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INTEGRATING HOME HEALTHCARE AND PATIENT TRANSPORTATION: A SAMPLE AVERAGE APPROXIMATION APPROACH TO OPTIMIZE SCHEDULING AND ROUTING

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ABSTRACT

This study introduces an innovative strategy for addressing the Home Healthcare and Dial-a-Ride Problem (HHCDAP) concerning the transportation of medical staff and patients, taking into account the stochastic nature of service and travel times. The problem involves assigning suitable medical staff to patients and clients, determining the order of visits, and identifying opportunities for medical staff and patients to share trips. We propose two objective functions to minimize travel time for drivers and medical staff. This problem adheres to numerous constraints, including maximum work duration, maximum waiting time, professional qualifications, and vehicle capacity limitations. We test our approach on a small-scale instance to understand the trade-offs between minimizing drivers' travel time and minimizing the travel and waiting times of medical staff and patients. Our results indicate that the proposed strategy enhances the efficiency of transporting medical staff and patients.

1 INTRODUCTION

Home healthcare encompasses a broad range of professional services designed to support clients in their daily lives at home. These services, including meal preparation, personal hygiene assistance, medication delivery, and medical treatments, cater to clients recently discharged from hospitals, those with mobility challenges, or individuals requiring long-term care due to chronic illnesses (Genet et al. 2011). The primary objective of home healthcare is to deliver high-quality, personalized care that fosters patient autonomy and enhances their quality of life. Home healthcare has gained significant traction in the healthcare sector as a more convenient and often more cost-effective alternative to hospital or other institutional care. Transportation is key in the delivery of home healthcare services (Voegl and Hirsch 2019). It facilitates the movement of healthcare professionals to and from clients' homes and ensures clients are transported to medical centers or hospitals for treatments that cannot be administered at home. This dual role underscores the importance of efficient and reliable transportation systems in successfully implementing home healthcare services.

The demand for home healthcare services is increasing due to several factors (Fathollahi-Fard et al. 2022; Jeong et al. 2023; Díaz Planelles et al. 2023). Firstly, there is an increasing trend of elderly individuals living alone, as families become more geographically dispersed and younger generations prioritize their careers. This demographic shift is leading to a greater need for in-home care services, as seniors prefer to age in place in their homes (Kumar et al. 2023). Additionally, medical advancements have increased life expectancy, leading to a larger aging population with more complex care needs (de la Escosura 2023). Furthermore, hospital stays are becoming shorter, with patients being discharged earlier and often requiring follow-up care at home. Finally, the COVID-19 pandemic has accelerated the shift towards home-based care, as it is safer for vulnerable individuals to receive care at home rather than in institutional settings (Majoor and Vorselaars 2023). These factors drive the demand for home healthcare services and highlight the importance of developing efficient transportation systems to support this growing need. This has subsequently led to an increase in the need for transportation of medical staff and patients, which is currently being done independently, leading to urban congestion (Voegl and Hirsch 2019).

In this study, we propose an integrated mobility concept to efficiently manage the transportation of medical staff and non-urgent patients. This concept considers the stochastic nature of service times and travel times, acknowledging that existing methods transport patients and medical staff separately and contribute to urban congestion. Our work is centered on coordinating patient and medical staff transportation—a critical issue within the home healthcare sector in Europe, particularly in the rural regions of countries like Germany and Austria, where these logistical challenges are pronounced (Lenz et al. 2021; Rutschmann 2017).

Motivated by the pressing need to address these logistical difficulties, especially the synchronized planning of patient transportation and medical staff assignment, this ongoing research project, currently in its initial stages, proposes an integrated approach. This approach seeks to enhance operational efficiency, curtail costs, and foster environmental sustainability, thereby improving both the quality of patient care and the overall performance of home medical service providers. The proposed integrated mobility concept introduces a trip-sharing system for medical staff and patients, inherently transforming the coordination of home healthcare services into a scheduling and routing problem. We focus on two types of users: non-critical patients receiving treatment at medical centers and clients receiving home care. The qualification level of each home care worker and the nature of each home care job are also taken into account to ensure efficient service delivery.

The complexity of integrating home healthcare and dial-a-ride services while considering stochastic service and travel times forms the core of this problem. We aim to develop a feasible scheduling and routing solution that maximizes resource utilization while minimizing travel and wait times for medical staff and non-urgent patients. In this pursuit, we employ the Sample Average Approximation (SAA) approach—a simulation-based optimization method that approximates the expected objective function of a stochastic optimization problem.

A series of computational experiments are conducted to measure the impact of the integrated transport system on travel and wait times for medical staff and non-urgent patients. We compare the results obtained using two distinct objective functions: minimizing the travel time of the driver and the medical staff. The insights derived from our findings could play a significant role in establishing standards for waiting and travel times. To the best of our knowledge, this is the first study to address the integrated planning of these services, presenting an innovative solution that accommodates the stochasticity of travel and service times and approximates the optimal solution using a simulation-based optimization approach.

2 LITERATURE REVIEW

The challenge of transporting medical staff and patients is usually tackled separately. Transporting medical staff has been characterized as a home healthcare problem, whereas transporting patients has been a dial-a-ride problem. In-home healthcare problems, several techniques have been suggested to address this problem. For example: Ichoua et al. (2000) presented a Tabu Search method that employs probabilistic knowledge to assign customers in real-time and a waiting strategy that depends on projected future requests. Hvattum et al. (2006) developed a multi-stage stochastic programming model and a heuristic approach that handles the home healthcare problem as a deterministic vehicle routing problem. Bent and Van Hentenryck (2004) proposed a dynamic vehicle routing problem with time windows to maximize daily visits and a multiple-scenario approach that creates routing plans for known and future clients. In the context of the dial-a-ride problem, multi-objective routing problems have grown in practical applicability. Recent research by Souza et al. (2022) on a bi-objective heterogeneous dynamic dial-a-ride problem for patient transportation in Brazil minimizes transportation costs and user inconvenience. Detti et al. (2017) discuss a multi-depot dial-a-ride problem for non-emergency patient transportation in a real-world healthcare application. Jorgensen et al. (2007) study the same problem, the authors apply an aggregated objective function to minimize transportation costs, excess user ride times, user waiting time, and route duration.

2.1 Optimization Criteria

Existing literature proposes optimization criteria categorized into response time and patient preferences, among others, which we considered in our solution.

2.1.1 Response Time

In terms of response time, the literature suggests minimizing total operating time and distance, minimizing waiting time due to synchronization or time windows (Fikar et al. 2016; Guericke and Suhl 2017; Zhan and Wan 2018; Chaieb et al. 2020; Euchi et al. 2020; Malagodi et al. 2021), and minimizing the number of routes needed, which relates to completion time (Quintana et al. 2017; Heching et al. 2019; Kandakoglu et al. 2020; Liu et al. 2021).

2.1.2 Patients' Preferences

Patients' preferences have also been considered, with a focus on minimizing costs related to overtime and reassignments (Lin et al. 2016; Rest and Hirsch 2016; Dekhici et al. 2019; Restrepo et al. 2019; Kandakoglu et al. 2020; Hassani and Behnamian 2021; Malagodi et al. 2021), minimizing violations of visit time windows (Rahimian et al. 2017; Euchi 2020), maximizing patients' preferences for skill and doctor-patient familiarity (Du et al. 2019; Mosquera et al. 2019; Grenouilleau et al. 2019; Li et al. 2021), and maximizing preferred time slots (Erdem and Bulkan 2017).

There is a research gap regarding the transportation of medical staff and patients on the same trip, which has mainly been studied as deterministic and two-independent problems. The independent consideration of both the assignment and transport of medical staff (home healthcare problem) and the transportation of patients (dial-a-ride problem), although valuable in optimizing specific variables such as response time or patient preferences, often results in locally optimal solutions. These solutions, while effective in isolation, may not offer the most cost-efficient or globally optimal strategies for home medical service providers or their clients. Logistical challenges become particularly pronounced for service providers in rural regions, necessitating an integrated approach to planning medical treatments at home and in medical centers. Such an integrated approach can amplify resource utilization, potentially reducing the vehicle fleet size necessary for service provision, thereby improving operational efficiency, cost-effectiveness, and environmental sustainability. However, despite the potential advantages of an integrated approach, existing literature scarcely addresses the combined consideration of home healthcare and dial-a-ride problems. Our study aims to fill this gap by examining the simultaneous resolution of these issues, with the goal of fostering both academic discourse and practical solutions to the logistical challenges inherent to home medical services. As proposed, an integrated perspective could pave the way for more comprehensive and effective strategies for in-home healthcare service delivery.

3 PROBLEM DESCRIPTION

The problem of home healthcare and dial-a-ride (HHCDAP) for medical staff and patient transportation, taking into account the stochastic service time duration (d_i) and travel time (tt_{ik}), can be delineated as follows: A cadre of medical staff is bifurcated into home care professionals and paramedics, and a collection of user homes consists of subsets of client and patient residences. Each client necessitates a home care service at their rural residence, and each patient requires medical treatment at an urban medical center, along with continuous accompaniment during transportation.

The home healthcare services spectrum ranges from simple to advanced medical treatments, including continuous accompaniment. Transporting medical staff for home healthcare services necessitates three pivotal decisions. Firstly, the assignment of medical staff to clients and patients must be based on their professional qualifications and specific service requirements. Secondly, the sequence of visits must be established upon the appropriate allocation of medical staff to each client and patient. Lastly, presuming the perpetual availability of vehicles and drivers for transporting medical staff and patients, determining which medical staff and patients can share the same journey forms the next critical decision.

In addressing the HHCDAP, we propose considering two distinct objective functions: minimizing driver travel time and minimizing medical staff travel time. Each of these objectives is employed independently to solve the problem. Subsequently, we outline the primary constraints of the problem:

- **Each client**
  … has a home care service that has a stochastic service time duration
  … requires at least one home care service during the day
  … requires a home care service associated with a qualification
  … has a home care service that must be started within its time window
- **Each patient**
  … requires at least one transport service and medical treatment during the day
  … has a medical treatment that must be started at a fixed time
  … has a medical treatment that has a stochastic service time duration
- **Each home care staff and paramedic**
  … has a maximum working time
  … has a maximum waiting time
  … has a certain qualification level. We consider four qualification levels
  … has an assigned driver
- **Each vehicle**
  … has an assigned route that complies with the maximum capacity of the vehicle, which is limited to 4 passengers
  … of each route starts and ends at the depot
  … the number of patients requesting a home care service is known at 5:00 p.m. the previous day
  … each vehicle has an assigned driver
  … downgrading of medical staff qualifications is allowed

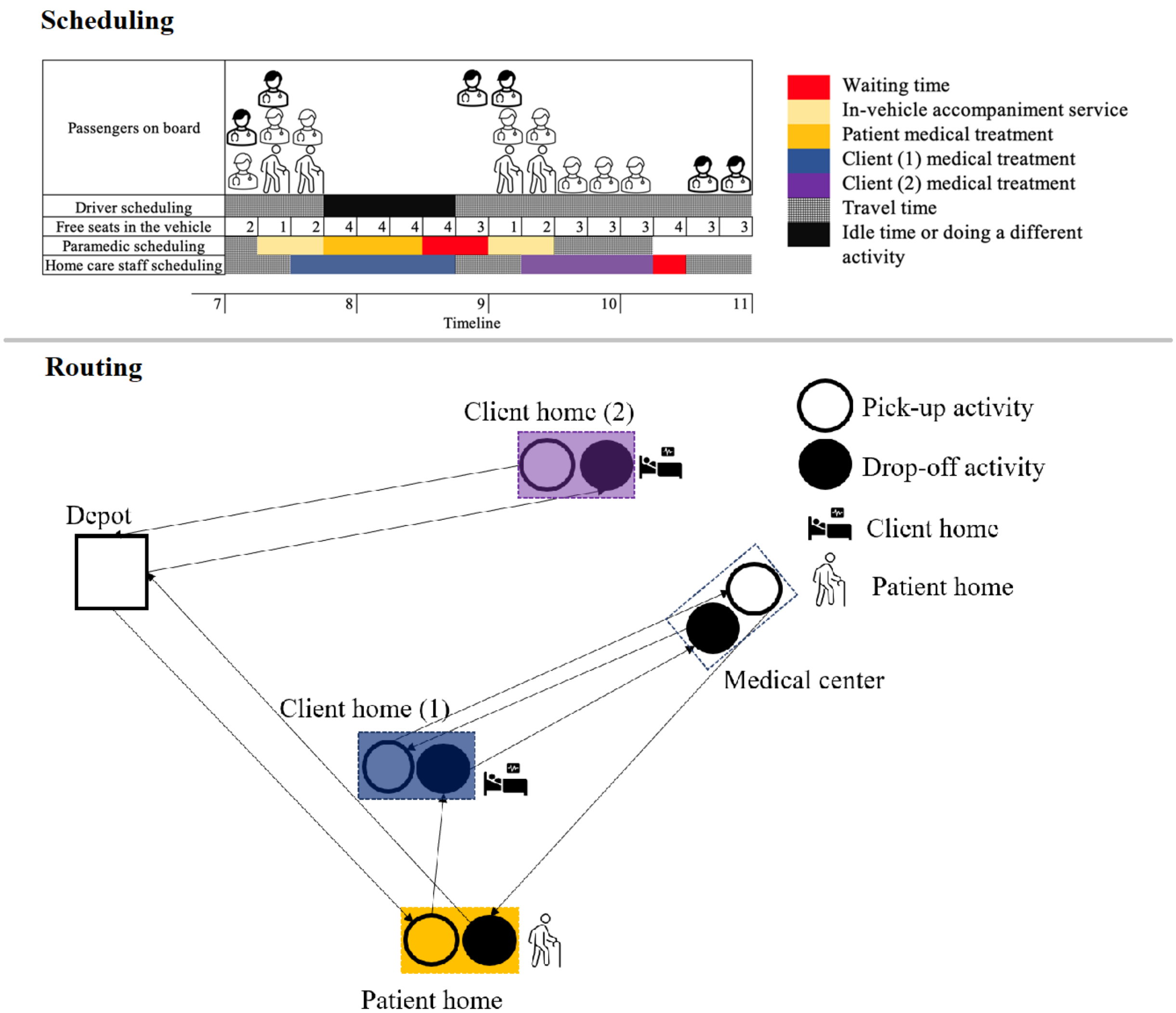
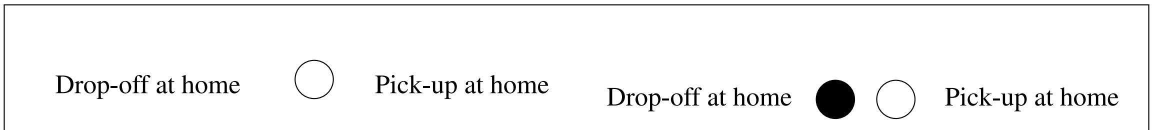


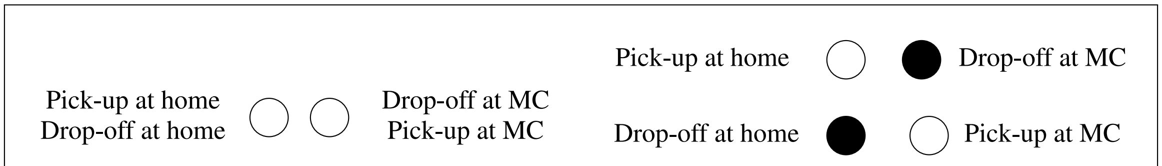
Figure 1: Exemplification of the integrated mobility concept.

Figure 1 illustrates an example of integrated mobility. In this scenario, there are two clients and a patient in a small instance. Clients 2 and 3 require medical treatment requiring medical staff with qualifications 2 and 4, respectively, while the patient requires a paramedic (qualification level 1). A home care staff with a qualification level of 4, a paramedic, and a vehicle with a driver. The maximum workday for medical personnel is assumed to be 4 hours, with a maximum wait time of 30 minutes. Client 1 has a time window of [7,9]am, client 2 [8,10]am, and the patient has a doctor's appointment at 7:45 am. The expected duration of medical treatment for clients 1 and 2 is 75 and 60 minutes, respectively, while the duration for the patient is 45 minutes. The top of the figure shows the scheduling of the vehicle and medical personnel, while the bottom shows the routing. The figure highlights how stochastic travel times and the stochastic duration of medical service can easily lead to an infeasible solution. A longer-than-expected medical service duration can lead to a route failure because it exceeds the maximum working hours. Similarly, stochastic travel times can lead to exceeding the maximum working hours, wait times, and failure to meet the time windows of clients and patients.



(a) Client job (b) Disaggregated client job

Figure 2: Processing of client requests.



(a) Patient job (b) Disaggregated patient job

Figure 3: Processing of patient requests.

4 METHODOLOGY

Our solution commences with the initial processing of both customer and patient requirements. Subsequently, we implement a solution approach that utilizes a variant of the Sample Average Approximation method (SAA). This is specifically designed to solve the Home Healthcare and Dial-a-Ride Problem (HHCDAP), which involves complexities related to stochastic service duration and travel time.

4.1 Input Data Preprocessing

The medical staff and patient transportation involve pick-ups and drop-off activities. We decided to duplicate the set of user homes and medical centers so that pick-ups and drop-off activities disaggregate the list of requests. Each request is considered a node (see Figures 2 and 3). Thus, each patient is involved in 4 nodes (including the drop-off and pick-up nodes at the medical center), and each client is involved in two.

Assume set N as the set of all requests, for each node $i \in N$ is considered a service time duration of d_i, and a time window is estimated, taking as a reference the input information of each patient's medical appointment time and the preferred time window of each client.

4.2 Sample Average Approximation Approach

We consider travel times between locations and service times as stochastic parameters. We propose a SAA approach which is a Monte Carlo approach. We use the Monte Carlo simulation to generate a set of samples Ξ of the stochastic travel time (tt_{ik}) and the service time duration (d_i) in the problem. Our solution approach leads to solving a deterministic optimization problem using samples $\xi_p \in \Xi$, with $p = \{1,...,P\}$. We assume that each sample ξ_p is taken with probability $\frac{1}{P}$. In our paper, we consider each sample as a possible scenario. Therefore, we will use the word scenarios instead of samples.

We obtain an approximation of the value of the objective function and constraints for the stochastic problem by the sample averages and then solve the approximation problem to obtain a solution. Scenarios are independent and identically distributed. The flowchart 4 describes the solution approach. Firstly, we assume that the travel time and service time duration follow a probability distribution. Then we generate scenarios for tt_{ik} and d_i using the following equations:

$$tt_{ij}(\xi_p) = \bar{tt}_{ij} \cdot \Delta_{tt}(\xi_p) \quad (1)$$

$$d_i(\xi_p) = \bar{d}_i \cdot \Delta_d(\xi_p) \quad (2)$$

The $\Delta_{tt}(\xi_p)$ and $\Delta_d(\xi_p)$ are vectors that represent all possible variations of tt_{ij} and d_i, respectively. We parallelize the solution process since each scenario can be considered independent. We use a mixed integer programming model for computing the optimal solution for each sample $\xi_p \in \Xi$. The equations 3 and 4 represent the objective functions of our stochastic problem. the problem is solved with one of the two objective functions. This is not a multi-objective problem. This means that our mathematical model is flexible enough to change from the objective function of minimizing the travel time of the driver ($\hat{f}_1(x)$) to the objective function of minimizing the travel and waiting time of the medical staff (and users) ($\hat{f}_2(x)$). The purpose of setting these two objective functions is to compare the total travel time and waiting time of users and medical staff reached under each objective function. By comparing the behavior of the solutions obtained from both objective functions, we gain insights into the trade-offs between the competing objectives. We can make informed decisions on how to balance them. The main variables and constraints of the model are presented below. However, not all constraints can be presented due to the limited number of pages of this paper.

Sets
$\mathscr{I}$: Set of nodes. 0 refers to depot node. Indexed i, j.
$\mathscr{C}$: Set of nodes i associated with medical staff dropped off. $\mathscr{C} \subset \mathscr{I}$.
$\mathscr{C}'$: Set of nodes i associated with medical staff picked up. $\mathscr{C}' \subset \mathscr{I}$.
$\mathscr{P}$: Set of nodes i associated with patient picked up. $\mathscr{P} \subset \mathscr{I}$.
$\mathscr{P}'$: Set of nodes i associated with patient dropped off. $\mathscr{P}' \subset \mathscr{I}$.
$\mathscr{M}$: Set of nodes i associated with a patient-paramedic couple dropped off. $\mathscr{M} \subset \mathscr{I}$.
$\mathscr{M}'$: Set of nodes i related to a patient-paramedic couple picked up. $\mathscr{M}' \subset \mathscr{I}$.
$\mathscr{V}$: Set of vehicles. $v \in \mathscr{V}$.
$\mathscr{S}$: Set of medical staff. $s \in \mathscr{S}$.
$\mathscr{Q}$: Set of qualifications. $q \in \mathscr{Q}$.
$\mathscr{S}_q$: Set of medical staff s with qualifications q.

Parameters
$tt_{ij}(\xi_p)$: Travel time from i to j in scenario (ξ_p).
a: Maximum vehicle capacity.
ρ_{ih}: Binary matrix 1 if node i is a predecessor of node j.
M: Sufficiently large number.
$d_i(\xi_p)$: Service time of client i in scenario (ξ_p).
l_i: End of the time window for medical treatment at node i.
e_i: Start of the time window for medical treatment at node i.
$\mathscr{O}$: Maximum allowed waiting time.
H: Maximum working hours.

Variables
$X_{ijv}(\xi_p)$= Binary variable. 1, if vehicle v visits node i after node j in scenario (ξ_p). 0 otherwise.
$Y_{iv}(\xi_p)$= Non-negative variable. Arrival time of vehicle v at node i in scenario (ξ_p).
$W_{si}(\xi_p)$= Binary variable. 1, if the staff provides medical s service at node i in scenario (ξ_p). 0 otherwise.
$\mathscr{E}_{is}(\xi_p)$= Non-negative variable. Start of the medical treatment provided at node i by medical staff s in scenario (ξ_p).
$\mathscr{F}_{is}(\xi_p)$= Non-negative variable. End of the medical treatment provided at node i by medical staff s in scenario (ξ_p).
$Cap_{vi}(\xi_p)$= Non-negative variable. Capacity of vehicle v after visiting node i in scenario (ξ_p).
$\phi_i(\xi_p)$= Non-negative variable. Waiting time at node i in scenario (ξ_p).

$T_s(\xi_p)$= Non-negative variable. Travel time of medical staff s including waiting time in scenario (ξ_p).
$\delta_s(\xi_p)$= Non-negative variable. Total working hours of medical staff s in scenario (ξ_p).

Objective functions

$$\min_{x\in X} \hat{f}_1(x) := \mathbb{E}(F_1(X,\Xi)) := \frac{1}{P}\cdot\sum_{p=1}^{p=P} F_1(X,\xi_p) := \frac{1}{P}\cdot\sum_{p=1}^{p=P}\sum_{i\in I}\sum_{j\in I}\sum_{v\in V} x_{ikv}(\xi_p)\cdot tt_{ij}(\xi_p) \tag{3}$$

or

$$\min_{x\in X} \hat{f}_2(x) := \mathbb{E}(F_2(X,\Xi)) := \frac{1}{P}\cdot\sum_{p=1}^{p=P} F_2(x,\xi_p) := \frac{1}{P}\cdot\sum_{p=1}^{p=P}\sum_{s\in\mathscr{S}} T_s(\xi_p) \tag{4}$$

Subject to:

$$\begin{aligned}
&\sum_{j\in\mathscr{I}} X_{jiv}(\xi_p) = 1 && \forall\, i\in\mathscr{I},\xi_p\in\Xi\\
&\sum_{j\in\mathscr{I}} X_{ijv}(\xi_p) = \sum_{j\in\mathscr{I}} X_{jiv}(\xi_p) && \forall\, i\in\mathscr{I},v\in\mathscr{V},\xi_p\in\Xi\\
&Cap_{vj}(\xi_p)\geq Cap_{vi}(\xi_p)+load_j-a\cdot(1-X_{ijv}(\xi_p)) && \forall\, v\in\mathscr{V},i,j\in\mathscr{I},\xi_p\in\Xi\\
&Cap_{vj}(\xi_p)\leq Cap_{vi}(\xi_p)+load_j+a\cdot(1-X_{ijv}(\xi_p)) && \forall\, v\in\mathscr{V},i,j\in\mathscr{I},\xi_p\in\Xi\\
&Cap_{vi}(\xi_p)\leq a && \forall\, v\in\mathscr{V},i,j\in\mathscr{I},\xi_p\in\Xi\\
&\sum_{j\in\mathscr{I}} X_{jiv}(\xi_p) = \sum_{j\in\mathscr{I}} X_{hjv}(\xi_p) && \forall\, i,h\in\mathscr{I}\mid(i,h)\in\rho_{ih},v\in\mathscr{V},\xi_p\in\Xi\\
&Y_{vi}(\xi_p)+tt_{ij}(\xi_p)\leq Y_{vi}(\xi_p)+M\cdot(1-X_{jiv}(\xi_p)) && \forall\, v\in\mathscr{V},i\in\mathscr{I}\backslash\{0\},j\in\mathscr{I},\xi_p\in\Xi\\
&Y_{vi}(\xi_p)\leq Y_{vj}(\xi_p) && \forall\, v\in\mathscr{V},i,j\in\mathscr{I}\mid(i,j)\in\rho_{ij},\xi_p\in\Xi\\
&\sum_{s\in S_q} W_{si}(\xi_p) = 1 && \forall\, i\in\mathscr{I},q\in\mathscr{Q},\xi_p\in\Xi\\
&W_{si}(\xi_p) = W_{sj}(\xi_p) && \forall\, i,j\in\mathscr{I}\mid(i,j)\in\rho_{ij},s\in\mathscr{S},\xi_p\in\Xi\\
&\sum_{s\in\mathscr{S}} \mathscr{E}_{is}(\xi_p) \geq \sum_{v\in\mathscr{V}} Y_{v,i}(\xi_p) && \forall\, i\in\mathscr{P}\cup\mathscr{P}'\cup\mathscr{C}\cup\mathscr{M},\xi_p\in\Xi\\
&\sum_{s\in\mathscr{S}} \mathscr{E}_{is}(\xi_p)+d_i(\xi_p) \leq \sum_{s\in\mathscr{S}} \mathscr{E}_{js}(\xi_p) && \forall\, i\in\mathscr{I}\backslash\{0\},(i,j)\in\rho_{ij},\xi_p\in\Xi\\
&\sum_{s\in\mathscr{S}} \mathscr{F}_{is}(\xi_p) = \sum_{s\in\mathscr{S}} \mathscr{E}_{is}(\xi_p)+d_i(\xi_p) && \forall\, i\in\mathscr{I}\backslash\{0\},\xi_p\in\Xi\\
&\sum_{s\in\mathscr{S}} \mathscr{F}_{is}(\xi_p) \leq \sum_{v\in\mathscr{V}} Y_{v,i}(\xi_p) && \forall\, i\in\mathscr{C}'\cup\mathscr{M}',\xi_p\in\Xi\\
&\mathscr{E}_{is}(\xi_p) \leq l_i && \forall\, i\in\mathscr{P}\cup\mathscr{C},\xi_p\in\Xi\\
&\phi_i(\xi_p) = \sum_{s\in\mathscr{S}} \mathscr{E}_{is}(\xi_p)-e_i && \forall\, i\in\mathscr{P}\cup\mathscr{C},\xi_p\in\Xi\\
&\phi_i(\xi_p) = \sum_{v\in\mathscr{V}} Y_{v,i}(\xi_p)-\sum_{s\in\mathscr{S}} \mathscr{F}_{is}(\xi_p) && \forall\, i\in\mathscr{P}'\cup\mathscr{C}'\cup\mathscr{M}',\xi_p\in\Xi
\end{aligned}$$

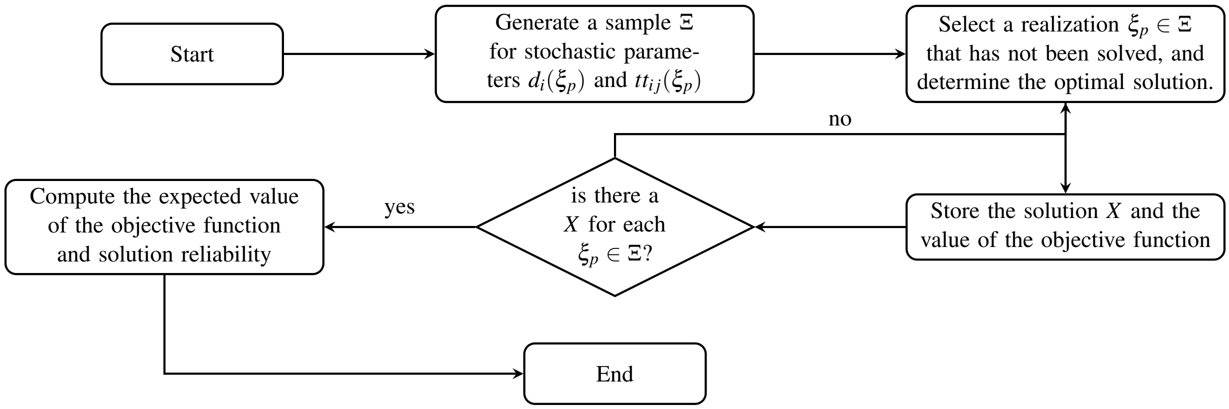


Figure 4: Flowchart of the sample average approximation.

$$
\begin{aligned}
\phi_i(\xi_p) \leq & \mathscr{O} && \forall\ i \in \mathscr{I}, \xi_p \in \Xi \\
T_s(\xi_p) = & \delta_s(\xi_p) - \sum_{i \in \mathscr{I}} d_i(\xi_p) \cdot W_{si} && \forall s \in \mathscr{S}, \xi_p \in \Xi \\
\delta_s(\xi_p) = & \max_{i \in \mathscr{I}} \mathscr{F}_{is}(\xi_p) - \min_{i \in \mathscr{I}} \mathscr{E}_{is}(\xi_p) && \forall s \in \mathscr{S}, \xi_p \in \Xi \\
\delta_s(\xi_p) \leq & H && \forall s \in \mathscr{S}, \xi_p \in \Xi
\end{aligned}
$$

In the SAA approach, each scenario $\xi_p \in \Xi$ is processed in parallel as an independent problem. We derive a set of deterministic solutions X upon solving all the scenarios. These solutions subsequently enable a robust approximation of the objective function value of the original stochastic problem. In pursuit of the expected values for $\hat{f}_1(x)$ and $\hat{f}_2(x)$, we first resolve the problem of prioritizing one objective function and then separately address the second objective function. In this context, when a particular objective function acts as the optimization criterion, the alternate function assumes the role of an outcome variable. This procedure assesses and quantifies the influence of one objective function on the other. Consequently, each sample $\xi_p \in \Xi$ possesses an optimal value for the objective function and an optimal solution $x \in X$, where X represents the set of solutions.

5 COMPUTATIONAL EXPERIMENTS

We design two artificial instances with 18 nodes (3 clients, 3 patients, and 3 medical centers) and 80 nodes (20 clients, 10 patients, and 10 medical centers). We assume that $\bar{d_i}$ for all clients and patients follow a truncated normal distribution $N(40,20)$ (Reuters Health 2017; NHS 75 Digital 2023), and $\bar{tt}_{ik}$ fit a uniform distribution $U(20,40)$. $\Delta_{tt}(\xi_p)$ and $\Delta_d(\xi_p)$ follow a truncated normal distribution, $N(0.5,2)$ and $N(0.8,1.5)$ respectively. The earliest and latest time windows vary between [8:00, 16:00]hr and [10:00,19:00]hr, respectively. The time windows have an amplitude of at most 4 hours. We generate a large number of 1000 samples. The study was implemented using a MIP model in GAMS 41/CPLEX, and the instances were solved to optimality.

Figure 5 presents the results. As expected, the results obtained with the model that minimizes the travel time of the medical staff provide minimum waiting time and travel time. Remember that patients are constantly accompanied by the paramedic, so indirectly, our model also minimizes patient waiting and travel time. In contrast, the solution provides long travel times for the driver. However, the model with an objective function Equation (3) provides long travel and waiting times for the medical staff while firing. Thus, minimizing the travel time of the driver does not mean minimizing the travel time of the medical staff.

Figure 5 is a visual representation of the solutions to facilitate the decision maker's perception of the impact of only minimizing the driver's travel time or minimizing the medical staff and patients travel time.

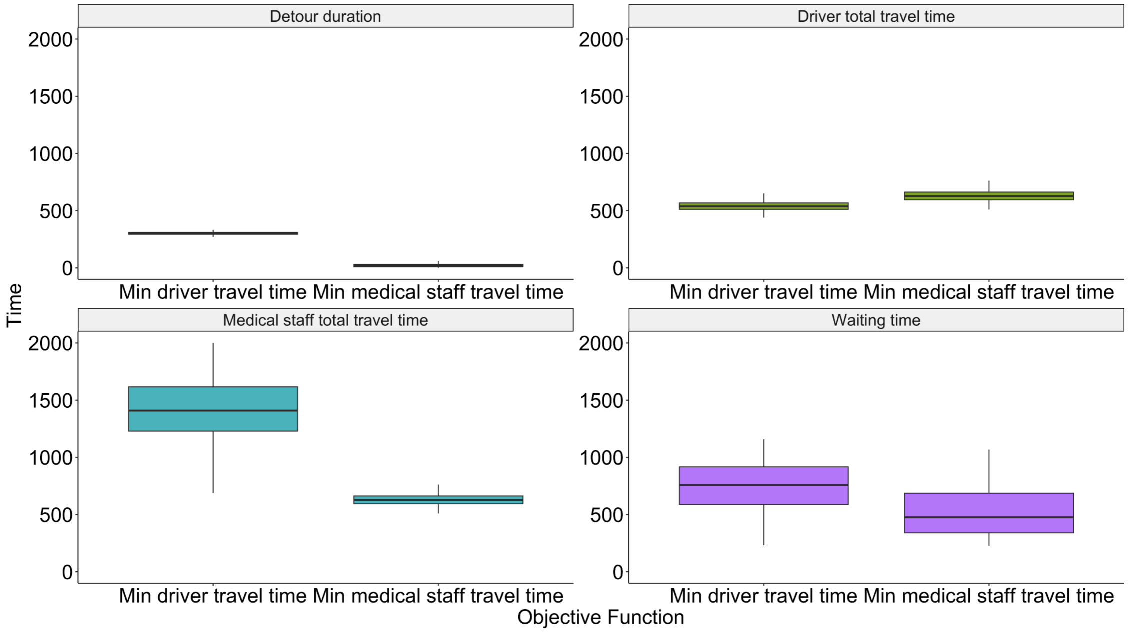


Figure 5: Example applications of artificial neural networks to deal with deadlocks in an automated guided vehicle system.

Minimizing the driver's travel time is an optimal solution for the logistics operator of home healthcare services. However, that solution may represent an increase of up to 93% of the waiting time and travel time for the medical staff. While minimizing the travel time of the medical staff can lead to a reduction of up to 15% in the driver's travel time.

Preliminary results from our model indicate that integrated trips generally lead to reduced travel times for both medical staff and patients, as well as the driver, and necessitate fewer vehicles and medical staff. However, it is essential to note that individual trips offer greater flexibility in scheduling and may be indispensable in certain circumstances. Overall, these findings suggest that optimizing for integrated trips can enhance the efficiency and cost-effectiveness of transportation for home care services.

6 CONCLUSIONS

The research presented in this paper is part of an ongoing project that is still in its initial stages. Consequently, this section does not offer definitive conclusions, but instead provides preliminary findings based on our initial experiments and analyses. We focus on minimizing travel time for medical staff and patients in the context of home healthcare services using the dial-a-ride problem as a framework. Through our initial findings, we have discovered that minimizing driver travel time does not always lead to minimizing travel time for medical staff and patients, indicating the need for a more nuanced approach. Furthermore, the preliminary results of our study show that minimizing the travel time of the medical staff leads to minimizing waiting time and travel time for both medical staff and patients. However, this solution may result in longer travel times for the driver. On the other hand, minimizing the driver's travel time may lead to longer travel and waiting times for the medical staff. Our study highlights that minimizing the travel time of one objective does not necessarily minimize the travel time of the other. As a working project, our next steps will involve developing a simulation-optimization algorithm tailored to handle large instances of the integrated home healthcare and dial-a-ride problem. The outcomes of this research will have practical applications in real-world home healthcare service providers, where efficient scheduling and routing can significantly impact the quality of care provided to patients.

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