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SIMULATION AND ANALYSIS OF DISRUPTIVE EVENTS ON A DETERMINISTIC HOME HEALTH CARE ROUTING AND SCHEDULING SOLUTION

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ABSTRACT

Due to the aging of populations and a desire to relieve the growing demand on medical structures in recent years, the demand for home health care services has been increasing, and the Home Health Care Routing and Scheduling Problem (HHCRSP) is now among the most intensely studied optimization problems. However, most studies on the HHCRSP are based on deterministic models that do not consider any disruptions that may compromise the execution of the schedules. In this paper, we analyze the impact of different sources of disturbances on a deterministic schedule : delays at the start of the route, variability of travel time, and variability of service processing time. Simulation has been chosen because it helps to easily model and analyze complex environments with several sources of variability. Graphical representations and an analysis of variance are presented to interpret the results, leading to several managerial insights and openings for future research.

1 INTRODUCTION

Thanks to the progress of science, the life expectancy of humans is constantly increasing. Thus, there are more and more people living longer lives. In France, for example, people over 60 years old represented around 25% of the population in 2018, compared to only 20% in 2000, and Brutel (2002) predicts more than 30% in 2050. In addition, there is a desire to reduce the demand on medical structures (such as hospitals), pushing people to return to their homes as quickly as possible. Consequently, the demand for services and home care has increased sharply in recent years, as have scientific studies on the subject (Di Mascolo et al. 2021).

The Home Health Care Routing and Scheduling Problem (HHCRSP), derived from the Vehicle Routing Problem (VRP) which has been studied for decades (Dantzig and Ramser 1959), consists in assigning tasks to staff members of an HHC agency, planning care visiting hours for patients at home, and designing the caregivers' routes. Many studies focus on HHCRSP, since several parameters can be considered: the objective function (cost minimization, maximization of stakeholder satisfaction, etc.), the constraints of the model (consideration of time windows, a matrix of feasibility between caregivers and services or patients, the workload rate of caregivers), the horizon studied (day, week, or month), the resolution approach or tool, and the stochasticity of the environment, etc. This last point is one of the least studied, and that is why in this article, we measure and analyze the impact of three different sources of disturbances on a deterministic schedule coming from a HHCRSP literature paper. Discrete-event simulation has been chosen because it easily allows complex environments with several sources of variability to be modeled and analyzed.

The paper is organized as follows: section 2 presents a brief literature review and concludes with the research question, section 3 introduces the use case and the methodology, section 4 presents the results, and section 5 is the conclusion and openings for future research.

2 LITERATURE REVIEW

There are many studies on the HHCRSP which have been recently reviewed in (Cissé et al. 2017; Di Mascolo et al. 2021; Grieco et al. 2020) and which explore a large range of problems presenting numerous and various features. As a result of the number of publications on the subject, we present in this section a non-exhaustive review of what has been studied to raise a relevant research question. We approach the literature review according to three criteria: objective function, resolution approach, and variability modeling.

2.1 The Objective Function

In the literature, the main objective function is cost minimization: Begur et al. (1997) minimize travel distances, while Szander et al. (2018) minimize transportation costs. Costs related to caregiver working time are also considered: Mısır et al. (2015) seek to minimize overtime and Luna et al. (2018) minimize the number of caregivers needed to provide services.

The other widely studied optimization criterion is the maximization of stakeholder satisfaction. For patient peace of mind, this essentially involves minimizing violations of time windows (Bertels and Fahle 2006; Trautsamwieser et al. 2011), and improving continuity of care, which is generally interpreted as assigning a unique caregiver to each patient (Trautsamwieser and Hirsch 2011) or minimizing the number of different caregivers (Wirnitzer et al. 2016). For the satisfaction of caregivers, Cappanera and Scutellà (2013) consider workload balancing, Zhang et al. (2021) work on balancing the difficulty of services and Rest and Hirsch (2016) minimize overqualified work.

2.2 Resolution Approaches

Derived from VRP, HHCRSP is NP-hard, so numerous exact or approximate approaches have been developed to tackle the problem, such as Mixed-Integer Linear Programming (MILP) (Cheng and Rich 1998), a branch and price algorithm (Liu et al. 2019), dedicated heuristics (Fathollahi-Fard et al. 2020), and a variable neighborhood search (Nasir and Dang 2018), etc.

Even though the majority of the articles have developed a centralized approach to routing and scheduling caregivers, some studies prefer distributed approaches. Marcon et al. (2017) propose an agent-based model to dynamically re-route caregivers according to a set of decision rules. Alves et al. (2018) use multi-agent simulation to deal with the perturbations due to vehicle problems and to re-schedule interventions. In Viana et al. (2017), the impact of various demand patterns is evaluated through an agent-based model and discrete-event simulation.

2.3 Variability Modeling

Fikar and Hirsch (2017) highlight the importance of taking uncertainties into account when solving the HHCRSP. Variability can come from many sources of disturbance, and can be modeled in several ways.

The first source of disturbance comes from the patients who may change their time slot (Lin et al. 2018), their frequency of visit (Mosquera et al. 2019), or cancel services (Yuan and Jiang 2017). Caregivers can also disrupt the system: for example, they may fall ill and change their availability (Xie and Wang 2017). The most widely studied source of variability is variations in travel time, due to traffic (Yalçındağ et al. 2016), breakdowns, parking and driving skills (Shi et al. 2019), and variations in service time (Yuan et al. 2015).

Two main approaches have been used to consider these disturbances. The first one is to predict the variations to obtain a robust solution that remains feasible even when the schedule is disturbed. Variability is then modeled either by a discrete set of scenarios (Cappanera et al. 2018; Rodriguez et al. 2015), or by intervals of values (Mosquera et al. 2019; Carello and Lanzarone 2014), and the values are arbitrarily uniformly or normally distributed.

2.4 Conclusion and Research Question

As a conclusion of this review, it is known that (i) there are many studies on the HHCRSP, that (ii) the minimization of travel distances is the most widely studied criteria, inherited from the VRP, but more and more studies are considering stakeholder satisfaction (patients and caregivers), that (iii) there are many tools and methods that have been developed over the years in the literature to solve the HHCRSP, but that (iv) the variability of the systems has only been studied for a few years without analyzing its impact on the performance of the solutions. One question thus arises: What are the impacts of disruptive events on the satisfaction of HHCRSP stakeholders?

To answer this question, we propose to study a short-term deterministic solution coming from a HHCRSP literature paper that considers stakeholder satisfaction, to model several sources of disturbances and variability using discrete-event simulation, and to analyze the impacts on performance measures.

3 METHODOLOGY

Our research strategy is based on the study of a use case inspired by Zhang et al. (2021). In this paper, we follow the procedure recommended by Montgomery (2017) for designing and analyzing experiments (Figure 1). The objectives of the experiments are to measure and quantify the impacts of different sources of schedule disruptions, including two sources of variation.

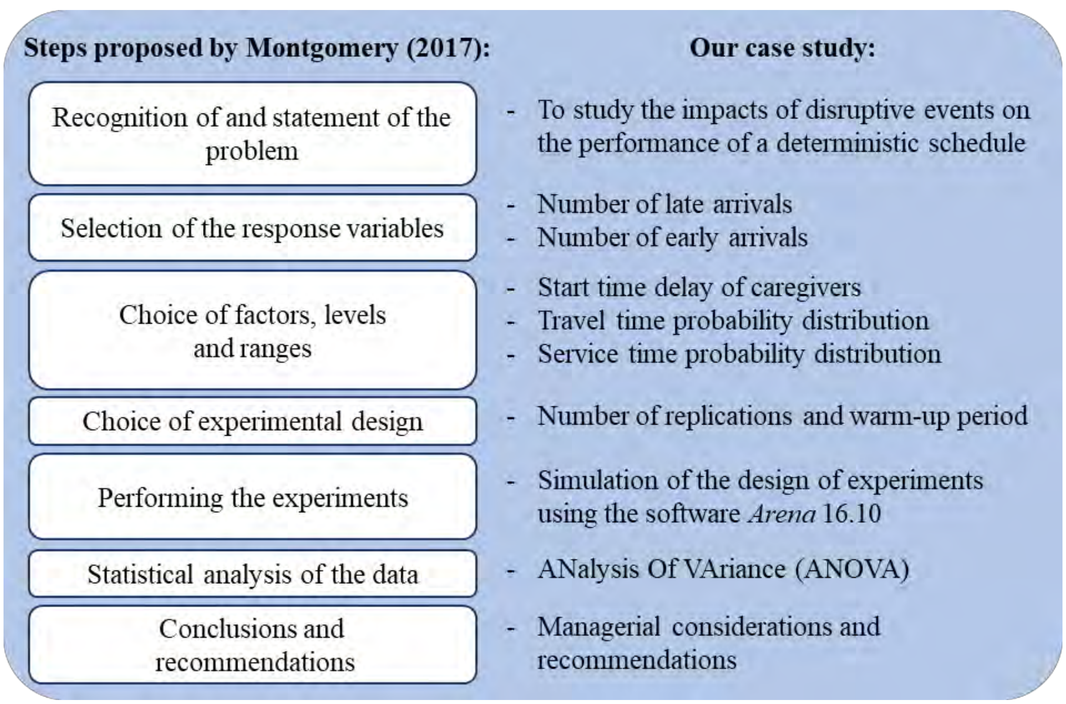

Figure 1: Steps of the methodology applied to our case study.

Discrete-event simulation has been chosen as the method because it allows complex environments with several sources of variability to be easily modeled and analyzed (Mourtzis 2020), and a lack of studies on the impact of the variability on deterministic schedules has been highlighted in the literature review.

3.1 Use Case and Deterministic Solution Representation

The chosen use case for experimental purposes comes from Zhang et al. (2021), where the objective is to provide a solution to the HHCRSP on a daily horizon. The data set was extracted from an existing HHC institution.

For the demand side, 28 patients are included in this case. Fourteen of them require only one care service, while the others have between 2 and 5 services during the day. For each care service, patients specify a one-hour arrival starting time window (from case study data), corresponding to the window during which the caregiver must come to start the service (the service can be finished after this time window). Fifty-five care services are requested by 28 patients. There are three types of services according to the temporal criteria: 15-minute short services, 30-minute medium services, and 60-minute long services.

For the offer side, there are 4 caregivers (who have undergone training in caregiving) to be dispatched to perform the 55 care services (refer to nursing care or home health aide services), hence the 4 different routes in Figure 2. The maximum workload is 10 hours per day for each caregiver.

Based on the MILP model described in Zhang et al. (2021), we obtain the optimum solution generated by CPLEX for our experimental use case. In this model, several specific parameters have been considered, such as the difficulty of care services and a feasibility matrix between caregivers and services. Furthermore, a series of soft constraints aimed at considering the satisfaction of all the stakeholders (patients and caregivers) have been taken into account: (i) for patients, the beginning of a service has to be scheduled as closely as possible within the requested time windows, and in the case of more than one care service requested by the same patient, the temporal interval between two successive services should be greater or equal to the requested inter-service time; (ii) for caregivers, the duration of a working round for one caregiver should be respectful of his/her allowed maximum working hours, and the set of rounds should be balanced according to the level of difficulty.

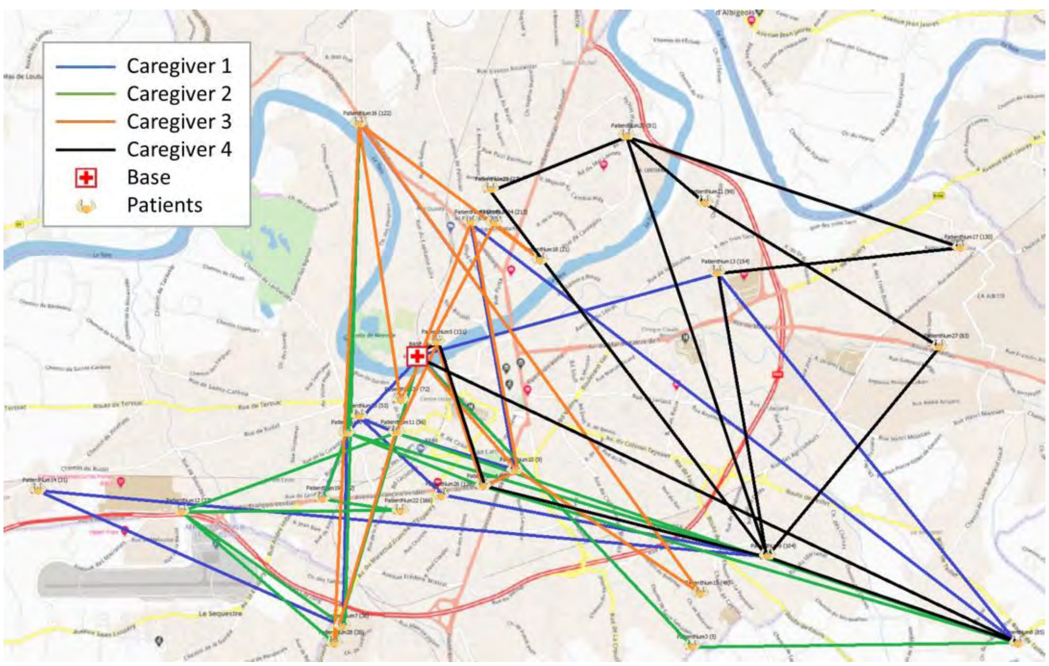

Figure 2: Routes of the model’s four caregivers.

Regarding the optimal and deterministic solution obtained by executing the described MILP-based model, the average workload rate of caregivers is 83% (between 76% for the least busy and 93% for the busiest). The workload rate includes travel time and care service time, divided by the 10 hours of work per day. In this case, travel time represents about one-third of service time. Travel time is calculated by taking the Euclidean distances (i.e., as the crow flies, Figure 2) between each patient, and dividing it by the average speed of 20 km/h. Finally, we must emphasize that the exact method-oriented MILP-based model described in Zhang et al. (2021) is a deterministic model, under two assumptions in terms of temporality: deterministic travel time and the operation time of each care service. In this paper, we propose to study the impact of variability on these times on the schedule. In addition, we study the impact of the delay of caregivers at the start of their routes.

3.2 Experimental Protocol

3.2.1 Statement of the Problem

In Zhang et al. (2021), the MILP-based model has been used to determine the optimal solution, which is a deterministic daily schedule. This solution does not consider any variation that could occur during the day (heavy traffic, car breakdowns, services taking longer than expected, etc.). Figure 3 presents the optimal schedule (due to limited space and the need for legibility, the afternoon schedule has not been shown), as well as the detailed routing results for the first caregiver (with time windows to respect for each patient). The routes are shown in Figure 2. Note that the execution of this schedule will be the baseline scenario for the design of the experiments, and it already includes several early arrivals (in yellow, Figure 3) and late arrivals (slashed and encircled in red).

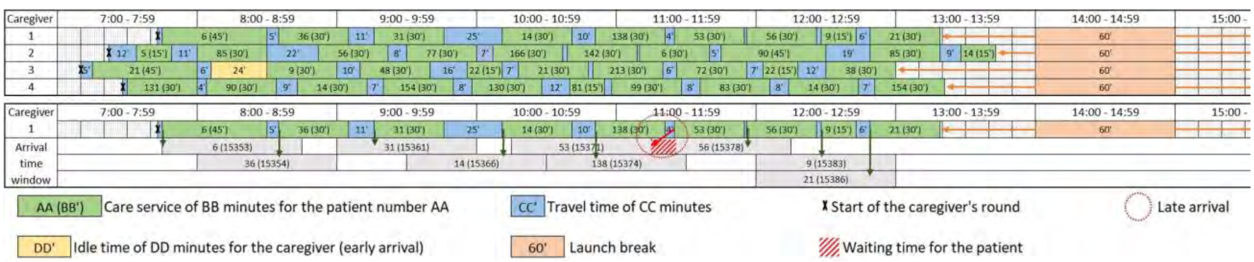

Figure 3: Start of the schedule determined by Zhang et al. (2021).

Data and calculated values are deterministic, i.e., they are considered to be fixed, without variation. For example, at 20 km/h, a 10 km trip will always take 30 minutes. The duration for performing a care service is also the fixed time. However, many unforeseen events can happen and disrupt the schedule, deteriorating its performance related to stakeholder satisfaction. Therefore, we propose to model different sources of variability and analyze their impacts on this deterministic schedule.

3.2.2 Selection of the Response Variables

Since we are interested in the satisfaction of all stakeholders involved in HHC, and we assume that the sources of variability introduced into the model may disrupt the schedule by shifting the care services, then the response variables are the total number of late arrivals and the total number of early arrivals.

A late arrival occurs when a caregiver arrives after the one-hour time window requested by the patient, and an early arrival occurs when a caregiver arrives before the time window. In the latter case, the caregiver has to wait for the start of the time window before entering the patient's home and then beginning the care service.

A tolerance of one minute early or late is considered. For example, if a caregiver arrives 15 seconds later than the end of the time window, this is not considered a delay.

3.2.3 Choice of Factors, Levels and Ranges

The choice of factors reflects the events that could modify the initial schedule and degrade the performance of the solution. Consequently, three sources of disturbances are considered in the model:

1. The delay at the start of the caregiver's daily working round (start time delay). This delay may be due to a car/bike breakdown, an unexpectedly difficult de-icing, a sick child to be looked after, etc.
2. The variability of travel time. It is important to highlight that in real life, travel times fluctuate constantly due to traffic congestion, traffic jams, accidents, etc.
3. The variability of service processing time. Two of the same care services never take exactly the same amount of time to be carried out, especially when considering the various human characteristics of caregivers and their proficiency when performing the same care services under different contexts on site. Care service processing time is highly variable and it is difficult to model these temporal events based on unpredictable human factors.

To assess the impacts of these different sources, four levels of variability have been designed: a deterministic one where there is no variation (as modeled in the reference paper), and three levels where values are uniformly distributed, as shown in Table 1.

Table 1: Levels and ranges for each source of disturbance.

Source of disturbance	**Levels and ranges**			
	Ø	Low	Medium	High
Start time delay	Deterministic	Uniform(0:10)	Uniform(0:30)	Uniform(0:60)
Travel time	Deterministic	Uniform(0.9:1.1)	Uniform(0.7:1.3)	Uniform(0.5:1.5)
Service time	Deterministic	Uniform(0.9:1.1)	Uniform(0.7:1.3)	Uniform(0.5:1.5)

For the start time delay, the three ranges for each uniform law are 0 to 10, 0 to 30, and 0 to 60, corresponding respectively to an average departure delay of 5, 15 and 30 minutes. We do not consider the case where a caregiver leaves early from home, since in this case the caregiver just has to wait before leaving. For the travel and service times, the three ranges correspond to ±10%, ±30%, and ±50% around the mean value of the deterministic model, to model different degrees of variability (low, medium, high). Therefore, with a range at ±50%, a 10-minute ride will be uniformly distributed between 5 and 15 minutes, and a 60-minute care service will be uniformly distributed between 30 and 90 minutes. The choice of uniform laws comes from the literature (Naji et al. 2017; Rodriguez et al. 2015).

3.2.4 Choice of Experimental Design and Performing the Experiments

The design of the experiments is composed of 4x4x4 = 64 scenarios.

The scenarios are compared to the baseline, which corresponds to the case where the caregivers start on time, and the travel and care service times are deterministic. The baseline is the solution obtained by running an MILP-based model developed in CPLEX. Each scenario is simulated with 100 replications (except for the baseline, which is deterministic and needs only one replication), and each replication lasts one day. The model being empty in the initial state, there is no warm-up period.

The modeling and simulation were performed with *Arena* software, version 16.10. A simplified version of the simulation model process flow is shown in Figure 4: the caregivers, entities of the model, are created (1); then they wait for a delay, depending on the simulated scenario, before getting their route information and making a first trip (2); the travel time is calculated according to a distance matrix and is subject to variability (3); the response variables are incremented if an early arrival (4) or a late arrival (5) occurs;

finally, the care service is carried out by considering variability (6), and the caregiver moves on to the next patient until the end of the route has been reached.

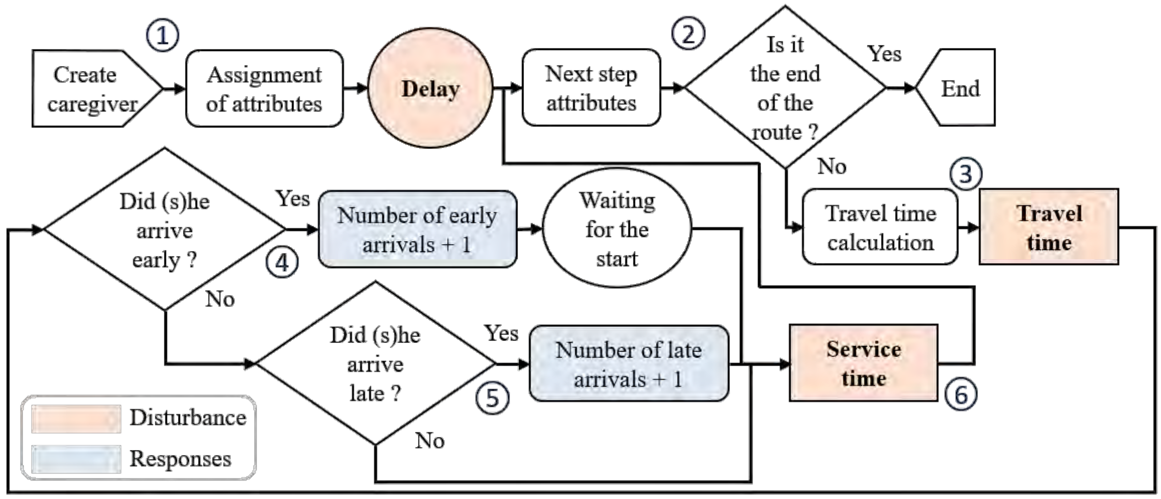

Figure 4: Simplified simulation model process flow.

4 RESULTS

4.1 Overview of Design of Experiment Results

The results of the 64 scenarios are represented in Figure 5: on the abscissa, the total number of early arrivals, and on the ordinate, the total number of late arrivals. Thus, the best scenarios are those at the bottom left of the graph. To differentiate the scenarios, the following legend has been used:

- The shapes (circle, square, triangle, rhombus) correspond to the different levels of the Start time delay (S) factor,
- The fill colors (green, orange, blue, grey) correspond to the levels of the Travel time (T) factor, and
- The border colors (same four colors but darker) correspond to the levels of the Care service time (C) factor.

The matches between shape, color and levels are shown in Figure 5. Moreover, each scenario has a specific name according to the level of its factors. For example, the scenario where the Start time delay (S) is between 0 and 10 minutes, the Travel time (T) is ±30% and the Care service time (C) is ±50% is named S10_T30_C50, and represented by a blue square outlined in dark gray. The scenario named S00_T00_C00 is the baseline.

For the baseline scenario, the total number of early arrivals is 5, and the total number of late arrivals is 4. It is the best compromise between a low number of early and late arrivals. By adding disturbance sources, the number of late arrivals increases to 20, and the number of early arrivals goes up to 8.

4.2 Graphic Visualization of the Effects of each Source of Disturbance

In order to better understand the effect of each factor on the number of early and late arrivals, Figure 6 presents three graphs where scenarios are grouped by color according to the level of each factor. The colors green, orange, blue and gray represent the different levels (deterministic and uniform distributions).

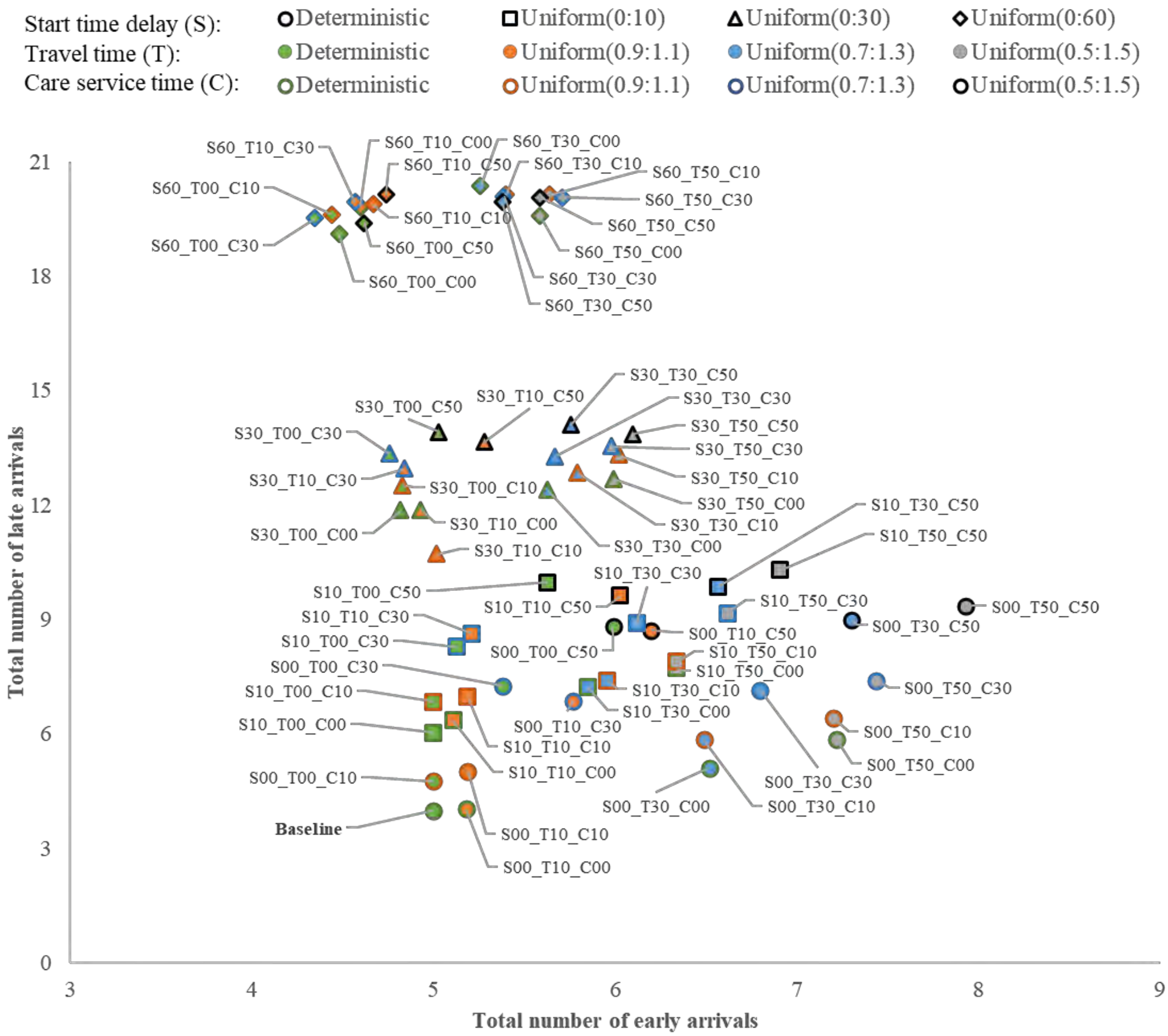

Figure 5: Total number of early arrivals and late arrivals for each scenario.

The start time delay increases the number of late arrivals but decreases the number of early arrivals: the more caregivers fall behind on their routes at the start of the day, the more they arrive late for services, thus reducing early arrivals. Moreover, the effect spreads throughout the morning: the caregiver is late for almost every morning service in Figure 7 (scenario S60_T00_C00). It is important to note that the lunch break (on the right, Figure 7) behaves as a time buffer, allowing the lateness of the morning to be absorbed, which thus has no impact on the afternoon care services (not represented), showing a solution for absorbing schedule variations.

Graphically, for the two sources of variability, variations in travel time mainly impact the number of early arrivals, while variations in service time affect the number of late arrivals for the caregivers (note that the axes of the graphs are not normalized). To mathematically confirm these observations, a two-way ANalysis Of VAriance (ANOVA) was carried out without considering any start time delay (S00).

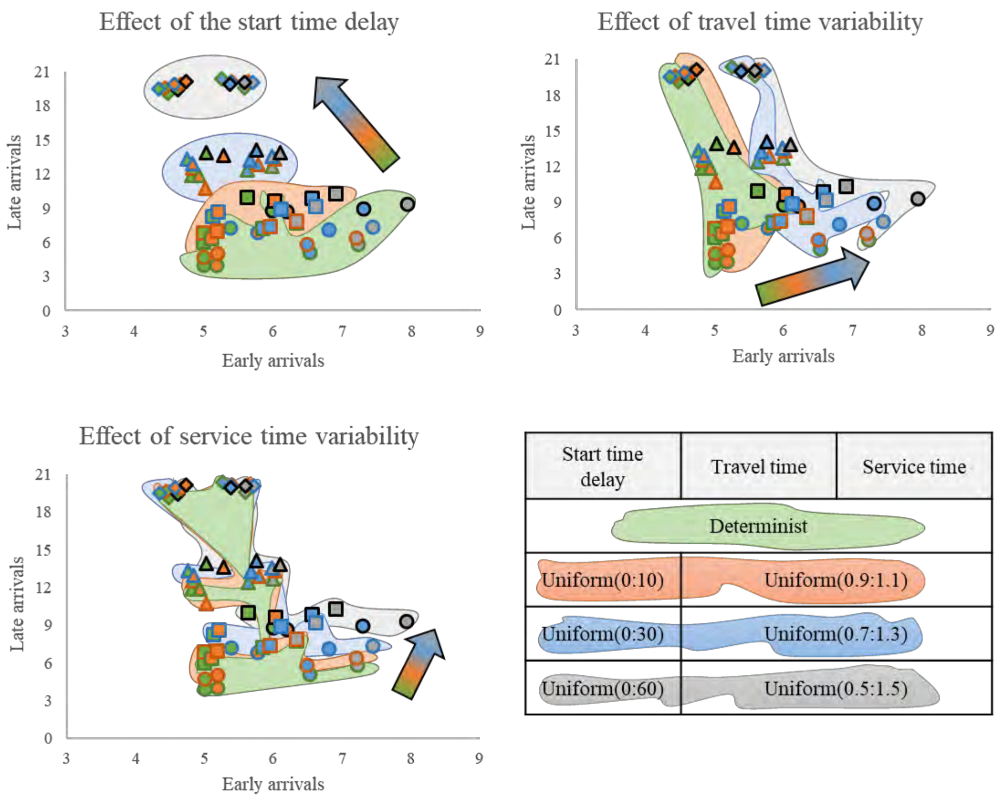

Figure 6: Effect of each factor on performance measures.

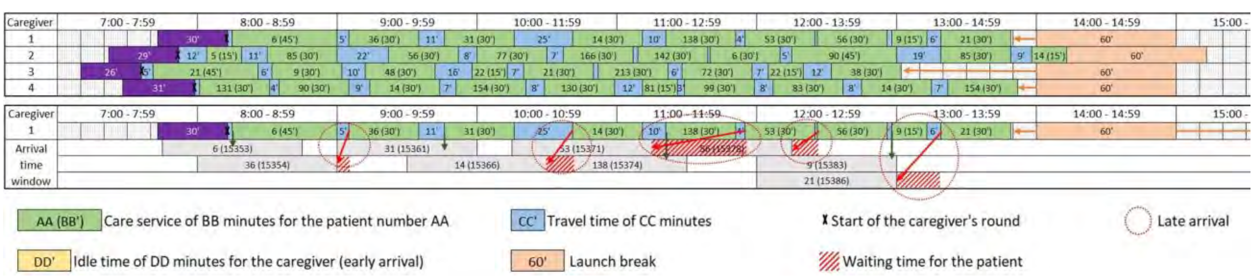

Figure 7: Execution of the schedule for scenario S60_T00_C00.

4.3 Two-Way ANOVA

An ANOVA is a statistical test used to analyze the difference between the means of different factors. A two-way ANOVA is used to estimate how the mean of a quantitative variable changes according to the levels of two categorical variables. In our case, the statistical test is used to measure the effect of the sources of variability in travel and service times that are observed in Figure 6. For the number of late arrivals, the results data are presented in Table 2, and the variance and F-value calculations are summarized in Table 3.

Since the F-values are greater than F_9^3(for alpha = 0.01) for both travel time and service time, they are both statistically significant, especially for the service time factor. The same statistical test has been performed for the total number of early arrivals, with F-values equal to 26.83 (for travel time) and 4.70 (for service time). Therefore, travel time is statistically significant but care service time is not.

Table 2: Results data of late arrivals and means calculation.

Late arrivals		Travel time factor				
		Deterministic	Uniform(0.9:1.1)	Uniform(0.7:1.3)	Uniform(0.5:1.5)	Mean
Service time factor	Deterministic	4.00	4.06	5.12	5.86	4.76
	Uniform(0.9:1.1)	4.77	5.03	5.86	6.42	5.52
	Uniform(0.7:1.3)	7.27	6.88	7.16	7.40	7.18
	Uniform(0.5:1.5)	8.83	8.72	8.98	9.36	8.97
	Mean	6.22	6.17	6.78	7.26	6.61

Table 3: Variance and F-value calculation for late arrivals.

Source of variability	**Sum of Squares (SS)**	**SS / SS(Total)**	**Degrees of freedom**	**Mean SS**	**F-value**	$F_9^3(99\%)$
Travel	3.19	7%	3	1.06	7.19	6.99
Service	42.06	90%	3	14.02	94.92	
Residual	1.33	3%	9	0.15		
Total	46.58					

In conclusion, the variability of service time mainly impacts the number of late arrivals, while the variability of travel time mainly impacts the number of early arrivals.

As 100 replications were simulated for each scenario, a two-way ANOVA with replications has been performed to assess whether there is an interactive effect between the factors. For late and early arrivals, the F-values of the interactive factor are respectively 2.21 and 0.52, while F_{1584}^{9}(for alpha = 0.01) is 2.41. We can conclude that the interaction factor is not statistically significant at alpha level 1%.

5 CONCLUSION AND OPENINGS

In this paper, we measure and analyze the impact of different sources of disturbances on a deterministic schedule coming from a HHCRSP literature paper. Three sources of disturbance have been modeled (delays at the start of the route, the variability of travel time, and the variability of service processing time), and the objective is to quantify their impacts on stakeholder satisfaction. Graphical representations and analyses of variances have been conducted, to conclude on the impact of disruptive events: this study emphasizes that it is unreasonable not to consider the variability of the HHCRSP environment when designing schedules.

To go further, it would be interesting to study what features of the model are affected by disturbances. For example, in our case study, travel time represents a third of service time: in another case, will the impacts of the sources of disturbances be different? Thus, we could create robust solutions depending on system features. Note that in our case study, although some patients require several services on the same day, there is no case where the delay of a caregiver leads to an overlap of services, further disrupting the schedule and its performance indicators.

The next step is to collect user data (patients and caregivers) to analyze whether the modeled disturbances are relevant, and to better understand stakeholder behavior.

Finally, several solutions (some of which already exist in the literature) can counteract the variability of the environment and disruptive events. Among the interesting solutions to study and explore, there are:

- Providing margins on travel time and service time. But how to optimize their sizing? Where to place them? What degree of conservatism for the robust solution?
- Rescheduling caregivers' routes in real time based on disruptions. But what tools to use? Which indicators? What are the consequences for patients?

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