Shift Scheduling for Electric Service Vehicles: A Public Transportation Case Study

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***Abstract*— As global efforts to mitigate climate change intensify, the electrification of road transportation has emerged as a key solution among strategies for reducing greenhouse gas emissions (GHG). For public transportation agencies such as the Société de transport de Montréal (STM), this transition extends beyond passenger buses to include the fleet of vehicles dedicated to maintaining bus service continuity (referred to as service vehicles). A significant challenge in this transition is the substantial capital investment required for electric vehicles, necessitating optimal fleet sizing to minimize costs while maintaining the same quality of service. This strategic problem is strongly related to the tactical issue of shift scheduling where shifts of vehicles are to be determined with variable start times and possible overlaps. This paper focuses on the integration of shift scheduling with the deployment of electric service vehicles in the context of a large metropolitan transit network. We propose a Mixed-Integer Linear Programming (MILP) framework to minimize the fleet size when deploying and scheduling electric vehicles shifts while ensuring charging feasibility based on forecasted demand. Numerical experiments demonstrate that small and medium-sized instances can be solved to optimality with a commercial solver. For large-scale instances, the model provides optimal or near-optimal solutions within a 30-minute computational limit. These preliminary results confirm the framework's effectiveness as a potential robust decision-support tool for assessing trade-offs between investment costs and operational efficiency, thus supporting the achievement of strategic sustainability goals in large urban transit environments.**

I. INTRODUCTION

The growing urgency of addressing climate change has placed the decarbonization of the transportation sector at the center of environmental strategies. Currently, transportation is responsible for approximately one-quarter of global greenhouse gas (GHG) emissions, with road transportation alone accounting for 72% [1]. As urban populations grow and the demand for mobility services increases, the transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs) has emerged as the most viable pathway toward achieving net-zero targets [2]. While much of the public discourse focuses on private passenger cars, recent literature suggests that the electrification of "third-party" vehicles offers a disproportionately higher environmental impact [3]. Indeed, the carbon abatement potential of a single commercial vehicle can be up to three times higher than that of a private car, given their higher daily mileage and intensive duty cycles.

For a major public transport agency like the Société de transport de Montréal (STM) (Québec, Canada), this transition is a complex and multi-layered. Alongside the electrification of the transit bus fleet, the agency is also converting its service vehicles (ICE-based technology) to electric vehicles [4]. These vehicles play a critical role in maintaining the service continuity of the bus network. They are primarily used by operations supervisors who operate 24 hours a day, 7 days a week, patrolling the various sectors of the Island of Montréal to provide real-time assistance. Because the entire bus network depends on their rapid intervention, any disruption in the availability of these service vehicles has a direct ripple effect on the effectiveness of public transport in the metropolitan area.

The transition to an electric service fleet involves a delicate balance of economic and environmental, and social imperatives. From an economic perspective, electric vehicles require significantly higher capital expenditures than traditional ICE vehicles due to the cost of battery technology and charging infrastructure. To make this transition financially sustainable, it is essential to minimize the fleet size through rigorous optimization, ensuring that the agency does not over-invest in useless assets. Environmentally, the shift supports the STM's 2030 sustainability goals by eliminating tailpipe emissions and reducing noise pollution in densely populated urban areas. Socially, the effectiveness of this fleet is tied directly to the quality of service provided to the public since it ensures the service continuity of the bus network, thereby increasing passenger satisfaction and contributing to the overall quality of service in a dense urban area with major transportation needs.

This research addresses a simultaneous deployment and shift scheduling problem within the context of STM's electric transition. The problem is formulated as a Mixed-Integer Linear Programming (MILP) model. At this tactical level, we consider only vehicle shifts without addressing driver turnover, focusing first on minimizing the number of vehicles required to cover a set of shifts for which starting times have to be determined such that temporal overlaps are possible. Beyond the specificities of the case study, the integration of vehicle charging requirements in this tactical schedule makes this problem an original one. Indeed, unlike conventional

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ICE vehicles, which can be refueled in minutes, electric vehicles require scheduled downtime for charging, which, in this study, occurs at the end of each shift within the assigned depot. By optimizing vehicle-to-shift assignments, we ensure that for each time period, demand is covered while respecting battery autonomy constraints. Therefore, the goal of this work is to provide the STM and other transportation organizations facing similar challenges, with a decision making approach that tackles strategic goals such fleet sizing while optimizing a tactical issue related to both deployment and shift scheduling for service vehicles.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature on shift scheduling and charging planning for electric vehicle fleets. Section 3 provides a formal description of the problem. Section 4 presents the proposed MILP formulation. Section 5 presents and analyzes the preliminary computational results. Finally, Section 6 concludes the paper and outlines future research avenues.

II. LITERATURE REVIEW

This section reviews works across two critical dimensions: vehicle shift scheduling and integrated charging planning for electric service vehicles within urban public transport networks. Research in this field has primarily focused on the electrification of transit buses [5], [6]. The work most closely related to our study concerns the optimization of bus timetabling, a term commonly used in both bus and rail operations. In the context of bus operations, timetabling has been extensively studied for several decades [7]. It refers to determining the departure and arrival times of each trip in a bus network, constrained by the given frequency and level of service of each line, which are determined based on passenger demand and line characteristics. Vehicle scheduling focuses on assigning specific buses to cover these timetabled trips [5]. Recent studies demonstrate that jointly optimizing timetabling and vehicle scheduling significantly reduces capital investment and enhances operational feasibility [8].

Unlike traditional transit buses, the service vehicle fleet investigated in this study diverges from the fixed-route case. Instead, because these vehicles must respond to stochastic incidents across a metropolitan area, their deployment aligns with the logic of workforce resource allocation. As noted by [9], service oriented applications ranging from toll collectors and telephone operators to baggage handlers, face a fundamental challenge: deploying physical and human resources to meet demand that fluctuates during time.

The literature on shift scheduling has expanded across diverse domains where service delivery is pivotal. In a recent review, [10] positions shift scheduling at the intersection of operational efficiency and service quality in sectors such as airlines [11], call centers [12], and healthcare [13]. Among these applications, home health care represents a particularly relevant analog. Here, scheduling determines the availability of caregivers to meet fluctuating patient needs while optimizing resource requirements [14]. Similarly, IT helpdesk environments face comparable decisions, where scheduling aims to balance high-quality support with cost-effectiveness, with demand often driven by stochastic calls [15].

A fundamental divergence exists between these models and our proposal. Standard workforce models focus on human-centric constraints, such as labor regulations, mandatory rest periods, and employee well-being. In our context, while we adopt the shift scheduling logic of these service sectors, we pivot the focus toward physical assets.

Moving from workforce-based services to mobility-oriented ones, a closely related application can be found in police patrol car allocation. In this setting, patrol units must be strategically distributed across a metropolitan area to minimize emergency response latency, which parallels the operational objectives of our service vehicle fleets [16].

Complementing shift scheduling, charging planning constitutes a core challenge, encompassing decisions on timing, duration, and energy requirements [5]. Historically, these tasks were decoupled due to computational complexity, with charging often modeled as a parallel machine scheduling problem [17]. While techniques like "timetable shifting" facilitate integration within fixed-route systems, their flexibility is constrained by rigid transit structures [18]. Although recent electric vehicle routing problems incorporate battery constraints,they primarily focus on the operational level, assuming a pre-determined fleet size for real-time task assignments [19].

Consequently, a significant research gap remains at the tactical level. To date, to the best of our knowledge, no research has addressed a simultaneous deployment and shift scheduling for service vehicles that have not a fixed routing with variable energy consumption.

Table I reports the closest works within some comparative elements such as: terminology, resource type, problem nature, shift decisions and definition, charging decisions, multi-depot aspect, and optimization objectives. To ensure a consistent comparison, varied objective functions are categorized into four primary categories: time (e.g., travel, waiting, and dispatch delays), cost (e.g., fleet investment and energy costs), Resource requirement (e.g., fleet size or staff size), and Service level (e.g., coverage penalties).

The taxonomy typically mirrors the application domain. For instance, "staffing" is used for human resources such as caregivers or call center agents, while "resource allocation" or "timetabling" is more common in police and transit bus contexts. Regarding the problem nature, the literature is divided between deterministic models and stochastic ones to cope with demand uncertainty. Furthermore, a clear distinction emerges in infrastructure requirements: while human-centric models do not require a physical depot layer, vehicle-based studies must account for central or multi-depot problems to manage fleet deployment.

The reviewed literature reveals several important gaps that motivate the present work. While shift scheduling has been extensively studied across service-oriented applications, these models are predominantly human-centric, overlooking the physical constraints inherent to vehicle-based fleets,

TABLE I: Comparison of different papers addressing related works

Papers	Problem	Resources	Problem nature	Shift Starting time	Shift definition	Charging decisions	Multi-depot	Objective
[11]	Workforce scheduling	Air traffic controllers	D	V	Work block	-	-	Cost, Service level
[12]	Staffing	Call center agents	S	V	Time pattern	-	-	Staff size
[13]	Shift patterns	Caregivers	D	V	Placeholder (slot of a route)	-	-	Time
[14]	Staffing	Caregivers	S	F	Staff size	-	-	Staff size, Time
[16]	Resource allocation	Police cars	S	F	Availability block (a period of readiness)	-	✓	Time
[6]	Scheduling	Buses	D	V	Vehicle block (itinerary of request)	-	✓	Cost
[5]	Timetable shifting	Electric buses	D	F	Trip chain	✓	-	Cost
Ours	**Shift scheduling**	**Service EVs**	**D**	**V**	**Vehicle block**	✓	✓	**Fleet size**

*Abbreviations: **D**: Deterministic, **S**: Stochastic, **F**: Fixed, **V**: Variable.*

particularly energy limitations. On the vehicle scheduling side, research on electric buses has made notable progress in integrating charging decisions, yet these contributions remain confined to fixed-route, single-depot contexts with predetermined fleet sizes at the operational level. Most critically, no existing work simultaneously addresses the tactical problem of shift scheduling, charging planning, deployment, and multi-depot fleet sizing for electric service vehicles. This combination remains entirely absent from the literature, representing the precise gap that this paper aims to fill.

III. Case Study and Problem Description

The metropolitan region under study is the Island of Montreal (Québec, Canada), which is geographically divided into 15 distinct geographical sectors. The STM operates from 8 strategic depots, which serve as the backbone of the transport system, providing parking, maintenance services, and the essential electric charging infrastructure. The service vehicles fleet operates on a continuous 24/7 basis to address a time-varying volume of service requests across the network.

This case study has already been addressed previously to deal with the operational level that is the dispatching problem in order to tackle the dynamic arrival of incidents to be handled. This problem has been modelled using a simulation-event software based on forecasting models for incidents demand. This model allows to estimate the service duration and per-incident energy consumption. However, the detailed demand considered in the dispatching problem is used to obtain an aggregated demand at the sector level over a planning horizon divided into discrete time periods. A fundamental operational constraint is the pre-assignment of sectors to depots, driven by geographical proximity and the need to minimize unproductive travel time. Consequently, each sector is served exclusively by vehicles from their pre-assigned depots, leading to a multi-depot network where vehicle assignment to demand should be performed respecting vehicle pre-assignment. The resulting scheduling problem allows to determine how many vehicles should be assigned to each depot by defining their respective shifts. In particular, the model defines each shift starting times coupled with battery charging planning. Indeed, beyond shift scheduling, there is a need to coordinate the temporal allocation and duration of charging times to ensure operational continuity. The idea is to ensure that every vehicle maintains sufficient battery levels to fulfill its assigned workload. As vehicles typically perform multiple shifts over the planning horizon, charging times are scheduled exclusively at the pre-assigned depot between duty cycles.

To formulate the mathematical model, the following assumptions are made:

- Vehicles are homogeneous, notably, in terms of battery capacity.
- Each depot has a sufficient pool of vehicles.
- A pre-assignment of sectors to depots is known in advance.
- Service durations are deterministic and vary according to the sector-depot pair.
- Shifts have a fixed, non-splitable duration, ensuring continuous service blocks.
- Each vehicle can perform multiple shifts.
- Multiple vehicles can be simultaneously assigned to the same shift starting time to meet demand.
- Each depot has a sufficient charging capacity.
- Vehicles must fully recharge after each shift.
- Vehicle energy consumption is assumed to be linear.

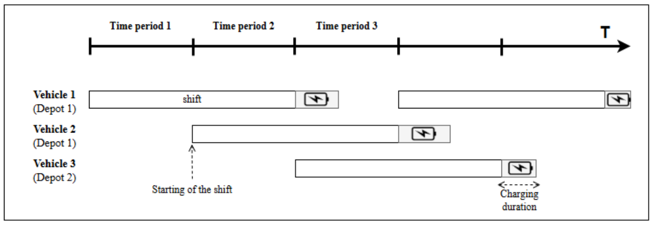

Fig. 1: Fleet schedule with integrated charging

Figure 1 illustrates a sample solution over a discrete planning horizon with a fixed two-period shift duration. The solution employs three vehicles across two depots (Vehicle 1 and 2 at to Depot 1, Vehicle 3 at Depot 2). The figure highlights the optimized synchronization between shift starts and subsequent mandatory charging times. This coordination ensures vehicle readiness for reuse, effectively minimizing the total fleet size required for full network coverage.

IV. MATHEMATICAL MODEL

We formulate the problem as a mixed-integer linear program using the following notation:

Sets and indices:

- $\mathcal{S}$ Set of sectors, indexed by s.
- $\mathcal{D}$ Set of depots, indexed by d.
- $\mathcal{K}_d$ Set of vehicles assigned to depot d.
- $\mathcal{K}$ Set of all vehicles ($\bigcup_{d\in\mathcal{D}} \mathcal{K}_d$), indexed by k.
- t Time period index.

Parameters:

- $N_{t,s}$ Demand at sector s during time period t (number of incidents).
- $T_{s,k}$ Total time required to handle one demand in sector s by vehicle $k \in \mathcal{K}_d$ (in minutes).
- $C_{s,k}$ Energy consumption required to serve one demand in sector s by vehicle $k \in \mathcal{K}_d$ (in kWh).
- $\mathcal{T}$ Number of time periods.
- L Duration of a time period (in minutes).
- τ Shift duration (in number of time periods).
- B Battery capacity of a vehicle (in kWh).
- α Charging time factor used to convert depleted energy into recharging time (in min/kWh).
- M Big positive number.

Decision Variables:

- y_k 1 if vehicle k is used, 0 otherwise.
- z_t^k 1 if vehicle k starts a shift during time period t, 0 otherwise.
- $x_{t,s}^k$ Demand level served by vehicle k in sector s during time period t.

The mathematical model is defined as follows:

$$\min Z = \sum_{k\in\mathcal{K}} y_k \tag{1}$$

subject to:

$$z_t^k \le y_k, \quad \forall k \in \mathcal{K}, \quad \forall t \in \mathcal{T} \tag{2}$$

$$\sum_{k\in\mathcal{K}} x_{t,s}^k = N_{t,s}, \quad \forall t \in \mathcal{T}, \quad \forall s \in \mathcal{S} \tag{3}$$

$$\sum_{s\in\mathcal{S}} T_{s,k} \cdot x_{t,s}^k \le L \cdot \sum_{t'=t-\tau+1}^{t} z_{t'}^k, \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{4}$$

$$\sum_{t'=t}^{t+\tau-1} \sum_{s\in\mathcal{S}} C_{s,k} \cdot x_{t',s}^k - M(1 - z_t^k) \le B, \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{5}$$

$$t' + M(1 - z_{t'}^k) \ge (t+\tau) \cdot z_t^k + \frac{\alpha}{L} \cdot \sum_{t''=t}^{t+\tau-1} \sum_{s\in\mathcal{S}} C_{s,k} \cdot x_{t'',s}^k$$
$$\forall t, t' \in \mathcal{T}, \quad t' > t, \quad \forall K \in \mathcal{K} \tag{6}$$

$$y_k, z_t^k, \in \{0,1\}, \quad \forall t \in \mathcal{T}, \forall K \in \mathcal{K} \tag{7}$$

$$x_{t,s}^k, \in \mathbb{N}, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \forall K \in \mathcal{K} \tag{8}$$

In this model, the objective function (1) aims to minimize the fleet size by minimizing the total number of vehicles used. Constraints (2) establish the activation logic, ensuring a vehicle is accounted for if assigned to at least one shifts. Constraints (3) ensure same-period demand satisfaction by requiring that all the demand is assigned across all vehicles for every sector and time period. Constraints (4) enforce the respect of time capacity during the shift. It ensures that a vehicle can only handle demand during the periods it is active. Battery management is addressed by constraints (5) which enforce energy autonomy limits. Crucially, constraints (6) synchronize shift sequencing and charging requirements, they prevent a vehicle from starting a new shift until both the previous shift duration and the subsequent mandatory charging duration have been completed (the parameter α represents the time required to recharge one unit of energy). Finally, constraints (7–8) define the domains of the decision variables.

The complexity of the studied problem can be established through a polynomial reduction to the *Generalized Assignment Problem* (GAP). As demonstrated by [20], the GAP is known to be NP-hard in the strong sense, as it generalizes the classic bin packing problem by introducing heterogeneous resource consumption coefficients. By restricting our model to a single time period ($T = 1$) with indivisible demand units, the problem reduces to a task-to-vehicle assignment configuration. In this context, the resource consumption is inherently heterogeneous: an incident at depot d consumes a battery amount $C_{d,k}$ if serviced by a local vehicle, whereas it consumes $C_{d',k} > C_{d,k}$ if assigned to a vehicle originating from a distant depot d'. This structure, where the weight of a task is dependent on the specific agent (vehicle) to which it is assigned, maps directly onto the fundamental structure of the GAP. Consequently, determining the minimum number of active vehicles ($\min \sum y_k$) required to satisfy the total demand under strict capacity constraints is at least as difficult as solving the GAP. Therefore, our problem is NP-hard.

V. EXPERIMENTAL RESULTS & DISCUSSION

The mathematical model was implemented in Java using IBM ILOG CPLEX Optimization Studio API version 12.51. All experiments were conducted on a computer equipped with an Intel Core Ultra 5 235H processor (14 cores, base frequency 2.40 GHz) and 32 GB of RAM, the following subsections describe the data generation procedure and provide a detailed performance analysis of the MILP model.

A. Data generation

The instance generation process is inspired by real-world data from the STM. We constructed several families of instances, each comprising 20 individual instances. Each family is characterized by a specific combination of four key parameters: the length of the planning horizon T, the number of sectors S, the number of depots D, and the total number of vehicles K. To evaluate the scalability of the proposed MILP, these parameters are progressively increased across families. The instance sizes are extended up to the point where optimal solutions can no longer be obtained within a time limit of 30 minutes.

Regarding the temporal structure, the shift length τ is calibrated to ensure each vehicle can perform at least two shifts within the planning horizon, thereby forcing the model to manage multiple shift-to-shift transitions. The fleet is composed of K vehicles, which are evenly distributed among the depots. To reflect real-world operational boundaries, a compatibility mapping defines the assignment of sectors to specific depots. This spatial pre-assignment governs service eligibility, ensuring that a vehicle can only be dispatched to incidents within its designated geographic jurisdiction.

To maintain the relevance of the electric layer, battery capacity is calibrated in such a way that, even for small instances, vehicles are required to recharge between shifts. This ensures that energy constraints remain binding and relevant across all instance sizes.

Finally, to ensure statistical robustness within each family, variations are introduced by regenerating the demand, as well as the sector–depot assignments. This allows us to obtain diverse instances with similar structural characteristics, enabling a comprehensive evaluation of the model's performance and stability.

B. Performance of the MILP model

To evaluate the computational efficacy of the MILP model, we conducted experiments across varying instance families, with preliminary results summarized in Table II. For each family, we report the problem scale (number of variables and constraints). We also report the percentage of instances solved to optimality (out of 20 instances), along with the average and standard deviation of the optimality gap for all instances. In addition, we provide the average execution time (in seconds) and its standard deviation for the instances solved to optimality.

The preliminary results demonstrate that the proposed MILP model exhibits high efficiency for small and medium sized instances. As the problem scales, the MILP continues to provide high-quality near-optimal solutions within the 30-minute computational limit. However, we observe that not all instances within the same family reach optimality within the allotted time, and that significant variability in computational performance exists across instances of identical size.

This variability is intrinsically linked to the structural properties of the instances rather than size alone. In particular, the number of incidents (i.e., demand levels), the sector–depot pre-assignment structure, and the choice of the shift length parameter have a strong impact on problem difficulty. Instances in which several sectors are assigned to multiple depots tend to be more difficult to solve, as they introduce additional flexibility and increase the size of the search space. Similarly, smaller values of τ, lead to more complex assignment decisions. These findings highlight that computational performance is not solely driven by instance size, but also by the structural properties of the scenarios. This emphasizes that beyond raw size spatial and temporal constraints are the primary drivers of problem difficulty.

To further validate the practical relevance of the proposed model, we applied it to a real instance provided by the STM. This instance was solved to optimality within seconds, reflecting the relatively moderate structural complexity of the STM's operational context: the network exhibits limited demand variability and a largely exclusive sector–depot assignment structure, with few sectors shared across multiple depots. This is consistent with our earlier findings, which establish that structural properties rather than raw size are the primary drivers of computational difficulty. Notably, the large-scale synthetic instances that proved most challenging to solve share precisely the structural characteristics that are absent in the STM case: high demand density and significant assignment flexibility. This confirms that the MILP model is not only theoretically sound but also practically deployable as a real-time decision-support tool within the STM's operational environment.

VI. CONCLUSION & PERSPECTIVES

This paper considers a real-life problem inspired from Montreal public transportation. We addressed a tactical problem related to both electric vehicles deployment and their shift scheduling considering charging. By integrating battery autonomy and synchronized charging windows within a MILP formulation, the proposed model successfully minimizes total fleet requirements while ensuring reliable service coverage across multi-depot network. Computational experiments conducted with the CPLEX solver confirm the model's viability as a tactical decision-support tool, providing optimal solutions for medium-scale scenarios. However, given the intrinsic NP-hard complexity of the problem, exact resolution reaches its limits as the instance size and the planning horizon expand. Consequently, a natural extension of this work involves the development of heuristic methods or decomposition approaches (temporal and spatial), to maintain computational tractability for large-scale, long-term operations.

TABLE II: Performance of the MILP

Class ($\|\mathcal{T}\|, \|\mathcal{S}\|, \|\mathcal{K}\|$)	**Depot**	τ	**Nb Var**	**Nb Cons**	**Solved Opt**	**Gap %**		**CPU time (s)**	
						Avg	**Std dev**	**Avg**	**Std dev**
(8,5,10)	2	3	490	560	100%	0.00%	0.00%	1.03	1.22
(10,5,15)	3	3	915	1175	100%	0.00%	0.00%	5.42	8.16
(12,6,20)	4	5	1700	2112	100%	0.00%	0.00%	13.69	14.79
(16,8,25)	5	5	3625	4328	95%	0.29%	1.31%	211.15	451.92
(18,10,30)	6	6	5970	6390	55%	4.75%	7.19%	249.30	388.65
(20,12,35)	7	6	9135	8990	40%	5.67%	6.16%	420.05	525.15
(24,15,40)	8	6	15400	14280	15%	6.02%	3.69%	550.03	176.67

Building upon this tactical foundation, future work will focus on increasing the granularity of the decision-making process to bridge the gap between planning and real-time execution. A primary objective involves the integration of shift scheduling with vehicle routing by transitioning from aggregated demand per sector to precise spatial-temporal incident data. This evolution will allow for a more accurate energy consumption profiles and the synchronization of charging activities with actual vehicle movements between incidents. Furthermore, integrating multiple performance metrics, with a particular focus customer service and response time will enable a more nuanced exploration of the Pareto frontier between fleet minimization and network resilience. These enhancements, combined with the inclusion of stochastic demand patterns, will ultimately provide a comprehensive framework to navigate the dual complexities of electrification and high-quality public service.

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