_{l\in V} x_{klk}}_{R} + \lambda_4 \times \underbrace{\mu}_{A} \tag{1}$$

The higher the value of the weight, the more important the specific criterion. By allowing changes in the values of λ_1 to λ_4, the HDSS provides program managers with the possibility of expressing the relative importance associated with each optimization criterion. For example, if a manager considers only one criterion to be relevant, then the rest can be ignored by setting the corresponding weight values equal to 0. In addition, a hierarchical solution approach can be used by setting strongly different weight values for different criteria. For example, setting λ_3 to a very high value, λ_1 to a much lower value, and λ_2 and λ_4 to 0 gives priority first to the minimization of the number of nurses and then to the total distance travelled. In this setting, among all the solutions with the minimal number of nurses, the one with the shortest distance travelled would be selected. If a manager's only concern is direct cost minimization, then the value of λ_2 should be set equal to 1 and all the other weight values should be equal to 0.

Constraints

The minimization problem is subject to several constraints. Constraint (2) ensures that each patient is visited by a nurse.

$$\sum_{k\in N}\sum_{l\in V} x_{ilk} = 1, \quad \forall\, i \in P \tag{2}$$

Constraint (3) represents inflow-outflow conditions. It guarantees that the nurse assigned to patient i leaves the patient to visit another patient or returns home after service completion.

$$\sum_{l\in V} x_{lik} = \sum_{l\in V} x_{ilk}, \quad \forall\, i \in P,\, k \in N \tag{3}$$

Constraints (4) and (5) make sure that all nurses visiting at least one patient (i.e., active nurses) start and finish their workday at home. Note that the model does not necessarily assign patients to all nurses (less than or equal to conditions) as one of the optimization objectives is to minimize the number of nurses required to visit all patients.

$$\sum_{i\in P} x_{kik} \le 1, \quad \forall\, k \in N \tag{4}$$

$$\sum_{i\in P} x_{ikk} \le 1, \quad \forall\, k \in N \tag{5}$$

Constraint (6) ensures that each active nurse takes a mealtime break during the day. Constraint (7) makes sure that a nurse can only take a break before or after visiting patient i if he/she has been assigned to that patient.

$$\sum_{i\in P} y_{ik} + \sum_{i\in P} y'_{ik} = \sum_{i\in P} x_{ikk}, \quad \forall\, k \in N \tag{6}$$

$$y_{ik} + y'_{ik} = \sum_{l\in V} x_{ilk}, \quad \forall\, i \in P,\, k \in N \tag{7}$$

Constraint (8) determines the service start time for a patient visited by a specific nurse based on the service start time, service duration and travel time associated with the previous patient visited by the same nurse. This constraint guarantees route feasibility with respect to service start times and patient locations as it enforces strictly increasing service start times along the route of a nurse. In doing so, it also avoids cycles in the routes because a return to an already visited patient would violate the constraint associated with the start time of the previous visit.

$$s_{ik} + st_i + t_{ij} \le s_{jk} + M(1 - x_{ijk}), \quad \forall\, i, j \in P,\, k \in N \tag{8}$$

Constraints (9)– (12) determine the start times of the mealtime breaks for all active nurses depending on whether they take the break right before or right after visiting a specific patient. Similar to Constraint (8), Constraints (11)– (12) ensure route feasibility with respect to mealtime break times, service start times, and travel times.

$$l_k + LBy_{ik} \le s_{ik} + M(1 - y_{ik}), \quad \forall\, i \in P,\, k \in N \tag{9}$$

$$s_{ik} + (st_i + t_{ij})(x_{ijk} + y_{jk} - 1) \le l_k + M(2 - x_{ijk} - y_{jk}), \quad \forall\, i, j \in P,\, k \in N \tag{10}$$

$$l_k + (LB + t_{ij})(x_{ijk} + y'_{ik} - 1) \le s_{jk} + M(2 - x_{ijk} - y'_{ik}), \quad \forall\, i, j \in P,\, k \in N \tag{11}$$

$$s_{ik} + st_i y'_{ik} \le l_k + M(1 - y'_{ik}), \quad \forall\, i \in P,\, k \in N \tag{12}$$

Constraint (13) guarantees that patient visits start within the corresponding earliest and latest service start times. This is considered a hard constraint as connecting and disconnecting patients from dialysis machines in a time-sensitive manner is critical.

$$a_i \le s_{ik} \le b_i, \quad \forall\, i \in P,\, k \in N \tag{13}$$

Similarly, Constraint (14) ensures that nurses take their mealtime breaks within pre-specified time intervals. This constraint allows the system to enforce mandatory breaks for nurses who work shifts of more than four hours.

$$al_k \le l_k \le bl_k, \quad \forall\, k \in N \tag{14}$$

Constraints (15) and (16) make sure that nurses complete their itineraries within the duration of their shifts. Constraint (15) guarantees that the start time of the first visit for each active nurse considers the travel time from the nurse's home to the main nephrology clinic. It allows the model to avoid infeasible itineraries that start far from the nurse's home. Similarly, Constraint (16) states the relationship between the service start time of the last visit for each nurse and the travel time from the last patient visited to the nurse's home. It also helps the model determine the amount of overtime required to complete the itineraries.

$$ws_k - M(1 - x_{kik}) \le \max\{t_{ki} - t_k, 0\}, \quad \forall\, i \in P,\, k \in N \tag{15}$$

$$we_k + M(1 - x_{ikk}) + over_k \ge s_{ik} + st_i + \max\{(t_{ik} - t_k), 0\}, \quad \forall\, i \in P,\, k \in N \tag{16}$$

Constraint (17), together with the objective function, helps the model determine the maximum workload across nurses (μ). Individual nurse workloads are computed as the sum of the corresponding total service time, total travel time, and mealtime break duration. This constraint is required to obtain a balanced workload assignment.

$$LB + \sum_{i\in P} t_{ki}x_{kik} + \sum_{i\in P}\sum_{j\in P}(st_i + t_{ij})x_{ijk} + \sum_{i\in P} t_{ik}x_{ikk} \le \mu, \quad \forall\, k \in N \tag{17}$$

Constraints (18) makes sure that nurses can only visit patients who live in their coverage area. Please note that floating nurses are allowed to provide service to all patients regardless of their geographical location. Thus, the value of R_{ik} for this type of nurse is equal to 1 for all patients. Following the same logic, Constraint (19) state that nurses can only have a mealtime break at the location of a patient they visit.

$$x_{lik} \leq R_{ik}, \quad \forall\, l \in V, i \in P, k \in N \tag{18}$$

$$y_{ik}, y'_{ik} \leq R_{ik}, \quad \forall\, i \in P, k \in N \tag{19}$$

Constraints (20) and (21) state the feasible values for the binary routing and mealtime break decision variables.

$$x_{lmk} \in \{0, 1\}, \quad \forall\, l, m \in V, k \in N \tag{20}$$

$$y_{ik}, y'_{ik} \in \{0, 1\}, \quad \forall\, i \in P, k \in N \tag{21}$$

Finally, the non-negativity Constraints (22)– (24) define the domain for the service start time, mealtime break time, overtime, and workload balance decision variables.

$$s_{ik} \geq 0, \quad \forall\, i \in P, k \in N \tag{22}$$

$$l_k, over_k \geq 0, \quad \forall\, k \in N \tag{23}$$

$$\mu \geq 0 \tag{24}$$

5. HDSS

The HDSS was developed using rapid prototyping combined with user-centred interface design. At each stage, the HDSS prototype together with the user interface option were presented to the hospital administrator (immediate end-user), management, and clinical leadership of the home dialysis program. Each modelling assumption and associated course of action was validated and each user interface option was presented and discussed with the help of mock-ups. Once consensus among the group members was reached, the system prototype was revised and a new one was created.

5.1. Analysis and design

This iterative stage started with learning about the requirements for the MILP model and expected functionality of the HDSS. It included a number of sessions where different versions of the model, HDSS prototypes and user interface mock-ups were presented and discussed. As a result of each session, revisions were introduced, described, tested on real data, and a short briefing document was communicated to hospital stakeholders. Simultaneously, alternative versions of the HDSS were developed to facilitate uncovering other not explicitly stated system requirements. When steady state was achieved (i.e., no more requirements were identified and the interface design was approved), we proceeded to the development of a full HDSS.

The development of the MILP model followed a slightly different process. It started with learning about basic requirements expected from the visit schedules and nurse routes. This allowed us to define decision variables, optimization criteria, and a core set of constraints. Having this information, we were able to establish data requirements for a full model development. As the MILP model plays a critical role in the HDSS, we presented, separately, alternative solutions derived for differently weighted criteria in the objective function, different values of the service times associated with different types of visits, and different assumptions regarding nurses' workday and scheduled breaks. By doing so, we were able to identify exceptions and additional requirements to be satisfied by the MILP model solutions.

The optimization-based decision support systems previously developed by Refs. [28], [30] and [23] for vehicle routing and scheduling problems gave us some ideas for the design of the HDSS.

5.2. HDSS architecture and implementation

The HDSS was designed as a stand-alone, single installation system with all the required software and database locally stored. The HDSS architecture consists of: a user interface module, a visualization module, a report generation module, an optimization module, a data module, and a map module. These modules are arranged and synchronized in three layers comprising presentation, execution, and data components, as shown in Fig. 1. The HDSS was implemented using Java 8.0 and open source libraries such as JXMapViewer, JGraphHopper, JFreeChart, and Apache POI.

The data module reads and writes all the information needed for generating visit schedules and nurse routes in a database. This is an exchange module between the different data sources and the other modules of the HDSS. The map module, which is based on the routing library GraphHopper, generates travel distance and travel time information for all address pair combinations using OpenStreetMap data

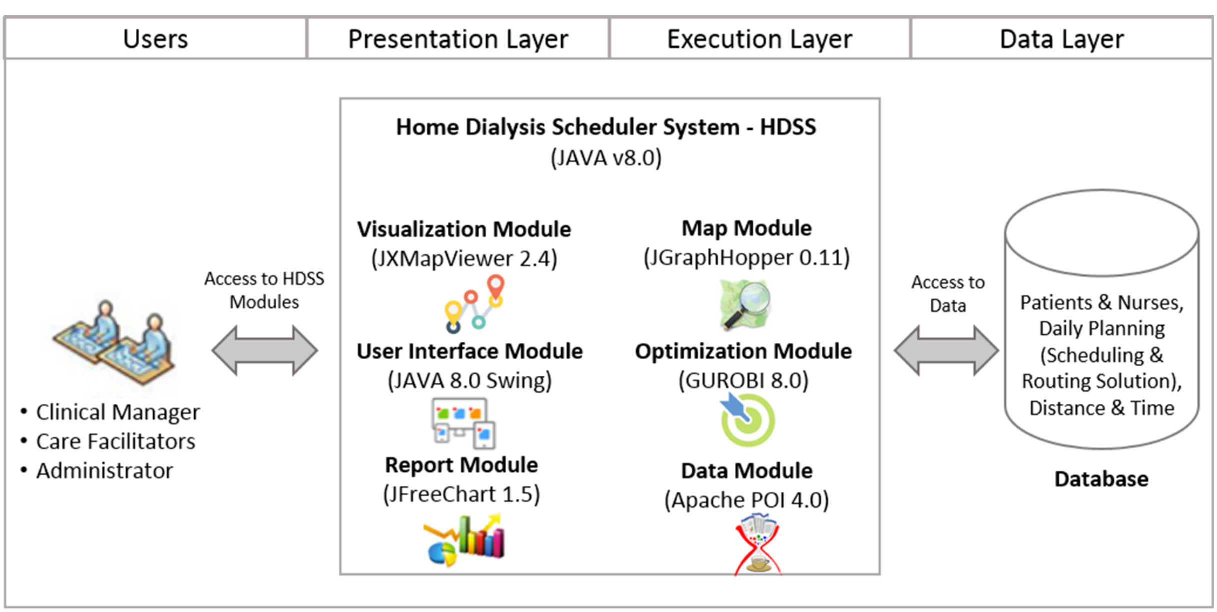


Fig. 1. HDSS architecture.

in Protocolbuffer Binary Format (https://www.openstreetmap.org) and stores it into the database. The core processing module of the HDSS, the optimization module, reads information about patients and nurses, optimization parameters, solver details, travel distances, and travel times from the database; generates the MILP model; invokes the Gurobi 8.0 solver (http://www.gurobi.com) to find an optimal solution to the model; and decodes and writes the solution (i.e., nurse itineraries and/or patient visit timetables) to the daily planning table in the database. The report generation and the visualization modules, accessible via the main user interface, are used together for presenting the optimal solution and generating several customized map visualizations and reports. For example, a nurse itinerary can be presented in a tabular format and/or using a map display as shown in Fig. 2. These modules have export capabilities that allow data exchange between the hospital administrator and the program managers. Finally, the main user interface module presented in Fig. 2 provides access to all the other modules to generate daily visit schedules and nurse routes.

5.3. User interface and visualization

The user interface, which is illustrated in Fig. 2, combines graphical and textual presentation and is divided into three major sections: the main menu and quick access toolbar, the navigation tree, and the work area. The main menu and quick access toolbar contain the menu and buttons for basic tasks such as opening a daily plan, validating the input for a daily plan, invoking the optimization solver to generate a daily plan, exporting a solution, etc. The navigation tree, on the left side, provides a simple way of representing a sequence of tasks for creating daily visit schedules and nurse routes. The work area includes interactive spreadsheet-like forms and tables for data manipulation tasks such as adding/removing patients, nurses and appointments. It also provides charts, map visualizations (i.e., routes in the solution) and reports required by the hospital administrator during daily operations.

6. Comparative evaluation

At the end of the system development cycle, we conducted a comparison of the schedules generated by the HDSS with those developed manually by the hospital administrator. All computations reported here were executed on a stationary computer with an Intel Core i3-2120 3.30 GHz processor with 4 GB RAM running the operating system Windows 7 Enterprise (64-bit). The execution times never exceeded 3 min.

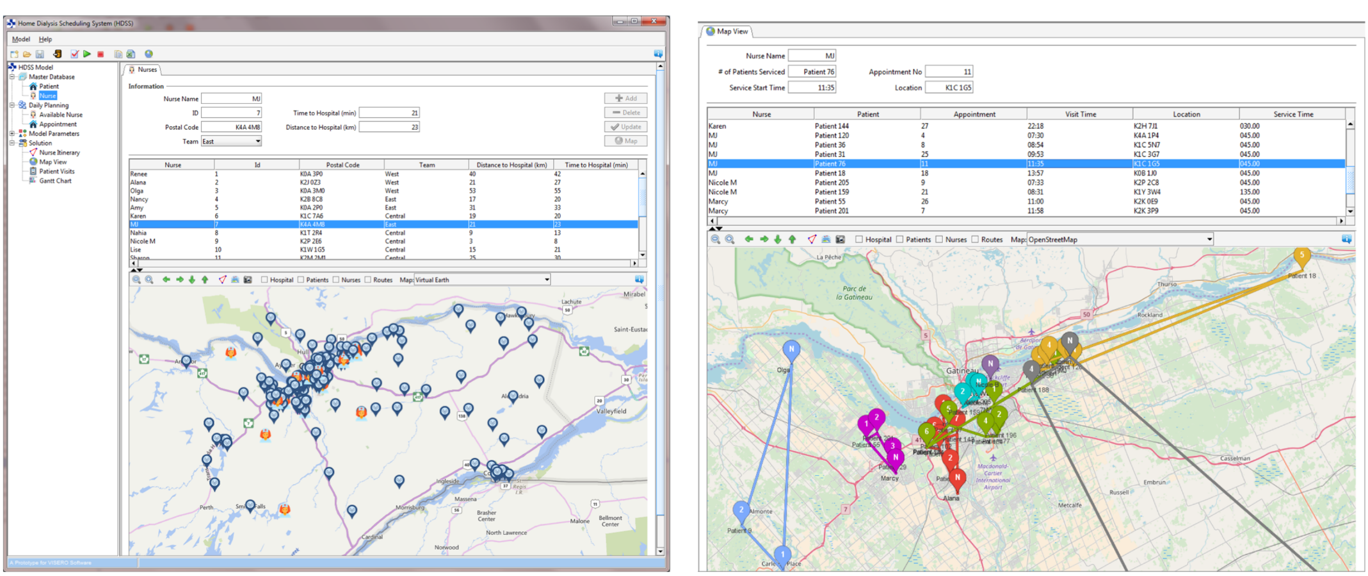
Table 3
Summary of the data used for the comparative evaluation for a typical week of 2018.

Day	Number of nurses	Number of patients
Monday	8	28
Tuesday	9	34
Wednesday	9	29
Thursday	9	34
Friday	9	34
Saturday	6	25
Sunday	6	24

6.1. Data

The comparison was first conducted for a typical week of 2018 and then using eight weeks of daily data from June 1 to July 26, 2019. During the typical week, a total of 53 different patients were visited, which translated into 208 patient visits. These visits were performed by a total of 15 different nurses. Daily details are provided in Table 3.

In each case, the data used by the care facilitator for daily scheduling and routing purposes was entered into the HDSS. This included visit time-window preferences generated separately by the administrator who took into consideration information about the specific patients and types of visits. For example, if a patient required two visits during the day, a realistic time window was assigned to ensure that the patient was connected to the cycler for an acceptable amount of time. Travel distance and travel time information was automatically generated by the HDSS map module. It was similar to what the care facilitator did while estimating the distances to be travelled by the nurses to reach the different patient locations. Travel times did not account for traffic conditions. This is because visits can take place at different times of the day and therefore longer travel times during peak-hours are compensated by shorter travel times during off-peak hours. However, the system considers a constant compensation time to deal with the variations in travel times due to traffic conditions and delays due to accidents, road works, and weather conditions.



(a) Master nurse and patient database (b) Overall solution display

Fig. 2. Screenshots of the HDSS.

Table 4
Comparison of HDSS and manual results for a typical week of 2018 when the primary goal is to minimize the total distance travelled.

	Total distance travelled (km)		Total travel time (min)		Required nurses	
Day	Manual	HDSS	Manual	HDSS	Manual	HDSS
Monday	930	693	895	721	8	6
Tuesday	1276	982	1153	879	9	8
Wednesday	1102	735	1072	665	9	7
Thursday	1223	955	1121	938	9	8
Friday	1253	793	1134	795	9	8
Saturday	931	705	807	639	6	5
Sunday	919	731	848	655	6	5
Total	7634	5594	7030	5292	56	47
Savings		**27%**		**25%**		**16%**

6.2. Results

Considering that the home dialysis program management was primarily interested in minimizing the total distance travelled by nurses because of its direct cost implications (mileage costs and possible overtime), the values of all the objective weights, except for the one associated with the cost criterion, were set to zero. Table 4 presents the results generated with the help of the HDSS and those generated manually by the hospital administrator for a typical week of 2018. As can be seen from the table, the use of the HDSS reduced the average total distance travelled and the average total travel time by about 27% and 25%, respectively. It is interesting to note that the optimized schedules freed up an average of 1.3 nurses per day while meeting the demand for visits. This finding was of special interest to the program management because of the difficulties recruiting nurses to participate in the home dialysis program and because of some other managerial implications discussed later.

As an example, Fig. 3 shows the visit schedules and nurse routes corresponding to Wednesday of that typical week. While the routes created manually are intertwined, the ones generated with the help of the HDSS are simpler and thus more efficient. Moreover, the HDSS allows the care facilitator to experiment with the impact of team composition (assignment of nurses to teams) on the total distance travelled and/or the total cost. After inspecting the HDSS schedule, we proposed a revised team composition for Wednesday and this revision resulted in an even better schedule that reduced the total distance travelled for that day by 41% (results not shown).

Table 5 presents the results generated with the help of the HDSS and those generated manually by the hospital administrator for a typical week of 2018 when the second most important goal for the home dialysis program management, balancing workload across nurses, is the main objective considered in the analysis. In this case, the values of all the objective weights, except for the one associated with the workload balance criterion, were set to zero. We can see from Table 5 that minimizing the maximum workload across nurses sometimes changes the solution provided by the system. However, despite the increase in the average total distance travelled, this alternative objective still allows the HDSS to achieve great results in terms of efficiency. The decrease in the total distance travelled goes from 27% to 17% and the reduction in the number of required nurses goes from 16% to 11% under this objective.

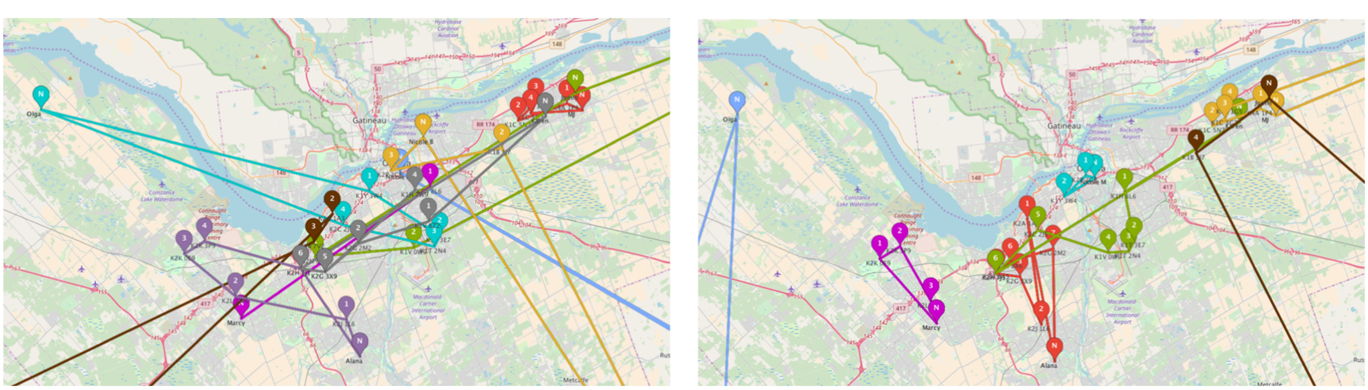
Table 5
Comparison of HDSS and manual results for a typical week of 2018 when the primary goal is to balance workload across nurses.

	Total distance travelled (km)		Total travel time (min)		Required nurses	
Day	Manual	HDSS	Manual	HDSS	Manual	HDSS
Monday	930	693	895	718	8	6
Tuesday	1276	1112	1153	956	9	9
Wednesday	1102	1002	1072	786	9	8
Thursday	1223	1059	1121	987	9	8
Friday	1253	1019	1134	946	9	8
Saturday	931	708	807	639	6	5
Sunday	919	747	848	661	6	6
Total	7634	6340	7030	5693	56	50
Savings		**17%**		**19%**		**11%**

Finally, Table 6 shows the results generated with the help of the HDSS and those generated manually by the hospital administrator for the other eight weeks of daily data considered in our analysis. As can be seen from the table, the use of the HDSS reduced the average total distance travelled and the average total travel time by about 38% and 33%, respectively. It is also important to note that the optimized

Table 6
Comparison of HDSS and manual results for eight weeks of daily data (from June 1 to July 26, 2019) when the primary goal is to minimize the total distance travelled.

	Total distance travelled (km)		Total travel time (min)		Required nurses	
Week	Manual	HDSS	Manual	HDSS	Manual	HDSS
Week 1	11,549	7145	9536	6321	47	42
Week 2	10,726	6981	8917	6275	47	43
Week 3	10,600	6625	8700	6153	47	43
Week 4	11,310	7588	9098	6177	45	41
Week 5	9797	5791	8094	5275	44	39
Week 6	11,060	6561	9217	5980	47	41
Week 7	11,055	6651	9057	5866	47	41
Week 8	10,702	6346	8817	5996	47	41
Total	86,799	53,688	71,436	48,043	371	332
Savings		**38%**		**33%**		**11%**



(a) Manual (b) HDSS

Fig. 3. Visit schedules and nurse routes corresponding to Wednesday.

schedules achieved these results with 11% fewer nurses per day while meeting the demand for visits. Based on these results and a compensation being paid to each nurse for the distance travelled of CAD 0.45 per km, we estimate the dialysis program could have saved almost CAD 1900 per week by using the HDSS, which translates into an estimated annual cost reduction close to CAD 100,000.

In summary, the results above show how well the HDSS performs and how scheduling and routing decisions can be improved in comparison to the manual approach. The HDSS and the schedules it generates were approved by the program management and the system is currently being deployed for everyday use.

6.3. Managerial implications

In addition to significant cost reductions resulting from more efficient visit scheduling and nurse routing decisions, we expect the daily use of the HDSS will bring with it important managerial implications for the workload of hospital administrators (immediate end-users) and nursing staff. For the former, the use of the HDSS will free them up to deal with other tasks that require more direct patient interaction such as appointment booking and addressing patient queries. For the later, the use of the HDSS will ensure that more nurses are available at the nephrology clinic for teaching purposes and for dealing with patients who can not receive care at home. From the home dialysis program perspective, other anticipated benefits from the use of the HDSS include reduced clerical rework, heightened visibility of nurses' daily workload, increased adherence to clinical guidelines, improved nursing staff utilization and coordination, and balanced workload. From the patient perspective, we expect the daily use of the HDSS will allow earlier appointment time confirmation and higher appointment time reliability (patients will know in advance the time of their appointments) and systematic consideration of patient preferences and restrictions for visit times.

To date, the overall managerial implications of using the HDSS have been in improving quality of care rather saving money. The system has allowed nurses to spend more time providing care to dialysis patients. In addition, the HDSS has allowed the home dialysis program management to assign hospital administrators and nursing staff to more important clinical and administrative tasks.

The home dialysis program at TOH is relatively new and as part of the program assessment the HDSS has been used both as an example of a successful collaboration between academia and management and as a tool that can be implemented across similar programs in the province. Thus, the development and implementation of the HDSS has helped with the decision of scaling the program to other regions in the province as it is expected to improve patient care and provide a significant reduction in the expenditure associated with travel distances. We believe the HDSS and the knowledge gained from its development are definitely transferable to other home dialysis clinics, in particular to those in the province and across Canada, that operate similarly. Location-specific processes will determine the extent of the implementability of the HDSS, although the general principle of increased efficiency in the creation of visit schedules and nurse routes should extend across practices. Some factors that would play a significant role in this process are the size of the clinic (i.e., number of patients and nurses, geographical area, etc.) and the specific scheduling practices.

6.4. Limitations

The HDSS and its optimization model have a number of limitations starting with the fact that the optimization model is a single-period one. This implies that a patient who requires assistance with the cycler (connection and disconnection) and for whom the connection visit needs to take place in the evening will have his/her disconnection visit on a different day, which corresponds to a different schedule. In addition to this, a patient who requires two nursing visits on the same day (connection and disconnection) is considered as two independent patients requiring one visit each. The time windows for these two patients are defined so there is a minimum wait time between the two visits. Dealing with these two situations requires manual tracing and recording by the care facilitator. Furthermore, the HDSS is purely a scheduling system and works under the assumption that the roster of nurses is given. Linking the HDSS with some rostering system might provide better results in terms of meeting the demand for home and satisfying additional staffing requirements at the main nephrology clinic.

Additionally, while having mutually exclusive teams of nurses and patients allows us to address continuity of care needs and improve model execution times, this problem setting may result in sub-optimal solutions due the number of nurse-to-patient assignment restrictions. Also, we believe that using deterministic travel and service times adequately reflects reality in this particular situation. However, one can argue that the use of stochastic values should make the model closer to how the actual schedules are developed. While we partially addressed the variability in travel and service times by introducing a compensation time as a model parameter, we suspect that the use of stochastic values in the model may result in unacceptably long execution times.

7. Conclusion

The use of home dialysis has increased over the last years because of the flexibility it provides to patients and the fact that is a cost-effective option for healthcare systems. Determining good visit schedules and nurse routes to meet patient requirements is one of the key tasks performed by home-dialysis care facilitators. This is because these decisions drive the program's operating cost, impact the quality of the service provided to patients, and influence nurses' job satisfaction.

In this paper, we describe the development of a decision support system, called Home Dialysis Scheduler System (HDSS), to address the real-world visit scheduling and nurse routing problem faced by the Home Dialysis Program run by the Division of Nephrology at The Ottawa Hospital (TOH). The HDSS utilizes a multi-criteria mixed-integer linear programming (MILP) model that takes into account the total distance travelled by all the nurses, the total cost (travel and overtime), the number of nurses required to visit all patients, and the workload balance across nurses as four objectives that can be optimized individually or in a weighted manner. The HDSS also allows considering other aspects of the problem such as patient-nurse compatibility restrictions (e.g, case complexity and geographical location), nurse availability (e.g., shift times, mealtime breaks, and overtime), service durations, travel times, travel distances, and multiple route start locations.

The HDSS and its use have been approved by the program management. In addition to producing schedules with significantly lower total distance travelled and balanced nurse workloads, the HDSS allows sensitivity analyses and a quick response to new operational requirements while reducing the tediousness and uncertainties inherent in the manual approach. It not only reduces the time spent in visit scheduling and nurse routing tasks from hours to minutes but also provides a graphical representation of the resulting itineraries in an appealing manner that is easy to interpret by care facilitators and nurses. While developed for TOH, the HDSS can be easily ported to home dialysis programs at other hospitals and regions because of the general applicability of the MILP model and easy-to-use interface that allows to edit all model parameters. The only additional task required will be the one-time development of the location and distances tables to reflect local conditions (i.e., patient locations, nurse locations, and available routes).

Nurse rostering and nurse routing problems in home health care delivery are interrelated. Linking these two problems might provide better results in terms of meeting the demand for visits and staffing requirements for home care services. As one of our future research initiatives, we plan to extend the HDSS to consider staffing and routing problems simultaneously.

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