Dynamic Electric Vehicle Dispatching Problem: A Simulation Modelling Framework

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Abstract — **A dynamic dispatching problem involving electric service vehicles used to maintaining bus service in operational conditions at the *Société de transports de Montréal (STM)* is studied. We provide a generic simulation modelling framework including a data analysis to estimate the interventions demand from historical data. Moreover, we propose a data scaling approach to complete the available data and address the issue of lack of data. We implement and evaluate several dispatching strategies within the simulation model, assessing their performance against key indicators to identify the best solutions for improving STM's operational efficiency.**

Keywords — *Vehicle Fleet, Transportation, Discrete event simulation, Assignment, Sizing*

I. INTRODUCTION

As part of its commitment to sustainability goals, the Société de transport de Montréal (STM), a public transportation organization in Québec (Canada), aims to electrify its entire fleet of buses and service vehicles by 2027 (STM, 2023). Among the service vehicles to be electrified, we distinguish those used by the Operations Supervisors (OS). These vehicles enable the OSs to intervene quickly on the bus network to resolve issues that could disrupt the bus service such as detours, signage problems, light equipment failure and passenger conflicts. The OSs' mission is to be present at all times on the Island of Montreal (Québec) in order to minimize the negative impact of these unforeseen events. The island of Montreal is divided into 15 sectors, within which the vehicles from eight Transportation Centers (TCs) operate. Indeed, the TCs serve as bus TCs but also as maintenance operations centres. When an incident occurs, the affected bus driver contacts the Central Operations Centers (COC), which is responsible for maintaining high bus service levels. Currently, the COC strategy consists in assigning the nearest available service vehicle to handle the incident. This strategy has the convenient to be easily implemented in practice and provide a quick answer to the vehicle dispatching problem. However, it might not be the most suitable decision-making approach for electric vehicles, regarding their strong autonomy constraints.

As the electrification of an entire vehicle fleet is very expensive and the right sizing of the fleet has not been addressed, the objective of our study is to determine the best size of the service vehicle fleet, i.e., the minimal number of vehicles while considering the specific constraints of using electric vehicles to support the STM in its vehicle electrification process while maintaining the efficiency of its service vehicle fleet. Furthermore, we propose different dispatching strategies in order to compare and improve the current company strategy. More precisely, we propose a demand estimation method to be jointly used with a discrete event simulation model in order to provide a modelling framework for the company vehicles fleet. The choice of the simulation model is justified by the stochastic nature of the studied problem especially the high variability of intervention demand in time and space. The proposed framework is proposed to evaluate and improve some performance indicators that have been defined in accordance with the company priorities which are: fleet size, handling time, traveling time, total traveling distance, and utilization rate. These indicators have a decreasing priority level from the most important one (fleet size) to the less important one that is utilization rate. We perform an experimental study to evaluate and compare the different dispatching strategies regarding these indicators while considering several scenarios for the density of interventions demand.

The remainder of the article is structured as follows: Section 2 presents the study's context. Section 3 presents a brief literature review, while Section 4 outlines the methodology. Section 5 presents our preliminary results and a discussion. Finally, our conclusions and research perspectives are presented in Section 6.

II. CASE STUDY

The Société de transport de Montréal (STM) is an organization responsible for operating public transportation in Montreal, namely the metro system and bus service. Its bus fleet consists of approximately 2,000 vehicles operating across the entire Island of Montreal. These vehicles may encounter disruptions during their routes, such as accidents, detours, altercations, etc. To address these issues, a team of agents, referred to as Operations Supervisors (OSs), is

dedicated to their resolution. Each OS operates with a service vehicle and is assigned to one of the eight TCs located in the Island of Montreal. Every month, a pre-assignment plan of the service vehicles is produced, indicating where the vehicles should operate for the 15 geographical sectors of the Island of Montreal during a 6-hour time slot, i.e., the OS work shift (see Figure 1). On the map shown in Figure 1, each coloured zone represents a sector, and each of the eight red dots indicates a TC.

Figure 1: Montréal Island spatial sectorisation with TCs location

Communication and coordination between Operations department (responsible for planning, managing, and monitoring transportation activities) and Maintenance department (responsible for managing, maintaining, and repairing infrastructure and equipment) are established through the Operations Control Centers (OCC), which, among others, centralizes calls from STM's bus drivers. When an incident occurs, the bus driver involved contacts the OCC, which based on the information available (e.g., GPS data of the service vehicles and surveillance video) assigns a service vehicle to the demand of intervention to reduce the impact of the incident on the bus service level (i.e., the percentage of time during which a bus is effectively in service). The current dispatching strategy involves allocating each new demand of intervention in a given sector to the nearest available service vehicle. Once the intervention is completed, the registration of the corresponding intervention demand is closed by the OCC and recorded in a dedicated database.

III. LITERATURE REVIEW

To the best of our knowledge, the topic of fleet sizing and vehicles dispatching problems have not been considered within the context of electric vehicles to maintain a transportation system in operational conditions in the literature. However, these problems have been studied within others applications such as emergency, firefighting, or police vehicles. In these works, the modelling formalism often used is mixed integer programming. As an example, Bélanger *et al.* (2019) provide an optimization model for the assignment of emergency medical vehicles. In this study, the authors explain how using optimization can improve decision-making, however they highlight the limits of a deterministic approach and suggest to adopt dynamic and stochastic approaches in order to tackle more realistic problems. Luzon *et al.* (2023) proposed an optimization model to determine the optimal size of a fleet of firefighting emergency vehicles. The authors obtain good results due to the fact that emergency vehicles are less subject to traffic.

The uncertainty of demand and other factors such as traffic, incidents on the road, and vehicle breakdown, prevents viable solutions from being obtained through optimization methods alone. Carter *et al.* (1970) already accounted for uncertainty when studying the deployment of firefighting resources in New York City using discrete event simulation (DES). Haghani *et al.* (2007) expanded on similar topics related to emergency vehicle fleets, including fleet sizing, fleet location, and response strategies, emphasizing the use of simulation modelling to compare different dispatching strategies for vehicles. Malan (2017) developed a simulation model to determine the size of a fleet of tractors operating in an underground coal mine. This study identifies configurations that improve costs and operational efficiency, demonstrating the value of simulation for fleet sizing and decision-making in realistic and complex environments.

IV. A SIMULATION MODELING FRAMEWORK

As previously discussed, we proposed a simulation-modeling framework for the sizing and dispatching problems to consider the dynamic behavior of the interventions demand. Indeed, the simulation modelling is particularly well-suited to represent the significant fluctuations of intervention demand, which vary both during time and space.

The first step of our approach consists in collecting and analyzing historical demands for intervention over four years (2020 to 2023). Based on the data analysis, we identified three levels of seasonality; daily, weekly and monthly. In other words, there is a repeated pattern for each day, week, and month so that interventions are higher during weekdays compared to weekends for example. Furthermore, there exists a downward trend on the number of interventions. Additionally, spatialization of interventions is dependent on time, meaning that the geographical repartition of interventions on the island of Montreal is not the same for every hour of the day.

A. Assumptions and performance indicators

1) Assumptions

In order to be able de develop a first simulation model that is the most faithful to the behaviour of the company fleet, some assumptions have been made as follows:
- Traveling distance are Euclidian distances, meaning that we do not consider the real map routes. However, we proposed to implement a correction coefficient to reduce the gap between the Euclidian distance and the real one.
- Due to insufficient data, it is impossible to implement prioritization between interventions. Therefore, the first intervention to appear will be the first one having an assigned vehicle (FIFO rule).
- Intervention time follows a Poisson Law.

2) Performance indicators

Before starting this project, the STM did not formally evaluate the interventions performance related to their service vehicle fleet. Therefore, in collaboration with three managers of the STM, we introduced five indicators and set a target for each one of them, as shown in Table 1. These indicators are used for evaluating the different dispatching strategies. Furthermore, we presented the indicators from the most important one to the less important one in accordance with the company perspective.

Table 1: Indicator descriptions and targets

Indicator	Description	Target
Fleet Size	Number of vehicles	< 30
Average Fleet Utilization Rate (UR)	Percentage of time, the vehicles are in use for an intervention in a day	>70%
Average Response Time	Average time between the call from the bus driver and the departure of an OS	$\leq 6\ mins$
Average Traveling Time	Average time between the departure of an OS and its arrival	None
Average Waiting Time	Sum of the Response Time and the Traveling Time	None
Total average daily traveling distance	Average distance each vehicle travels in a day	$\leq 150\ km$

B. The simulation model

The proposed simulation model can be divided into four sequential processes as shown in figure 2.
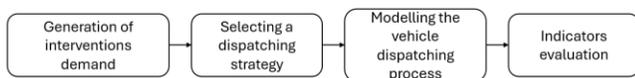
Figure 2: Macro processes of the simulation model

The first step is the generation of intervention demands, that are space and time dependent. The second step is the dispatching strategy of the vehicles, i.e., the decision-making rule to be used to assign vehicles to interventions. Finally, the third part evaluate all the operations performed by the vehicles after being dispatched, such as traveling and operating the required tasks. This model aims to define the best dispatching strategy regarding the company's performance indicators.

Concerning the first step, our model spatially locates interventions generated based on historical data, depending on the time of the day and the day of the week. This process is performed in two sequential phases. First, based on the time distribution that has been obtained when analyzing the historical data, the intervention is generated in a given sector, then it is associated to a random address in that sector. It is supposed that vehicles travel at an average speed of 25 km/h, which is adjusted by a coefficient based on road traffic depending on the time the vehicle departs. Each vehicle starts from its corresponding Transportation Center (TC) to the intervention site that is assigned to it. The time duration of interventions follows a Poisson law, with a mean that is obtained from the data analysis. Each vehicle waits in the intervention site and its location is registered after completing the corresponding intervention, meaning that it does not return to the TC. However, once they finish their shift they travel back to the TC. Therefore, the simulation model calculates the distance between each vehicle's current position and the potential next intervention location.

C. Estimating the demand of interventions

For this study, the data required primarily consists of the historical data of interventions. Nevertheless, the available data set was not complete. Therefore, we propose to use the available data as an initial sample to build a complete data set. More precisely, since the company can have a precise evaluation of their vehicle utilization rate, we propose to use it in order to scale the data related to the demand interventions. This scaling process is performed in the simulation model in an empirical way by implementing various levels of intervention demands until the vehicles reach the average utilization rate targeted. A sensitivity analysis can be performed, in case the estimated utilization rate proves incorrect.

D. Dispatching Strategies

The dispatching strategies that we implemented in the simulation model are presented in table 2.

Table 2: Description of the dispatching strategies

Current rule (CR)	Each intervention is assigned to the nearest available vehicle.
Centralized depot with current rule (C-CR)	A centralization of all service vehicles is considered instead of the current geographically dispersed TCs. The dispatching strategy is the same as the current one, i.e., each intervention is assigned to the nearest available vehicle.
Priority to the vehicle with the greatest remaining autonomy (GRA)	Each intervention is assigned to the vehicle with the greatest remaining autonomy. The idea is to smooth battery consumption amongst the fleet.
Priority to the least used vehicle (LUV)	Each intervention is assigned to the least used vehicle available. The idea of this rule is to balance the load of the OSs.
Random (RA)	Each intervention is assigned to a random vehicle of the fleet.

Since the aim of the simulation model is, first to evaluate the dispatching strategy of the company fleet and second to improve it by reducing the size of the fleet, we propose to compare the dispatching strategies described above. To do so, we propose an iterative process so that in each iteration we run the simulation model with a given number of vehicles. In particular, we start this process with the current number of vehicles in service and at each iteration we remove the least used vehicle (those with a utilization rate under a predefined threshold) until all indicators respect the targets of all indicators. Consequently, the process stops with the last iteration that provides the minimal number of vehicles that respects the indicators' allowed limits. This process is described in Figure 3.
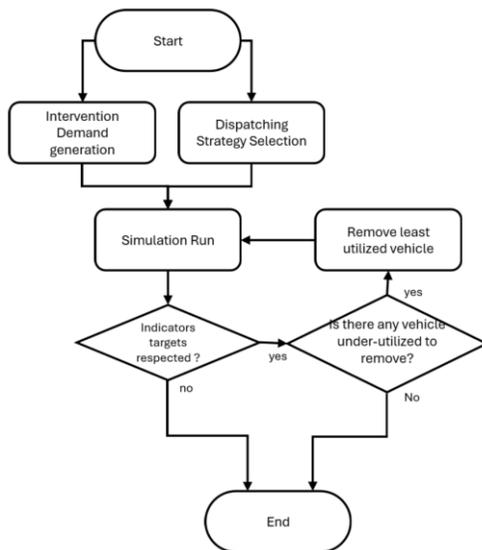
Figure 3: The simulation iterative process used.

The data analysis and the simulation model were performed on a computer equipped with an i7-11800H processor @ 2.30GHz, 16GB of RAM, and an RTX 3060 graphics card.

To get rid of the warm-up period of the system, it was necessary to identify and respect the steady-state regime. To achieve this, the indicator curves were plotted over a one-week duration, monitoring until the transient regime (warm-up period) concluded. Therefore, we considered data obtained during the steady state regime. Finally, it is crucial to define a reasonable number of replications to ensure reliable results within a reasonable computation time. We used the recommendation of Hoad *et al.* (2010) to determine the correct number of replications based on results obtained from an arbitrary number of initial replications. Applied to our case, the total number of replications provided is 30.

A. Data generation of interventions demand

As mentioned before, the available data set that provides the interventions demand is not complete. Therefore, we needed to estimate this demand in order to reach the most realistic demand level of STM. Since the company has an idea of the utilization rate of the vehicles, we propose to scale-up the available incomplete data in order to obtain the utilization rate provided by the company by using our simulation model. Indeed, since the simulation model reflects real-world conditions, we can use it to evaluate several levels of daily interventions and evaluate at the same time the overall utilization rates of the service vehicles. The idea of this sensitivity analysis is to provide a valuable comparison of the dispatching strategies by considering different demand scenarios. These tests are based on utilization rates from a weekday since they are the most representative days of the week. Nevertheless, it could be easily done for week-ends days.

After validation with the STM, we set utilization rates of the vehicles at 50%. We obtained for this utilization rate, a total number of 173 interventions per day.

B. Dispatching Strategies comparison

We initialize the simulation model with the current company vehicles fleet size which is composed of 38 vehicles. As explained before, the simulation modelling approach is an iterative process (see Figure 3) such that each iteration corresponds to a simulation run with a given number of vehicles. The results presented in Table 3 are those of the last iteration satisfying STM's indicators targets. They are obtained with a demand of 173 daily interventions for a weekday. The values of the indicators are the means of the indicators, respectively, obtained for 30 replications.

Table 3: Results of the dispatching strategies for 173 interventions/day

173 Int / Day	Number of vehicles	UR (%)	Waiting Time (min)	Distance (km)
CR	16	53,37	27,93	90,78
LUV	19	51,89	38,06	104,59
GRA	15	56,04	35,39	114,64
C-CR	16	52,71	28,22	91,51

By comparing the dispatching strategies to each other, it is obvious that the GRA consistently shows better results compared to the others. In fact, this strategy requires the least number of vehicles necessary to respond to all interventions while respecting all indicators' targets. These results have to be considered carefully as this strategy does not take into account the position of the vehicles and how far they are from the interventions. Finally, the strategy based on the utilization rate does not seem to perform well as we always get lesser interesting results compared to the others. Regarding the CR strategy, it is important to note that relocating the entire fleet in one centralized TC, while providing better results compared to the current company's strategy, none of the eight TCs is currently designed to deal with the entire fleet. Further analyses should be done to evaluate the feasibility of a centralizing TC.

C. Sensitivity analysis

Since the available number of interventions estimated during a weekday is obtained with incomplete data set, we propose to perform a sensitivity analysis with different demand levels. Therefore, we define different scenarios such that each one corresponds to a given demand level. Each demand level provides a different utilization rate. We evaluated the dispatching strategies for the following scenarios:
Scenario 1: 98 interventions and a utilization rate of 30%
Scenario 2: 143 interventions and a utilization rate of 40%
Scenario 3: 209 interventions and a utilization rate of 60%
Scenario 4: 241 interventions and a utilization rate of 70%

The results of all scenarios are presented in Table 4.

When analyzing the results presented in Table 4, we confirm the dominance of the GRA strategy for all scenarios since it always provides the minimal number of vehicles. The sensitivity analysis allows to obtain robust findings regarding the potential incomplete data. It is obvious that the GRA strategy provides also the best utilization rate, since the least vehicles we have the higher is the utilization rate to handle the same demand level. Another expected result is the travelled distance by the vehicles, which is higher for GRA since there are less vehicles used to satisfy the demand.

Table 4: Dispatching strategies results obtained for different scenarios

Scenarios		Number of vehicles	UR (%)	Waiting Time (min)	Distance (km)
Scenario 1	CR	10	51,05	29,65	85,79
	LUV	12	48,40	38,36	99,63
	GRA	8	56,86	38,49	122,23
	C-CR	10	49,76	28,27	84,36
Scenario 2	CR	14	51,65	30,56	91,48
	LUV	17	49,68	36,91	102,56
	GRA	14	52,68	36,53	114,68
	C-CR	14	51,02	29,07	90,45
Scenario 3	CR	19	54,47	29,79	89,32
	LUV	24	50,25	38,70	104,24
	GRA	19	55,27	37,01	117,82
	C-CR	19	53,52	27,39	91,60
Scenario 4	CR	23	50,87	27,27	82,09
	LUV	26	51,86	38,57	108,17
	GRA	20	56,94	34,71	115,69
	C-CR	22	52,24	27,09	88,35

VI. CONCLUSION

We proposed a simulation modelling framework for the sizing and dispatching problems with a real case study in public transportation. The problem is observed in the Société de transports de Montréal (STM) which aims to maintain the operational conditions of its bus fleet. In particular, the Canadian company aims to convert their service vehicles to electric ones leading to the need for a decision-making tool to determine the best fleet size while maintaining their indicators' targets. Therefore, we proposed as a first contribution a simulation modelling framework in order to represent the real behaviour of the company fleet. Then, we proposed and implemented several dispatching strategies to improve the current company's dispatching strategy considering different performance indicators with different priorities. The simulation model considers the constraints related to the electric vehicle autonomy. The preliminary results showed that the dispatching rules based on the autonomy of the vehicles outperform the other ones.

As future work, we will investigate advanced forecasting methods, such as Machine Learning to improve the forecasting accuracy for the interventions demand. It could be also beneficial to consider the road network to estimate more precisely vehicles' traveling times. Another important aspect to consider is the vehicle charging operations. Since, it is not realistic to charge all the vehicles in their dedicated TCs at the same time, it would be necessary to plan charging some of them during their routing, which may lead to reducing the number of available vehicles available during a shift. Finally, stochastic or dynamic optimization approaches could be investigated to determine the optimal vehicle fleet size and alternative dispatching.

VII. Acknowledgments

VIII. References

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