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**Article — Published Version**

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Decision Sciences

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*Suggested Citation:* Abdelwahed, Ayman; van den Berg, Pieter L.; Brandt, Tobias; Ketter, Wolfgang (2024) : A real-time decision support system to improve operations in electric bus networks, Decision Sciences, ISSN 1540-5915, Wiley, Hoboken, NJ, Vol. 56, Iss. 2, pp. 193-212, <https://doi.org/10.1111/dec.12633>

This Version is available at:

<https://hdl.handle.net/10419/323717>

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## ORIGINAL ARTICLE

# A real-time decision support system to improve operations in electric bus networks

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## Funding information

The Ministry of Economic Affairs, Industry, Climate Action and Energy, Grant/Award Number: 731198

## ABSTRACT

Electrifying transit bus networks (TBNs) has recently become a challenging problem that many public transport operators around the world are facing. Due to the limited driving range of electric buses, electric TBNs are more sensitive to operational delays and uncertainties. Moreover, the impact on sustainability is most profound when the buses are powered by renewable energy resources, which are often subject to intermittency and uncertainty. In this work, we tackle the complicated problem of planning charging schedules amid these various sources of uncertainty. We develop a real-time decision support system that uses real-time data, predictions, and mathematical optimization to update the charging schedules and mitigate the impact of operational uncertainties. Our results show that the online strategy can maintain higher reliability and renewable energy utilization levels compared to other charging strategies. The study has been carried out in cooperation with the public transport operator in Rotterdam in the Netherlands to assist them in their TBN transition process.

## KEYWORDS

electric transit bus networks, real-time decision support system, renewable energy, smart charging, sustainable public transport

## 1 | INTRODUCTION

Transportation is a sector critical to achieving environmental sustainability. The International Energy Agency estimates that investments in transportation amounting to 15.7 trillion USD are necessary to limit the global temperature increase to 2°C by 2050 (International Energy Agency, 2012). Specifically, in urban areas, fossil fuel-based transportation contributes significantly to emissions and air pollution, adversely affecting both the environment and public health. Consequently, the transportation sector is compelled to shift toward sustainable, emission-free energy sources in the coming years. This transition includes replacing conventional diesel and gasoline-powered vehicles with electric vehicles.

In addition to transitioning to electric vehicles, reducing the total number of vehicles on roads by increasing the adoption of shared mobility and mass transit can further enhance the environmental sustainability of urban mobility (Paundra et al., 2017). Among the various vehicle-based transporta-

tion modes in urban areas, public transit emerges as the most carbon-efficient solution for meeting the transportation needs of urban residents (Kammen & Sunter, 2016). However, achieving zero-emission public transit systems requires additional efforts. The International Association of Public Transport (2014) identifies the electrification of transit bus networks (TBNs) as a crucial step toward this goal. In this work, we contribute to addressing these challenges by investigating the problem of electrifying TBNs in urban areas.

The transition to electric buses (EBs) introduces several operational challenges. Notably, the range of EBs on a single charge is shorter compared to conventional diesel buses, and recharging requires substantially more time (Li, 2016). Integrating short battery recharging sessions into daily bus schedules makes the impact of delays more significant, rendering bus operations increasingly sensitive to uncertainty. Moreover, while electrification diminishes local emissions and air pollution from buses, achieving carbon-neutral tran-

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sit operations is contingent on the use of renewable energy sources. Given that wind and solar power rely on intermittent exogenous factors, this reliance introduces an additional layer of uncertainty to the operational challenges (Seddig et al., 2017).

In this article, we investigate how online, data-driven operational strategies can mitigate these challenges. The advent of the Internet-of-Things and other smart city technologies is revolutionizing our capacity to tackle transportation issues by facilitating real-time coordination among system actors (Mahmassani, 2016). We apply this concept to the operation of EBs that are partially powered by intermittent renewable energy sources. Our approach takes into account the uncertainties associated with both trip delays and energy generation under real-world conditions. Through this examination, we aim to provide valuable insights into a problem that is pivotal for the successful transition toward smart and sustainable cities globally.

Our work is set in context of the RUGGEDISED project, a large-scale smart city transformation project supported by the European Union's Horizon 2020 framework program. As part of this project, the city of Rotterdam moved to replace its bus fleet with EBs. This resulted in a close collaboration spanning several years between RET, the city's public transit operator (PTO), and Rotterdam School of Management, Erasmus University as the academic partner specialized in data-driven operations and transport optimization.

This article builds upon our previous work in Abdelwahed et al. (2020), where we compared various optimization techniques to optimize the charging schedules of electric TBNs. Based on this foundation, we now explore the impact of charging from renewable energy resources and the negative effects of operational uncertainty on the performance of the electric TBN, two factors that have been identified as significant in the practical implementation of EBs. Specifically, we contribute to the existing body of literature by investigating the following research questions:

1. What is the impact of operational uncertainty on the performance of the electric TBN?
2. How can online optimization alleviate the adverse effects of operational uncertainty and improve coordination with the variable output of renewable energy generators (REGs)?

To address these questions, we develop a discrete-event simulation, enabling us to evaluate and compare various charging strategies under conditions of uncertainty. In addition, we enhance our optimization model from Abdelwahed et al. (2020) and integrate it with the discrete-event simulation to assess the efficacy of our proposed online optimized approach. Applying our simulation framework to the case of RET, our study offers insights and results that have significantly aided their transition process, particularly in the first phase of the city's TBN electrification project. This collaboration has also led to the development of a real-time monitoring and control system, a direct outcome of our research. We continue in the next section with an overview

of related previous work. Section 3 details our problem and outlines the main assumptions. Our methodology and mathematical formulations are presented in Section 4, followed by the results from the case study in Section 5. The final section concludes the article, summarizing our key findings and suggesting avenues for future research.

## 2 | BACKGROUND AND RELATED WORK

The electrification of TBNs introduces a range of strategic and operational challenges for PTOs (Perumal et al., 2022). Transitioning from conventional fuel buses to electric ones necessitates significant network redesign and re-planning. This process begins with strategic decisions involving the selection of suitable charging techniques, optimization of infrastructure and bus types, and the placement of charging stations (He et al., 2019; Kunith et al., 2017; Liu et al., 2021; Uslu & Kaya, 2021; Xylia et al., 2017). The challenge then extends to trip scheduling, which may require substantial modifications to accommodate the locations and capacities of charging stations (Wang et al., 2022). A recent study by Dirks et al. (2022) presents an integrated optimization model that concurrently addresses both strategic and operational decisions. Their model encompasses strategic choices concerning the characteristics of EBs and charging infrastructure, while also optimizing vehicle scheduling at an operational level.

Furthermore, optimizing the charging schedules represents a significant emerging challenge for PTOs with the advent of electric TBNs. The critical nature of this optimization is underscored by the substantial time required for EBs to recharge their batteries and the influence of various internal and external factors on their energy consumption, including weather conditions, route topologies, driving styles, and passenger load (Kontou & Miles, 2015; Zhou et al., 2016). Additionally, the electrification of TBNs imposes a considerable additional load on the electricity grid, presenting a further challenge in planning. Mohamed et al. (2017) demonstrate through simulation that the existing power infrastructure could potentially limit the adoption of EBs, especially in the context of fast-charging technologies that demand high power outputs. Consequently, several studies have focused on optimizing the charging schedule and its integration with grid operations to minimize the impact of TBN electrification (Abdelwahed et al., 2020; He et al., 2020). Another research direction explores the introduction of local REGs, which can directly charge EBs, potentially alleviating the stress on the power grid (Manzoli et al., 2022). For example, Arif et al. (2020) investigate the integration of energy storage systems (ESSs) and renewable energy with EB charging schedules, finding that this approach can help reduce peak load on the grid and lower charging costs for PTOs. Heinisch et al. (2021) highlight the potential benefits and opportunities of using locally generated renewable energy to supply a substantial portion of the energy required for EBs.

However, TBNs are highly vulnerable to delays and uncertainties, which can significantly affect the charging schedules and thus become critical to the operations of electrified networks. Missing scheduled charging events or underestimating energy consumption could jeopardize operational feasibility. Consequently, several recent studies have concentrated on examining electric TBN planning and operations in the context of uncertainty. Several studies have focused on predicting the energy consumption of EBs under various operational conditions (Chen et al., 2021; Hjelkrem et al., 2021). In the strategic planning phase, An (2020) developed a stochastic integer programming model to optimize the infrastructure of TBNs, accounting for uncertainty. Specifically, the model optimizes the allocation of charging stations and fleet size while considering random variations in charging demand. In addition, Liu et al. (2018) address the allocation problem for fast-charging stations, factoring in stochastic energy consumption rates of buses. At a more advanced planning stage, other studies investigate the trip scheduling issues of electric TBNs under stochastic traffic conditions and/or variable energy consumption (Bie et al., 2021; Tang et al., 2019).

In summary, existing research on TBN electrification encompasses various challenges, ranging from optimizing infrastructure and charging station placement, to planning trip and charging schedules, and exploring the integration of energy storage and REGs to alleviate the power grid's load. However, no prior studies have delved into optimizing electric TBN charging schedules under the dual uncertainties of traffic conditions and renewable energy generation. Our study considers three main sources of uncertainty: traffic delays, bus energy consumption, and renewable energy generation. The first two factors can jeopardize the operational feasibility of buses if not properly accounted for in charging schedules, while the third could lead to suboptimal charging if not synchronized with the renewable generation profile. Addressing this research gap, our work develops a data-driven decision support system that employs online optimization. This system dynamically adjusts EB charging schedules in response to real-time data on energy generation, weather forecasts, and bus delays and consumption. Our approach significantly contributes to the expansive body of literature on decision support systems for bus operations (e.g., Arampatzis et al., 2004; Chu et al., 2020; Smith et al., 1990), particularly by incorporating the complexities introduced by electric powertrains and renewable energy sources. In the following section, we detail our system and the operational challenges it addresses.

### 3 | PROBLEM DESCRIPTION

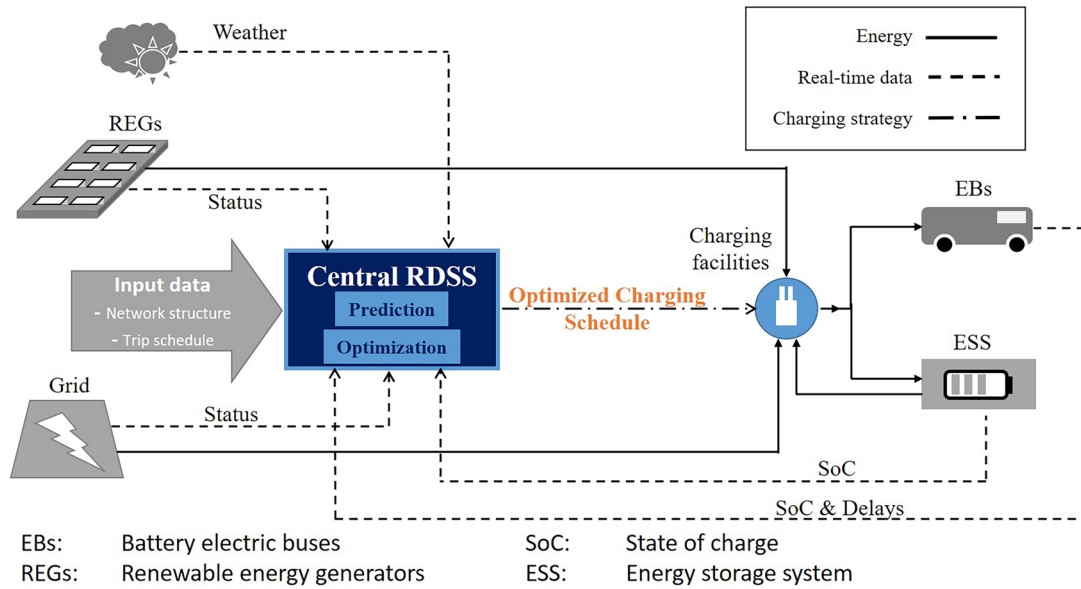
In TBNs, opportunity charging encompasses two techniques: en route charging and terminal-station charging. En route charging involves recharging buses at intermediate stops with passengers onboard, while terminal-station charging occurs during layovers at the end of a trip, typically allowing for longer charging periods. PTOs may utilize either method or a combination of both. In our study, we focus on terminal-

station charging only. As such, line or route structures are not a primary consideration in our charging schedule optimization. Instead, critical factors include the estimated energy consumption for each trip, the timing, duration, and locations of bus layovers at terminal stations with charging facilities, and the specifics of the charging infrastructure—namely, the number of chargers at each station and their power ratings.

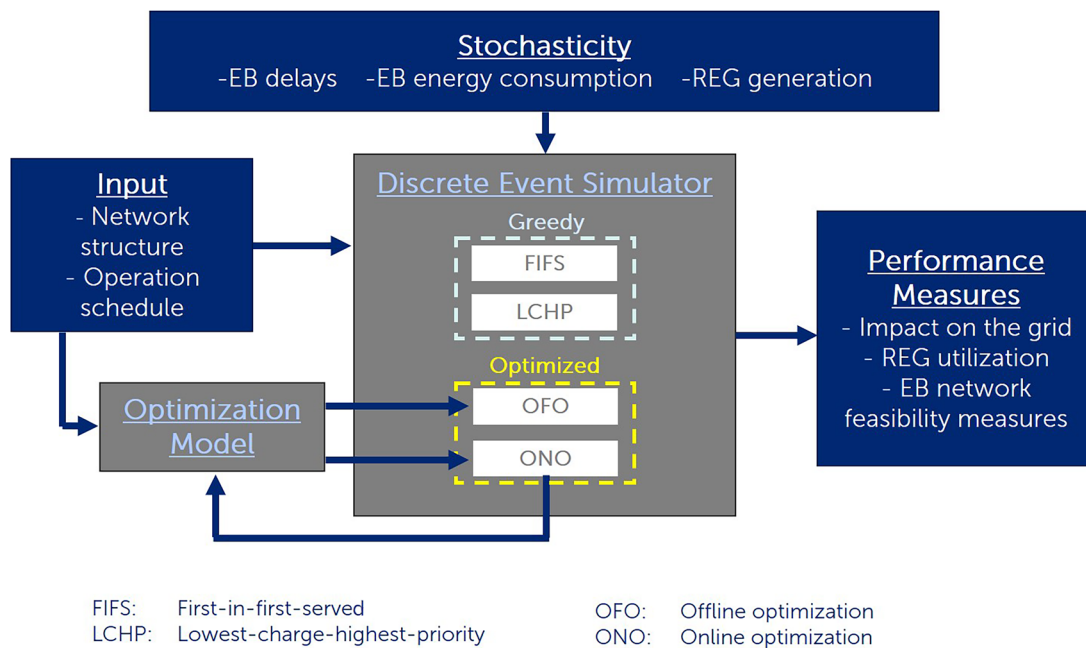
The infrastructure for charging is a strategic decision made in the TBN planning phase, while the details of bus layovers, including their locations and durations, are determined during trip assignment scheduling. The optimization of the charging schedule thus involves deciding which layovers, characterized by their location and timing, are best suited for charging each bus throughout the day. Our study assumes infrastructure and bus location data as given inputs, with further details provided in the case study section.

From the perspective of the grid operator, integrating a fully electrified fleet into a TBN represents a significant additional electrical load, necessitating careful planning. Conflicts between the objectives of the grid operator and the PTO can arise in this scenario. While the grid operator typically aims to minimize EB charging during peak electrical loads to alleviate strain on the system, the PTO may find it necessary to charge during these periods to ensure the TBN operates reliably. Our study seeks to mediate between these conflicting goals, proposing charging schedules that ensure the TBN's operational reliability for the PTO while simultaneously minimizing the impact on the electrical grid. Furthermore, integrating renewable energy sources presents an opportunity to further alleviate grid strain. By synchronizing EB charging schedules with the availability of locally generated renewable energy, the TBN can enhance its utilization of green power sources, contributing to a more sustainable and efficient urban transit system.

A key challenge in managing a TBN, particularly when integrating REG operations, is the high degree of uncertainty inherent in these systems. Our focus is primarily on the decisions made by the PTO at the operational level, particularly regarding the optimization and real-time adjustment of EB charging schedules amidst this uncertainty. To aid the PTO, we develop a real-time decision support system (RDSS) that guides decisions on when, where, and for how long each EB should be charged, considering the assigned trip schedules and available charging locations within the network. Figure 1 illustrates the primary components of our proposed system, highlighting the flow of real-time information and energy. At the heart of this system is the RDSS, tasked with aggregating real-time data from various system components and dynamically adapting the charging strategy. This approach is aimed at minimizing the grid impact of EB load while ensuring feasible TBN operations. Moreover, we consider local REGs in our case study which means that they belong to the PTO. Thus, it is particularly important to incorporate the goal of maximizing the usage of the locally generated renewable energy. Hence, we also evaluate the potential benefits of integrating an ESS into this framework, specifically focusing on how it could enhance renewable energy utilization.



**FIGURE 1** Main components and structure of the system. RDSS, real-time decision support system.



**FIGURE 2** Integrated optimization and simulation framework. EB, electric bus; REG, renewable energy generator.

## 4 | METHODOLOGY

In this study, we introduce a framework composed of two principal elements: a discrete-event simulation (DES) and an optimization model, as depicted in Figure 2. The DES primarily serves to assess the impact of various charging strategies on our objectives amid operational uncertainties. We consider three forms of uncertainty: trip delays, EB energy consumption, and renewable energy generation. The DES, constructed

using the Python programming language and the SimPy library, processes inputs like the trip assignment schedule, the network's structure (including charger locations and quantities), and the power output profile of the REGs. It simulates network activities such as EB operations, charging sessions, and ESS dynamics, under uncertain conditions to evaluate different charging strategies.

For our analysis, we examine two optimized strategies: offline optimized (OFO) and online optimized (ONO), and



benchmark them against two intuitive, greedy approaches: first-in-first-served (FIFS) and lowest-charge-highest-priority (LCHP). This leads to a comparative analysis of four distinct charging strategies. The optimization model, responsible for crafting the charging schedules, tackles a mixed-integer linear programming (MILP) problem. This optimization process, crucial for both offline and online strategies, is detailed in Section 4.1. For the online approach, a feedback loop integrates the optimization and simulation models, allowing real-time adjustment of the charging strategy based on actual TBN operational uncertainties. This is achieved through a rolling horizon optimization framework, with modifications to the optimization model explained in Section 4.2.

In the OFO strategy, the EB charging schedule is determined before the day's operations begin, using day-ahead forecasts of renewable energy generation. Once set, this schedule remains fixed throughout the day, without any modifications regardless of unexpected uncertainties or deviations in the system.

In contrast, the ONO strategy is more adaptable, incorporating real-time data related to renewable energy generation and operational delays to make periodic adjustments to the charging schedule during the day. This strategy makes the most of updated real-time predictions of renewable energy, aiming to enhance the utilization of renewables and minimize grid strain. It also uses real-time data, like TBN delays or other unplanned events, to ensure network reliability. Accordingly, the ONO strategy modifies the charging plan to better meet performance objectives.

Should an EB miss its scheduled charging window, the ONO strategy has the flexibility to either schedule additional charging during subsequent layovers at terminal stations with chargers or initiate an earlier charging session than initially planned. Furthermore, it can reallocate charging slots between buses if required, especially during periods when there are more buses than available chargers. However, one strict rule is that the ONO strategy will not delay the start of any trip merely to extend a charging session.

For the greedy strategies, FIFS arranges EBs in the charging queue based on their arrival times, while LCHP prioritizes them according to their state of charge (SoC), with the EBs having the lowest SoC receiving the highest priority. Replacing an EB that's currently charging with an arriving one that has a lower SoC is allowed, given that the charging EB has reached a predetermined SoC threshold and has been charging for a minimum duration. It is crucial to note that in all strategies, including the ONO, starting trips on time is prioritized over charging. Therefore, delays in EB departures to facilitate additional charging are not permitted, preventing unplanned queues at charging stations. In summary, each charging strategy is briefly described as follows:

- **OFO:** Utilizes day-ahead estimates of trip durations, EB energy consumption, and predictions of renewable energy generation to create optimized charging schedules. The

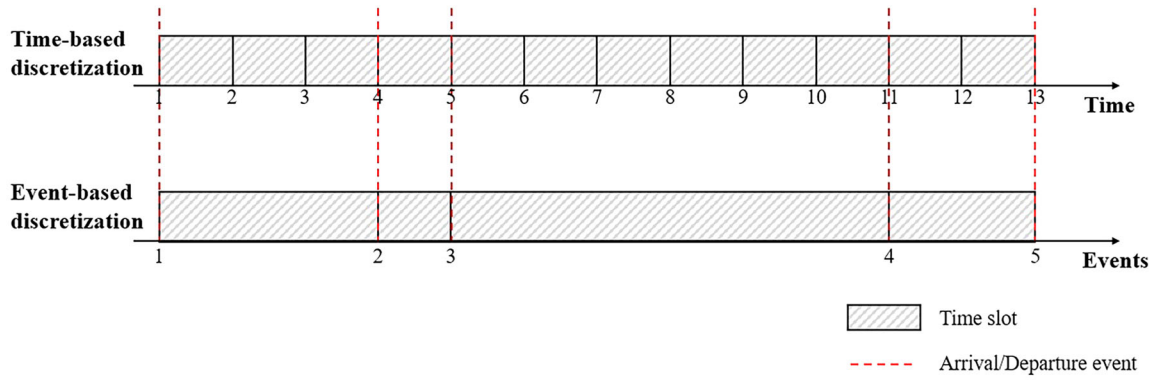
PTO adheres to this day-ahead schedule without making any adjustments, regardless of discrepancies between estimated and actual conditions.

- **ONO:** Starts the day with the same day-ahead optimized schedule as the OFO. However, this strategy updates the charging schedules every hour, incorporating real-time data and updated predictions for renewable energy generation, as well as actual energy consumption and trip durations for completed trips.
- **Greedy strategies (FIFS and LCHP):** These are reactive strategies that do not require predictions or estimations for energy consumption, delay, and renewable energy generation. Charging decisions are made on the spot at the charging station based on each strategy's specific rules as mentioned above.

Finally, it is essential to emphasize that all strategies are assessed via simulation, which reflects the actual uncertainties experienced. Therefore, even the predictions in the ONO strategy about renewable energy will contain some level of error.

Our primary performance indicators are the reliability of TBN operations, the impact on the grid, and REG utilization. These factors are either optimized or maintained within specified limits in our optimized strategies, namely, the OFO and ONO. To assess the reliability of TBN operations, we monitor the minimum SoC of each bus throughout the day. The impact on the grid is evaluated by minimizing a cost function that reflects grid status at various times. Charging during peak hours, when balancing supply and demand is more challenging for the grid, incurs a higher cost compared to off-peak hours. Ideally, this function would use detailed data on anticipated and actual demand–supply balance, but due to practical constraints in our case study, we use day-ahead energy prices as a proxy. REG utilization is measured by the ratio of the utilized renewable energy to the total generated during the day. Prioritizing these performance metrics is crucial; we place the highest priority on the reliability of the bus network's operations. Consequently, we model reliability as a constraint (ensuring that the SoC of each bus remains above a specific threshold), while the grid impact and renewable energy utilization are included in the objective function.

In the next section, we present the mathematical model used for optimizing the charging schedule and reflecting these considerations. This model is applied in day-ahead settings to generate the OFO strategy's charging plan. The ONO strategy recalculates this schedule at regular intervals throughout the day, using a rolling horizon approach. Necessary model adjustments for this process are discussed in Section 4.2. Given the impracticality of continuous reoptimization or adjustments at every unforeseen event, the ONO strategy reoptimizes the schedule periodically, such as every hour, during the day. Section 4.3 will detail how the ESS manages uncertainties that arise between these optimization intervals.



**FIGURE 3** Illustration of the difference between time-based and event-based discretization.

#### 4.1 | Mathematical optimization model

To manage our time-dependent problem, we utilize discretization, focusing on computational efficiency for our online optimization. We adopt an event-based discretization approach, as detailed in Abdelwahed et al. (2020), offering a more compact and computationally manageable problem compared to traditional discretization approaches using fixed increments. This method considers the commencement of EB charging only at moments of arrival or departure, leading to nonuniform time slots that align with these events, as depicted in Figure 3. Through this approach, we effectively reduce the optimization problem's size, demonstrated by the decrease from 13 to 5 time slots in the example in Figure 3. Our previous study (Abdelwahed et al., 2020) confirms that this method substantially cuts down computational time with minimal effect on solution quality. However, the extent of size reduction inversely correlates with the network size and the frequency of events, as constant arrivals or departures at every minute would negate this benefit. Moreover, this approach yields a more pragmatic and feasible charging schedule for the PTO, as it implies the presence of a driver to connect the bus to the charger at these event-based intervals.

For the mathematical formulation, we build upon the MILP formulation for optimizing EB charging schedules developed in Abdelwahed et al. (2020), which primarily focused on grid-based charging. We expand the model to accommodate EB charging from three sources: the grid, REGs, and the ESS, as shown in Figure 4. Time slots, denoted by  $E$ , start and end with arrival or departure events, covering a full day of operations. The set of EBs is represented by  $B$ , and terminal stations are denoted by  $S$ . Table 1 lists the mathematical notations used and their definitions.

Our objective is to minimize the total charging costs  $Q$  across the network as formulated in Equation (1). Here, the decision variables  $\Pi_{se}^G$ ,  $\Pi_{se}^R$ , and  $\Pi_{se}^{Z-}$  represent the charging power in kW<sup>1</sup> from the grid, the REG and the ESS, respectively, for EBs during time slot  $e$  at station  $s$ . Correspondingly,

$P_{se}^G$ ,  $P_{se}^R$ , and  $P_{se}^Z$  are the charging costs per kilowatt-hour (€/kWh). The term  $T_e/60$  converts the duration of time slot  $e$ , originally in minutes, to hours, facilitating the calculation of energy consumption in kilowatt-hours (kWh) when multiplied by the charging power.

$$Q = \min \sum_{e \in E} \sum_{s \in S} (P_{se}^G \Pi_{se}^G + P_{se}^R \Pi_{se}^R + P_{se}^Z \Pi_{se}^{Z-}) \left( \frac{T_e}{60} \right). \quad (1)$$

As marginal costs of REG generation are assumed to be zero, our objective inherently promotes the use of available renewable energy. Constraint 2 represents the power balance equation at each station for every time slot. In this constraint,  $N_{se}^A$  indicates the number of active chargers (engaged in charging EBs) at station  $s$  during time slot  $e$ .  $\overline{\Pi}_s$  denotes the rated power of the EB chargers,<sup>2</sup> while  $\Pi_{se}^{Z+}$  refers to the rated charging power of the ESS.

$$\Pi_{se}^G + \Pi_{se}^R + \Pi_{se}^{Z-} = N_{se}^A \overline{\Pi}_s + \Pi_{se}^{Z+} \quad \forall s \in S, e \in E. \quad (2)$$

Constraints (3)–(5) set the power limits for the REGs and the ESS.

$$0 \leq \Pi_{se}^R \leq \overline{\Pi}_{se}^R \quad \forall s \in S, e \in E, \quad (3)$$

$$0 \leq \Pi_{se}^{Z-} \leq \overline{\Pi}_s^{Z-} \quad \forall s \in S, e \in E, \quad (4)$$

$$0 \leq \Pi_{se}^{Z+} \leq \overline{\Pi}_s^{Z+} \quad \forall s \in S, e \in E. \quad (5)$$

Here,  $\overline{\Pi}_{se}^R$  represents the forecasted renewable energy generation at station  $s$  during time slot  $e$ , while  $\overline{\Pi}_s^{Z-}$  and  $\overline{\Pi}_s^{Z+}$  signify the rated ESS discharging and charging powers, respectively.

Let  $L_{bse}$  be a binary parameter which specifies the location of each EB during each time slot, with  $L_{bse} = 1$  if bus  $b$  is at station  $s$  during time slot  $e$ . Constraint (6) limits the charging time  $Y_{be}$  of bus  $b$  to the length of time slot  $e$ , and ensures that

<sup>1</sup> Electrical power is the amount of electrical energy that can be transferred per unit time from the charger to the bus battery. It is measured in watt (W) in the SI stan-

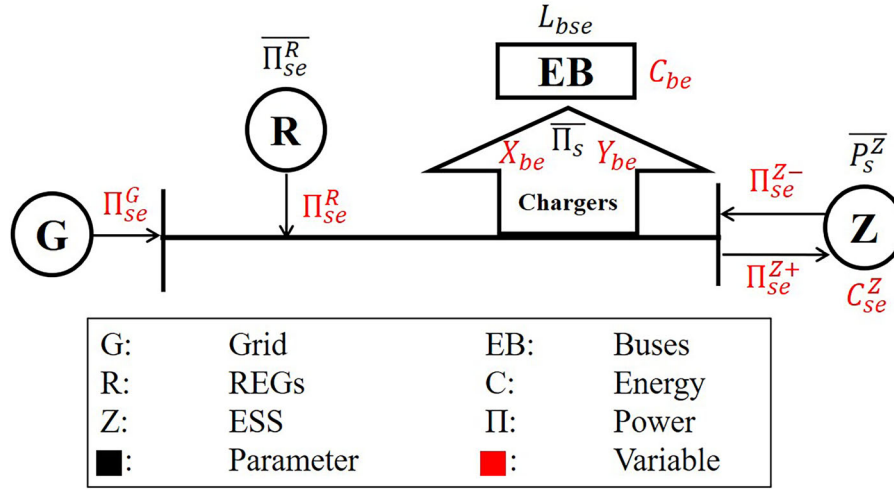
dard measurement system. We use kilowatt (kW) in our study as we deal with high power applications.

<sup>2</sup> Rated electrical power is the maximum electrical power that a charger can deliver or a battery can receive.

**TABLE 1** List of mathematical notations and definitions.

<b>Sets</b>	
$E$	Set of time slots with index $e$
$B$	Set of EBs with index $b$
$S$	Set of stations with index $s$
<b>Target variables</b>	
$Q$	Total charging costs in €
<b>Decision variables</b>	
$\Pi_{se}^G$	Average power drawn from grid at station $s$ during time slot $e$ in kW
$\Pi_{se}^R$	Average power drawn from REGs at station $s$ during time slot $e$ in kW
$\Pi_{se}^{Z-}$	Discharging power of ESS at station $s$ during time slot $e$ in kW
$\Pi_{se}^{Z+}$	Charging power of ESS at station $s$ during time slot $e$ in kW
$Y_{be}$	Charging time of bus $b$ during time slot $e$ in minutes
<b>State variables</b>	
$C_{be}$	Effective energy stored in bus $b$ at time slot $e$ in kWh
$X_{be}$	Indicator, 1 if bus $b$ is charging during time slot $e$
$I_{be}$	Indicator, 1 if bus $b$ starts charging at time slot $e$
$N_{se}^A$	Number of active chargers at station $s$ during time slot $e$
$C_{se}^Z$	Energy stored in ESS at station $s$ after time slot $e$ in kWh
$U_{be}$	Binary product between $X_{b,e}$ and $X_{b,e-1}$
<b>Parameters</b>	
$L_{bse}$	Locations of buses, 1 if bus $b$ is at station $s$ during time slot $e$
$T_e$	Length of time slot $e$ in minutes
$H_{se}$	Event at station, 1 if a bus arrives or departs at station $s$ at time slot $e$
$W_{be}$	Energy consumed by bus $b$ to perform a trip starting at time slot $i$ in kWh
$\overline{C_b}$	Battery capacity of bus $b$ in kWh
$\overline{C_s}$	Capacity of the ESS at station $s$ in kWh
$N_s$	Number of chargers at station $s$
$\overline{\Pi_s}$	Rated power of chargers at station $s$ in kW
$\overline{\Pi_s^{Z-}}$	Rated discharging power of ESS at station $s$ in kW
$\overline{\Pi_s^{Z+}}$	Rated charging power of ESS at station $s$ in kW
$\eta_s$	Efficiency of chargers at station $s$ , $0 \leq \eta_s \leq 1$
$\overline{\Pi_{se}^R}$	Average generated electrical power from REGs at station $s$ during time slot $e$
$P_{se}^G$	Cost of electrical energy drawn from grid at station $s$ and time slot $e$ in €/kWh
$P_{se}^R$	Cost of electrical energy drawn from REGs at station $s$ and time slot $e$ in €/kWh
$P_{se}^Z$	Cost of electrical energy drawn from ESS at station $s$ and time slot $e$ in €/kWh
$\tau^s$	Setup time to connect buses to chargers in minutes
$\tau^m$	Minimum allowed charging time in minutes
$V_e$	Number of time slots starting with (and including) time slot $e$ required to cover minimum charging time + the setup time
$e^f$	Index of last time slot of the day before start of next day's operation
$\epsilon_b^g$	Index of time slot at which bus $b$ arrives after finishing all trips
$\epsilon_b^n$	Index of time slot at which SoC of bus $b$ drops below 90% for first time
$\alpha_{be}^u$	Upper limit relative SoC for bus $b$ at time slot $e$ , is set to 0.9 for $e_b^n \leq e \leq e_b^g$ and to 1 otherwise
$\alpha_b^l$	Lower limit relative SoC for bus $b$ throughout the day





**FIGURE 4** Illustration of charging sources. EB, electric bus; ESS, energy storage system; REGs, renewable energy generators.

it only charges when it is at a station.

$$Y_{be} \leq (T_e) \left( \sum_{s \in S} L_{bse} \right) \quad \forall b \in B, e \in E. \quad (6)$$

The binary variable  $X_{be}$  is equal to one if bus  $b$  is charging during time slot  $e$  and zero otherwise. It is evaluated through the next two big-M constraints, where the M value is set to be  $T_e + 1$ .

$$Y_{be} \geq 1 - (T_e + 1)(1 - X_{be}) \quad \forall b \in B, e \in E, \quad (7)$$

$$Y_{be} \leq (T_e + 1)(X_{be}) \quad \forall b \in B, e \in E. \quad (8)$$

Given the value of  $X_{be}$ , the number of active chargers at station  $s$  during time slot  $e$  can be evaluated as follows:

$$N_{se}^A = \sum_{b \in B} (X_{be} \times L_{bse}) \quad \forall s \in S, e \in E. \quad (9)$$

Constraint (10) enforces the capacity constraint, which ensures that the number of charging EBs at station  $s$  during time slot  $e$  does not exceed the available number of chargers  $N_s$ .

$$N_{se}^A \leq N_s \quad \forall s \in S, e \in E. \quad (10)$$

The binary variable  $I_{be}$  indicates whether bus  $b$  starts charging during time slot  $e$ . It is evaluated through the binary variable  $U_{be}$ , which is the binary product of  $X_{be}$  and  $X_{b,e-1}$  as shown in constraints (11)–(14).

$$I_{be} = X_{be} - U_{be} \quad \forall b \in B, e \in E, \quad (11)$$

$$U_{be} \leq X_{b,e-1} \quad \forall b \in B, e \in E, \quad (12)$$

$$U_{be} \leq X_{be} \quad \forall b \in B, e \in E, \quad (13)$$

$$U_{be} \geq X_{be} + X_{b,e-1} - 1 \quad \forall b \in B, e \in E. \quad (14)$$

For practicality and streamlined operational implementation, charging is permitted to commence at a station only if an EB arrives or departs there, as this suggests that an employee

is present who can start or stop the charging process. Constraint (15) enforces this rule:  $H_{se}$  is a binary parameter set to one when an arrival or departure event occurs at station  $s$  during time slot  $e$ .

$$I_{be} \leq L_{bse} \times H_{se} \quad \forall b \in B, e \in E, s \in \{S : L_{bse} = 1\}. \quad (15)$$

The energy<sup>3</sup> stored in the ESS at station  $s$  after time slot  $e$ , denoted by  $C_{se}^Z$ , is evaluated as shown by Constraint (16). We assume that the ESS is fully charged at the beginning of the day, where  $\bar{C}_s$  is the capacity of the ESS at station  $s$ .

$$C_{se}^Z = \begin{cases} \bar{C}_s - \Pi_{se}^{Z-} \left( \frac{T_e}{60} \right), & \text{if } \forall s \in S, e = 0, \\ C_{s,e-1} + (\Pi_{se}^{Z+} - \Pi_{se}^{Z-}) \left( \frac{T_e}{60} \right), & \text{otherwise.} \end{cases} \quad (16)$$

Constraint (17) ensures that the energy stored in the ESS remains within the permissible range. Constraint (18) sets the final SoC after the last time slot, denoted as  $\epsilon^f$ . Given that the charging duration is formulated as an integer variable, attaining an exact final SoC of 100% may not always be feasible. Therefore, we permit the final SoC to be slightly less than 100%, accommodating a deviation equivalent to the energy that would be gained from 1 min of charging.

$$0 \leq C_{se} \leq \bar{C}_s \quad \forall s \in S, e \in E, \quad (17)$$

$$C_{se} \geq \bar{C}_s - \frac{\Pi_s^{Z+}}{60} \quad \forall s \in S, e = \epsilon^f. \quad (18)$$

The effective energy stored in each EB  $b$  after each time slot  $e$  is denoted by  $C_{be}$ , as determined by Constraint (19). For EB  $b$  at time slot  $e$ , the effective energy is calculated by

<sup>3</sup> Electrical energy refers to the power consumed or stored over a period of time in the bus battery. It is measured in kWh. A kWh quantifies the energy equivalent to a power consumption of 1 kW sustained for 1 h. For example, a battery storing 100 kWh can provide 1 kW of power for 100 h, or it can deliver 100 kW of power for 1 h, subject to the constraints of the battery's rated capacity and discharge rate.

adding the energy acquired from charging and subtracting the total energy required to perform a trip starting at that time slot, indicated by  $W_{be}$ .  $\bar{C}_b$  denotes the energy capacity of a fully charged battery in EB  $b$ ,  $\tau^s$  represents the setup time required for connecting an EB to a charger, and  $\eta_s$  signifies the charging efficiency.

$$C_{be} = \begin{cases} \bar{C}_b - W_{be}, & \text{if } e = 0, \\ C_{b,e-1} - W_{be} + (Y_{be} - I_{be} \times \tau^s) \left( \sum_{s \in S} L_{bse} \times \frac{\bar{\Pi}_s}{60} \times \eta_s \right), & \text{otherwise.} \end{cases} \quad (19)$$

Constraints (20) and (21) are implemented to maintain the EBs' SoC within specified upper and lower limits throughout the day. Constraint (22) ensures that all EBs achieve 100% SoC prior to the commencement of the next day's operations.  $\alpha_{be}^u$  represents the upper limit of the relative SoC for bus  $b$  during time slot  $e$ . This is set to 0.9 once an EB's SoC falls below 90% for the first time during the day, remaining at this value until the bus returns to the garage for overnight charging. Otherwise, it is set to one. In addition,  $\alpha_b^l$  denotes the constant lower limit of the relative SoC for each bus throughout the day. The second term on the right-hand side of Constraint (22) addresses the potential impracticality of achieving a final SoC that is precisely 100%, due to the integer nature of the charging duration variable.

$$C_{be} \leq \alpha_{be}^u \times \bar{C}_b \quad \forall b \in B, e \in E, \quad (20)$$

$$C_{be} \geq \alpha_b^l \times \bar{C}_b \quad \forall b \in B, e \in E, \quad (21)$$

$$C_{be} \geq \bar{C}_b - \left( \sum_{s \in S} L_{bse} \times \frac{\bar{\Pi}_s}{60} \times \eta_s \right) \quad \forall b \in B, e = e^f. \quad (22)$$

Constraints (23) and (24) ensure that charging events with durations less than the prespecified minimum charging time, denoted by  $\tau^m$ , are not permitted. The parameter  $V_e$  represents the number of time slots, starting from and including time slot  $e$ , required to encompass both the minimum charging time and the setup time,  $\tau^s$ .

$$\sum_{e^* \geq e}^{e^* \leq e + V_e - 1} Y_{be^*} \geq (\tau^s + \tau^m) \times I_{be} \quad \forall b \in B, e \in E, \quad (23)$$

$$\sum_{e^* \geq e}^{e^* \leq e + V_e - 1} X_{be^*} \geq V_e \times I_{be} \quad \forall b \in B, e \in E. \quad (24)$$

Constraint (25) is introduced to preclude EBs from charging for three or more time slots without fully utilizing all intermediate time slots, thereby prohibiting interrupted charging.

$$Y_{be} \geq U_{b,e+1} \times T_e \quad \forall b \in B, e \in E. \quad (25)$$

To align with practical considerations and the PTO's operational requirements (manual action may be necessary), EBs are permitted to initiate charging solely once during overnight sessions, as reflected by Constraint (26). In this context,  $\epsilon_b^g$

denotes the time slot when bus  $b$  reaches the garage and has no further scheduled trips.

$$\sum_{\substack{e \leq e^f \\ e \geq \epsilon_b^g}} I_{be} \leq 1 \quad \forall b \in B. \quad (26)$$

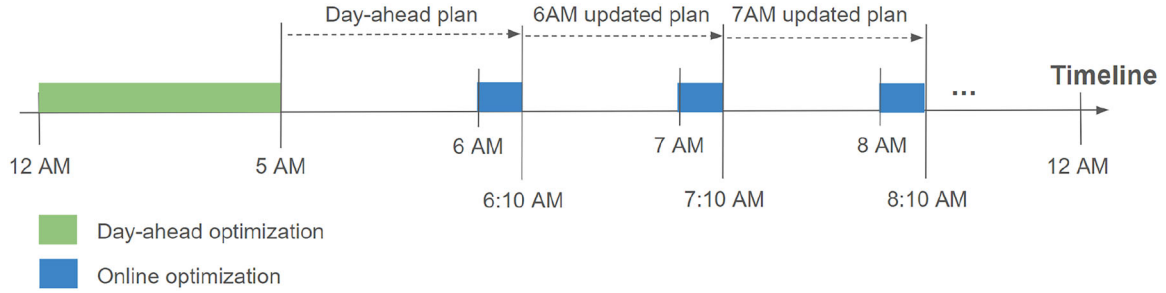
As outlined earlier, the OFO strategy formulates the charging schedule optimization once prior to the commencement of daily operations. Utilizing the mathematical model described above, we devise the charging strategies for both EBs and ESSs. Inputs for the parameter  $\bar{\Pi}_{se}^R$  include day-ahead forecasts of renewable energy generation. In addition, the PTO's anticipated delay projections are incorporated into the calculated durations of trips.

## 4.2 | The online optimization

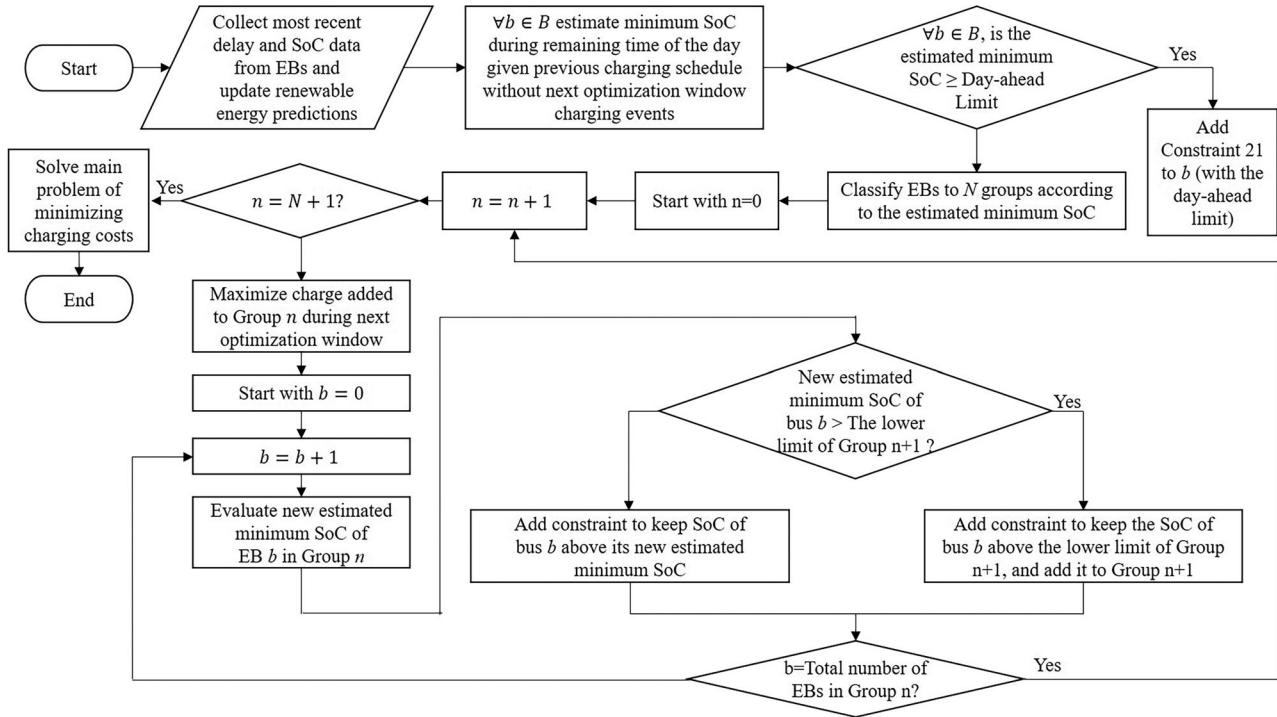
The ONO strategy employs the same mathematical model as the OFO, including the identical objective function. The central RDSS executes the optimization model periodically (e.g., hourly) throughout the day, adjusting the charging schedule in response to the real-time network status. Crucially, the ONO strategy leverages improved real-time predictions of renewable energy, as opposed to day-ahead forecasts, potentially enhancing REG utilization. However, adopting the ONO strategy necessitates certain modifications to the mathematical model, primarily due to uncertainties that may lead to constraint violations.

Unexpected trip delays can result in EBs missing planned charging sessions, either partially or entirely. Furthermore, unforeseen factors like delays and adverse weather conditions may increase energy consumption (notably through heightened HVAC [heating, ventilation, and air conditioning] system usage), often leading to a lower than anticipated SoC for EBs. Prioritizing network reliability over minimizing grid impact, our online algorithm focuses on offsetting this unexpected excess energy consumption by EBs by using the real-time information of the system. Subsequently, it addresses the primary optimization problem of minimizing charging costs, effectively also reducing grid impact through the use of the locally generated renewable energy by using the updated and improved predictions.

Figure 5 shows an example of the implementation of the rolling horizon online optimization we propose. The day-ahead planning uses the day-ahead renewable energy generation predictions and the anticipated delays to optimize the charging schedules. Afterward, the online optimization runs hourly using the current system information and updated predictions and reoptimizes the charging schedules. The updated plan will be followed until the next scheduled update after a period of time which can be set by the operators based on the nature of their network and the amount of divergence between the data estimates used in planning and the actual events. While the day-ahead optimization has ample time available for execution, the online optimization is limited to



**FIGURE 5** Rolling horizon online optimization.



**FIGURE 6** Flowchart for the logic of the online optimized (ONO) strategy. EBs, electric buses; SoC, state of charge.

a very short time frame of just a few minutes. The event-based discretization explained in the previous section allows the operators to solve the optimization problem within this short period of time and reach a close-to-optimal solution.

Figure 6 illustrates the logic of our online algorithm. In the online scenario under uncertainty, there is a possibility of violating Constraint (21) during the day's reoptimization of the charging schedule. This violation may occur if an EB's SoC cannot be maintained above the prespecified day-ahead limit  $\alpha_b^l$  due to real-world operational conditions. To address this, we omit this constraint from the initial mathematical model and substitute it with a customized constraint tailored to each bus. During each reoptimization instance, we gather the latest data on delays and excess energy consumption from the EBs. Our primary goal is to swiftly compensate for any missed charging opportunities, aiming to avert more severe impacts later. Consequently, we first replan the imminent charg-

ing events within the next optimization window (spanning from the current to the subsequent optimization instance). This replanning involves reallocating available charging slots among the EBs, prioritizing them based on their current needs and conditions.

We achieve this by calculating the minimum SoC for each EB during its remaining operations of the day, considering only the planned charging events scheduled after the next optimization window from the previous charging plan (i.e., excluding the earlier planned charging events within the upcoming optimization window). If the anticipated minimum SoC exceeds  $\alpha_b^l$ , then Constraint (21) is reapplied for that particular EB. In all other scenarios, EBs are categorized into  $N$  groups based on their estimated minimum SoC. Group 1 encapsulates the most critical EBs, those with the lowest predicted minimum SoC, whereas Group  $N$  consists of EBs with minimum SoC levels approaching  $\alpha_b^l$ . For instance, assuming

$N$  is set to 4 and  $\alpha_b^l$  is 40%, Group 4 would include EBs with an estimated minimum SoC ranging from 30% to 40%, and Group 1 would encompass those with a minimum SoC lower than 10%. Correspondingly, EBs with an estimated minimum SoC between 10% and 20% would fall into Group 2, while those with SoC ranging from 20% to 30% would be classified under Group 3.

Subsequently, for each EB, we implement a constraint to maintain its SoC above the lower limit of the succeeding group (for Group 1, this is 10%; for Group 2, 20%; and for Group 3, 30%). We then conduct  $N$  optimization iterations, commencing with Group 1. In each iteration, we focus on maximizing the charge added to the EBs of the respective group during the forthcoming optimization window, while imposing a penalty on EBs that are unlikely to reach the subsequent group. Based on this maximization process and the projected charging schedule for the day's remainder, we recalibrate the minimum SoC for each EB within the group. If this newly calculated minimum SoC surpasses the threshold of a higher group, we introduce a constraint to uphold the SoC above that group's lower limit and reassign the EB to this higher group. If not, we enforce a constraint to maintain its SoC at the highest attainable minimum level. This methodology is replicated across each group, ensuring that we redistribute the available charging slots within the next optimization window to the EBs according to their excess unplanned lost charge. Upon completing these iterations, our focus shifts to resolving the principal minimization problem throughout the remaining operational duration of the day.

Besides uncertainties in traffic conditions and energy consumption rates that may impact the reliability of the network, deviations between predicted and actual renewable energy generation can also occur. Although EB charging schedules are influenced by forecasted renewable energy availability, our highest priority is maintaining the bus network's reliability. Consequently, we do not permit real-time adjustments to the charging schedules based on actual renewable energy generation. Therefore, if the actual renewable energy falls short of predictions, EBs compensate by drawing additional power from the grid. For instance, suppose a charging plan is optimized at 7:00, anticipating that an EB will charge 50 kWh at 7:30, using 20 kWh from renewable sources and 30 kWh from the grid. If, at 7:30, only 10 kWh of renewable energy is available, the bus should then draw the shortfall of 40 kWh from the grid. Conversely, if renewable energy generation exceeds expectations, EBs should prioritize using all available renewable power before resorting to grid resources.

### 4.3 | ESS charging strategy

In contrast, we permit modifications to the ESS's optimized charging schedule, introducing an additional layer of complexity due to the need for a real-time decision model to

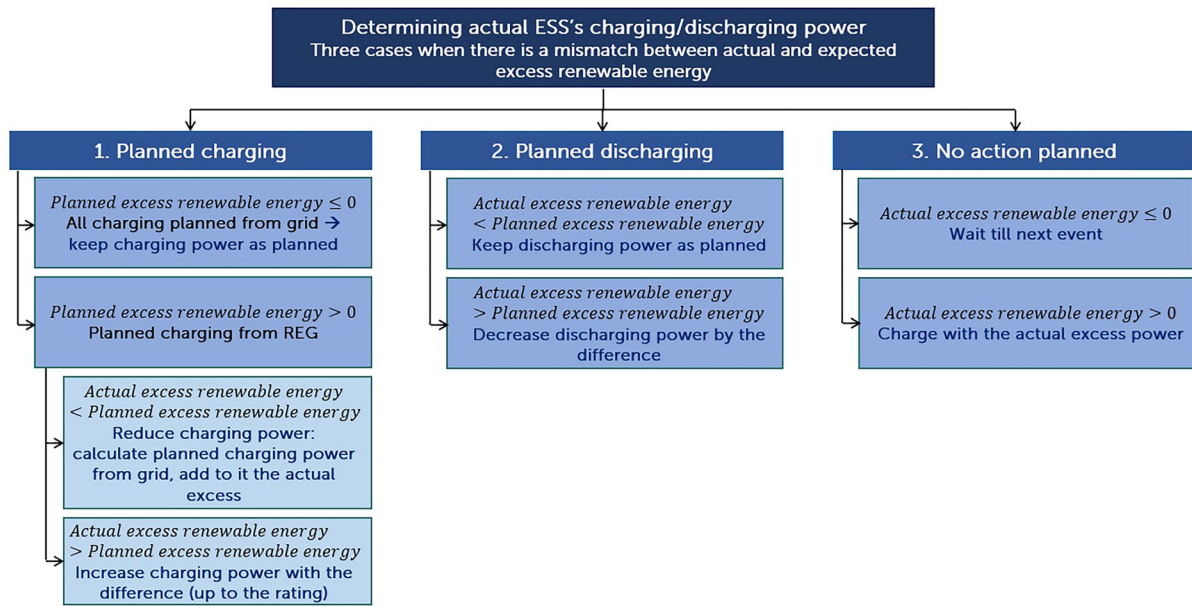
dynamically adjust the ESS's (dis)charging plans. This model fundamentally relies on comparing the expected (planned) and the actual excess renewable energy. We define "excess" renewable energy as the available power from the REGs for ESS charging, after accounting for the EBs' charging demand. Therefore, the actual excess renewable energy is calculated by subtracting the actual EB charging load from the actual renewable energy generated. Correspondingly, the planned excess renewable energy is the difference between the forecasted renewable energy generation and the planned EB charging load.

A decision on the ESS's charging or discharging power is necessary each time an EB begins or concludes charging, resulting in a change in the EB charging load, and in case of fluctuations of the actual power output of the REG. Three potential scenarios can arise from the mismatch between the planned and actual excess power of the REG, each addressed as outlined in Figure 7. If the ESS's charging is scheduled but without any planned excess REG power, this implies that the charging was intended to be sourced entirely from the grid. Consequently, the ESS's charging power remains as initially planned. On the other hand, if the ESS's charging was planned with an expected (partial) reliance on excess REG power, two scenarios are considered. First, if the anticipated excess REG power surpasses the actual output, the ESS cannot offset this deficit by drawing additional power from the grid. Therefore, the actual charging power is limited to the sum of the planned grid power and the actual excess REG power. Second, if the actual excess REG power exceeds the forecast, indicating a surplus of REG power, the ESS charging power is adjusted upward to maximize the use of the available renewable energy.

If ESS discharging is planned, there are two possible outcomes. First, if the actual excess REG power is less than anticipated, we refrain from increasing the ESS discharging power. Consequently, any shortfall in EB charging power is compensated by drawing from the grid. On the other hand, if the actual excess REG power exceeds the planned excess, implying a surplus of renewable energy, this power can be directed toward charging the EBs, rather than the ESS. Therefore, we decrease the ESS discharging power by the difference between the actual and the planned excess REG power. Finally, in situations where neither charging nor discharging of the ESS is scheduled at a given time, but there is surplus renewable energy and the ESS is not fully charged, we utilize this excess power from the REG to charge the ESS.

For the greedy strategies, we employ a simple decision procedure for charging and discharging the ESS, which involves charging the ESS only with any excess renewable energy generated after accounting for the EB load. We discharge the ESS if the total power required for EB charging exceeds the total power available from the REG. We also make sure to fully recharge the ESS during the night when the cost of energy from the grid is lower than during the day. This ensures that the ESS is always fully charged at the beginning of the EBs' operation each day.





**FIGURE 7** Logic of adjusting the energy storage system (ESS) (dis)charging schedule with optimized strategies. REG, renewable energy generator.

## 5 | CASE STUDY

This study is carried out in collaboration with RET, the PTO in the city of Rotterdam in the Netherlands. The city has a very extensive TBN which also extends into some neighboring cities and suburbs. The whole network is on route to be fully electrified within the next few years. At the time of this study, managers and decision makers from the PTO, the municipality, and the grid operators have been studying the implications of electrifying a part of the network in the southern part of the city by using renewable energy from a solar park. This exemplifies the practical contribution of our optimization model and RDSS as they supported these decision makers in this process.

The network includes eight lines which are planned to be served by 50 EBs with 240 KWh batteries. Six fast chargers of 300 kW charging power are due to be installed in the central station of the southern network, where the solar panels will be installed as well. Thus, in our case study there is only a single central terminal station that will be used for opportunity charging. Furthermore, four fast chargers will be installed at the garage where some EBs have layovers between their assigned trips during the day. Finally, slow chargers of 50 kW will be installed in the garage for overnight charging. To assess the impact of these infrastructure decisions, we compare the different charging strategies for varying numbers of fast chargers. We set the highest number of fast chargers that we consider for the central station to be equal to the maximum number of EBs that are simultaneously located at that station during the day according to the trip schedule. This results in having six fast chargers at the central station in this scenario. At the garage, there would be four fast chargers and as many slow chargers as there are EBs.

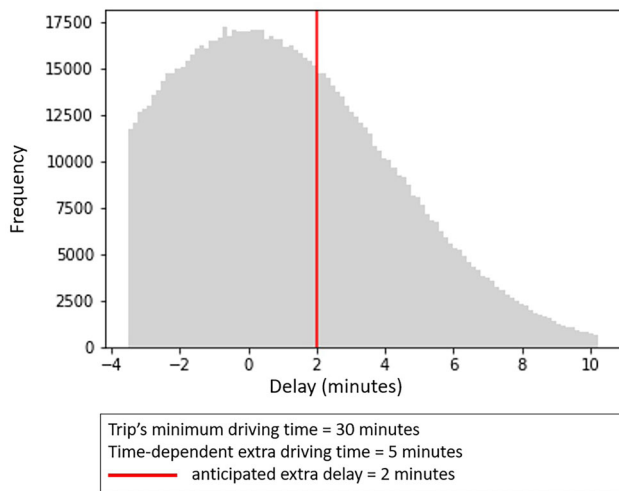
Thus, each EB can find a slow charger for overnight charging once it arrives at the garage.

For the renewable energy generation, we use open data of solar energy generation provided by Elia Group in Antwerp, Belgium, a city very close to Rotterdam, from 2018 (Elia Group, 2019). The data include actual renewable energy profiles, day-ahead predictions, and real-time predictions, which are updated four times during the day. We adapt these data for our models, scaling it to match the planned installed capacity in our case study. Then, based on the data's 15-min resolution, we calculate the average solar power generated in each time slot in our event-based discretization model.

In our case study, the available area for installing the solar park at the central station is approximately 15,000 m<sup>2</sup>. The grid operator and the municipality suggest a peak power density for the solar panels of 175 W/m<sup>2</sup>. Therefore, the maximum solar power capacity—assuming full use of the available area—is about 2.625 MW. This exceeds the power requirements of eight fast chargers. However, according to the renewable generation data, the annual average solar power at noon is only 38.1% of the installed capacity. Seasonally, the average is 53.2% during summer and 26% in winter. The highest recorded power generation throughout the year reaches just 76.5% of the rated peak power. Consequently, fully utilizing the 15,000 m<sup>2</sup> would provide sufficient power for an average of 4.6 chargers at noon during summer and 2.3 chargers in winter.

Furthermore, the ESS under consideration at the central station has a capacity of 600 kWh with a rated power of 300 kW, as suggested by the PTO. In addition, we assume that the energy cost from the renewable source is zero. While installing REGs involves significant infrastruc-





**FIGURE 8** An example for the distribution of delays used in the study.

ture costs, the primary goal of the stakeholders in Rotterdam is to achieve sustainable and clean operations. Hence, the decision to install solar panels is beyond the scope of our work; our focus is on analyzing the operational impact of having renewable generators.

For energy consumption, we use two different values provided by the PTO. In summer, the average consumption is assumed to be 1.55 kWh/km, while in winter, it increases to 1.93 kWh/km due to heating systems. The PTO also specifies passive power consumption—power consumed by EBs during layovers due to the HVAC system—as 6 kW in summer and 18 kW in winter. To account for uncertainty, we equate additional power consumption due to delays with the passive power consumption rate. Consequently, a delayed EB consumes twice the energy per minute compared to its on-time consumption, as it operates longer with passengers onboard. Conversely, arriving early reduces energy consumption for a trip by 1.25 times the passive power consumption rate multiplied by the time difference, as the EB operates with passengers for a shorter duration when arriving early.

To model delays, we employ truncated normal distributions, created using parameters that closely approximate actual delay occurrences. These distributions and their parameters are based on expert insights from the PTO, drawing on their knowledge of the road network, and historical delay data (refer to Figure 8 for an illustration). The mean and standard deviation of the delay distribution for each trip are determined by three factors: the minimum driving time, the time-dependent extra driving, and the anticipated extra delay, as provided by the PTO.

The minimum driving time represents the quickest possible journey between two terminal stations on a route, assuming optimal traffic conditions throughout the day. Time-dependent extra driving refers to the additional time built into the trip schedule to accommodate expected traffic

variations at different times of the day. Finally, the anticipated extra delay is an additional buffer incorporated into trip durations during planning by the PTO, based on their historical experience.

Figure 8 presents an example delay distribution for a trip with a minimum driving time of 30 min, a time-dependent extra driving time of 5 min, and an anticipated extra delay of 2 min. In the context of optimized strategies, the anticipated extra delay, highlighted by a red line in the figure, represents the value factored into planning.

We assume that the setup time, which is the time required for connecting EBs to chargers, is 1 min. The minimum net charging time, defined as the charging time minus the setup time, is set to 2 min. Therefore, if an EB arrives at a charging station with less than 3 min remaining before its next trip, it will not initiate charging, regardless of its SoC. As previously noted, the upper SoC limit during the day is set to 90%. Consequently, EBs are not permitted to charge beyond this 90% threshold during daylight hours. For the optimized strategies, we establish a lower SoC limit, denoted as  $\alpha_b^l$ , at 30%. This means that the planned SoC for all EBs should remain above 30% throughout the day. In the case of the LCHP strategy, the minimum parameters for charging are set to a charging time of at least 3 min and a minimum SoC of 50%, below which an EB engaged in charging cannot be replaced by another EB.

The TBN's operations in the city commence at 5 a.m. and conclude around 1 a.m. the following day. In the ONO strategy, we reoptimize the charging schedule hourly, beginning at 7 a.m. and concluding at 11 p.m., considering that only a limited number of trips occur outside this time frame. A 10 min interval is allowed between the commencement of reoptimization and the implementation of the revised schedule. Therefore, if reoptimization is triggered by the RDSS at 7:00 a.m., the updated schedule is applied at 7:10 a.m. The optimization process terminates upon either reaching the 10-min mark or achieving a solution with an optimality gap of 1%. In our case study, at the early instances of the day, we always reach the 10 min time limit with an optimality gap ranging from 2% to 4%. As the day proceeds, the optimization problem gets smaller, as fewer buses are included, and the 1% optimality gap target is achieved in less than 10 min. It is also important to notice that the average duration required by the algorithm to reach the 1% optimality gap is always 50% less in winter compared to summer instances. This could be due to the excess renewable energy available in summer which increases the size of the solution space. Finally, these computational results were achieved by CPLEX solver on a Windows machine with 16 GB of RAMs and eight CPUs.

Regarding the minimum SoC constraint levels (as discussed in Section 4.2), we employ thresholds of 10%, 20%, and 30%. For enhanced practicality, if an EB's charging event, planned in the preceding schedule, is ongoing at the time of the schedule update, we require that this charging event is neither canceled nor shortened in duration.

This ensures that changes do not need to be immediately communicated in case manual action is required.

In the following subsections, we conduct a series of comparative studies. First, we contrast the OFO charging strategy with various greedy charging strategies, featuring different numbers of chargers within the network, to highlight the advantages of optimizing the charging schedule. Subsequently, we examine the effect of the quality of REG predictions on the optimized charging schedule. Thereafter, we compare both offline and greedy charging strategies against the online strategy in scenarios with uncertain trip delays, to assess the effectiveness of the RDSS. Lastly, we explore the benefits of incorporating an ESS in enhancing our performance metrics.

## 5.1 | Optimizing the charging schedule

### 5.1.1 | The value of optimizing the charging schedule

In our initial study, we focus on the strategic decision of optimizing the charging schedule, setting aside online optimization for now. We compare optimized strategies with greedy ones in a deterministic setting, where trip delays are assumed to be consistent with the expected delay values provided by the PTO, foregoing the use of the delay distribution mentioned earlier. However, uncertainty remains in the form of renewable energy generation. In the optimized strategy, we use day-ahead predictions of renewable energy, evaluating performance measures against actual renewable energy generation values. It is important to highlight that this uncertainty in renewable energy generation does not compromise the reliability or feasibility of the TBN's operations.

As previously indicated, the largest reasonable number of fast chargers is six at the central station, ensuring a charging slot for each bus on arrival, and four at the garage. Under these conditions, both the FIFS and the LCHP strategies represent the upper limit of system reliability in this base case, with no need to prioritize buses, leading to indistinguishable performance between the two strategies. We then experiment with reduced numbers of fast chargers, creating constraints on charging slot availability. Initially, we remove two fast chargers from both the central station and the garage, leaving four and two, respectively. In the FIFS strategy, this reduction equates to about 197 min of charging time in the base scenario. In the next phase, we further decrease the count by one more charger at each location, leaving three at the central station and one at the garage, resulting in an additional reduction of 408 min of charging time from the base scenario.

To assess the seasonal impact, we conducted simulations for two complete months, January and July 2018, applying each charging strategy. We utilized the previously outlined winter and summer energy consumption rates for January and July, respectively. In addition, we based our calculations

on the day-ahead predicted renewable energy generation values within the optimized strategy. The results, depicted in Table 2, demonstrate the advantages of an optimized charging schedule over the greedy strategies. Utilizing the maximum number of fast chargers, the optimized strategy ensures a reliable charging schedule for the TBN, simultaneously reducing the charging costs (our proxy for grid impact) by 25.8% in summer and 15.1% in winter. The more significant summer reduction is attributable to higher renewable energy generation. Both figures underscore the strategy's enhanced alignment with the power grid, leading to reduced energy costs. Owing to the high renewable energy generation, the optimized strategy raises the average minimum SoC of the EBs above the 30% threshold set within the strategy during summer. Consequently, the strategy effectively maximizes daytime energy absorption from the REGs—incurring no charging costs—thereby minimizing the need for costlier overnight charging at the garage.

Moreover, the optimized strategy can slightly better utilize renewable energy during the day compared to greedy strategies. This is because there may be situations where an EB is at a station generating renewable energy but cannot use it, as its SoC has already reached the 90% upper limit. The optimized strategy can better plan the charging schedule to avoid this issue. However, this advantage is less significant in winter due to the limited generation of renewable energy. Therefore, any disparity between predicted and actual renewable energy generation directly impacts the performance of the optimized strategy.

When we move to the scenarios with reduced numbers of chargers, Table 2 shows that the optimized strategy is able to maintain higher levels of reliability compared to the greedy strategies, especially during winter when energy consumption increases. In the scenario with four chargers in total, FIFS has one infeasibility during summer and six during winter. While the LCHP strategy performs better in that regard and achieves feasible operations in both seasons, the minimum SoC still drops below the critical levels of 10% for 12 EBs. In contrast, the optimized strategy is feasible in both seasons while maintaining a minimum SoC level above 30% and 15% during summer and winter, respectively. The optimized strategy also reduces the charging costs by around 26% and 11% compared to LCHP during summer and winter, respectively.

The results suggest that using the maximum number of chargers may be a conservative approach, yet the PTO opted for this setup due to their initial unfamiliarity with EB operations. Preferring to err on the side of caution, they chose this strategy for the initial phase. In addition, it is important to note that the network is expected to incorporate more EBs in the coming years, which will utilize the same charging infrastructure. However, the present trip schedule is designed based on the existing fleet size and the maximum charger capacity. Therefore, our subsequent analyses will be based on these current operational settings, utilizing the full capacity of fast chargers.

**TABLE 2** Comparative study between the charging strategies with different number of chargers under deterministic delay settings.

Number of fast chargers		Performance measures				
Total\Central station\Garage	Charging strategy	Average daily grid charging costs(€)	Average daily renewable energy utilization (%)	Number of infeasible EBs with SoC% = 0	Number of EBs with $0 < \text{SoC} \% \leq 10$	Average lowest SoC%
(a) Summer (July 2018): Average daily renewable energy generation: 14,079.17 kWh						
10\6\4	Optimized	410.68	46.11	0	0	43.09
	FIFS	553.43	44.91	0	0	62.20
	LCHP	553.43	44.91	0	0	62.20
6\4\2	Optimized	412.07	45.95	0	0	42.99
	FIFS	554.09	44.66	0	0	61.41
	LCHP	543.46	44.50	0	0	55.62
4\3\1	Optimized	421.10	44.59	0	0	41.76
	FIFS	531.12	43.87	1	1	54.86
	LCHP	570.13	40.57	0	0	48.40
(b) Winter (January 2018): Average daily renewable energy generation: 1488.79 kWh						
10\6\4	Optimized	1021.48	91.00	0	0	31.06
	FIFS	1203.22	91.97	0	0	49.36
	LCHP	1203.22	91.97	0	0	49.36
6\4\2	Optimized	1032.67	91.59	0	0	31.12
	FIFS	1193.50	92.17	0	0	46.54
	LCHP	1166.54	90.02	0	1	32.40
4\3\1	Optimized	1005.17	92.65	0	0	15.02
	FIFS	1044.00	92.28	6	4	29.84
	LCHP	1128.89	85.80	0	12	19.04

Abbreviations: EBs, electric buses; FIFS, first-in-first-served; LCHP, lowest-charge-highest-priority; SoC, state of charge.

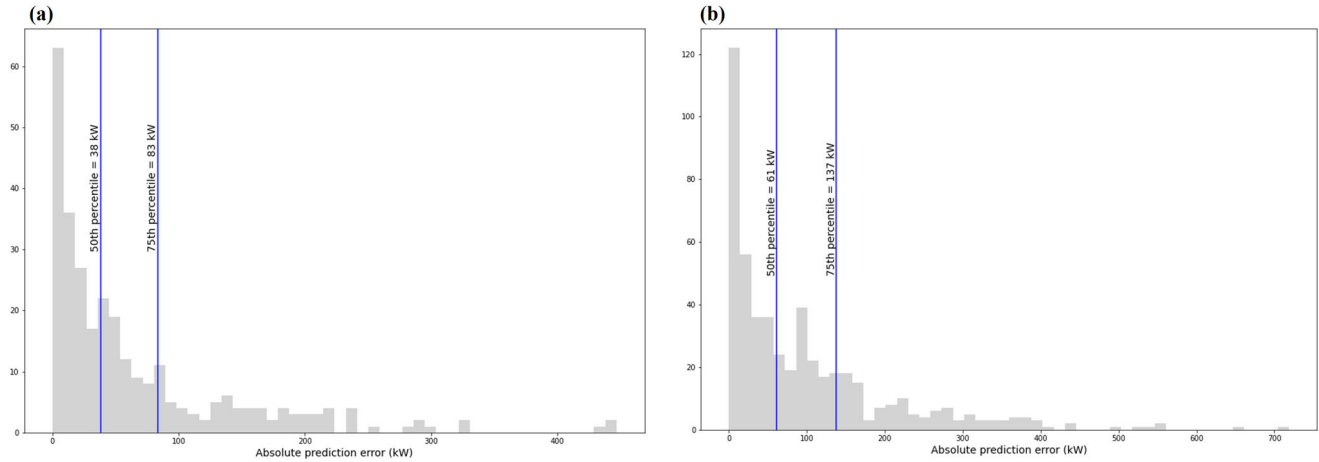
### 5.1.2 | The impact of renewable energy prediction quality

The decision to invest in enhancing renewable energy predictions poses a critical question for PTOs. In this analysis, we explore the impact of errors in renewable energy predictions on the primary performance metrics of the TBN. We reduce our original prediction errors by 50% and 100% (i.e., no error), and evaluate the average values of our performance metrics in winter and summer. The results show that neither the charging costs nor the renewable energy utilization improves when the renewable generation predictions improve. There is only a slight and negligible improvement of around 0.5% and 0.05% in the renewable energy utilization in winter and summer, respectively.

Improving predictions does not significantly enhance performance, as the optimized charging schedule remains largely unchanged with increased prediction accuracy. Essentially, the optimal charging slots continue to be the same. This is because buses can only charge at the full rated charging power of 240 kW. Therefore, the absolute error in predictions must be substantially large relative to the charger's rated power to impact the optimized schedule. For instance, in the case of underprediction, if the actual renewable power during a

specific hour is 480 kW (equivalent to two chargers) and the predicted power is 440 kW (resulting in a -40 kW error), it would still be optimal to charge two buses. In this scenario, the PTO would only have to compensate for the 40 kW shortfall from the grid, which is of limited impact particularly if grid charging costs at that hour are relatively low. Similarly, in cases of overprediction, with a predicted 520 kW (+40 kW error), the optimal decision hinges on the grid charging costs at that time. If grid costs are high, the best choice would be to charge only two buses, as charging a third would require drawing an additional 200 kW from the grid. Conversely, if grid costs are low, charging three buses becomes the optimal decision, as it is cost-effective regardless of available renewable energy.

Thus, enhancing prediction accuracy would only improve the network's performance when the prediction errors are close to the chargers' rated charging power of 240 kW, and the grid charging costs during that specific hour are comparatively high. Figure 9a,b illustrates the distribution of the absolute error in renewable energy generation predictions for winter and summer, respectively. In winter, the 50th and 75th percentiles of this distribution are 38 and 83 kW, corresponding to about 16% and 35% of a single charger's 240 kW power. In summer, the absolute error values are naturally



**FIGURE 9** Hourly average actual and predicted generated renewable power in (a) winter and (b) summer.

higher due to increased renewable energy generation. However, this does not affect the EBs' charging schedule since there is generally an excess of renewable energy available in summer, sufficient to power all chargers.

## 5.2 | The value of online optimization

The previous section's results highlight the effectiveness of optimizing the charging schedule compared to greedy strategies. However, to determine if the optimized strategy maintains its superiority under uncertainty, we conducted a comparative study. This study compares the OFO and ONO strategies, the greedy strategies, and a perfect information (PI) scenario under stochastic operating conditions. We base the study on the actual network configuration with the maximum number of chargers, ensuring that each EB arriving at a terminal station with charging facilities can access a free charger. Consequently, there is no functional difference between the FIFS and LCHP strategies in this setup, as both maximize network charging. We therefore collectively refer to them as "greedy" in the results.

Similar to the previous study, we simulate two distinct months, January and July of 2018, incorporating the respective energy consumption rates. In this analysis, we introduce stochastic delays into trip durations based on the distributions previously established. To allow for comparison between the operating conditions in the two seasons, identical delays are added to corresponding days of both months (e.g., trip delays on the first day of January mirror those on the first day of July). In the PI scenario, we generate the charging schedule using actual renewable energy generation and trip delay data, providing upper bound benchmarks for all system performance metrics.

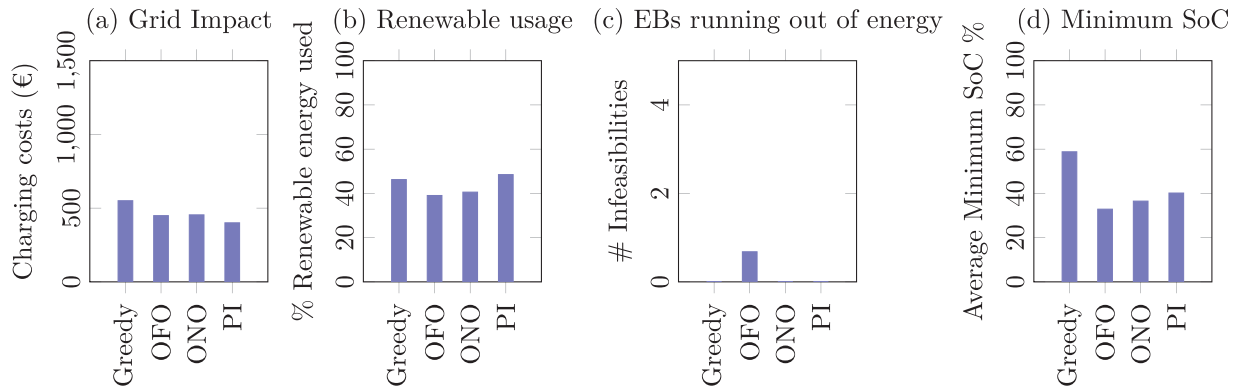
The results for July and January are shown in Figures 10 and 11, respectively. The PI scenario sets the benchmark, and exhibits the highest reliability (Figures 10c and 11c) and renewable energy usage (Figures 10b and 11b) in the 2 months. In the summer, the ONO provides the best per-

formance compared to the greedy and OFO strategies. It maintains the system reliability and guarantees that no buses would run out of energy, which cannot be achieved with the OFO strategy (Figure 10c). It also uses 1.5% more renewable energy compared to the OFO strategy (Figure 10b). The greedy strategy can also guarantee the same levels of system reliability as it uses every potential charging slot for each bus while there are enough chargers for all the buses. However, this results in excessive daytime charging and higher impact on the grid (Figure 10a), as well as significantly higher unneeded average lowest SoC levels (Figure 10d).

In the winter, only the greedy strategy can consistently achieve the reliability levels of the PI due to increased energy consumption (Figure 11c). While the ONO strategy still outperforms the OFO strategy, it results in an average of two buses running out of energy per day. Hence, the PTO should decide for one of the following options:

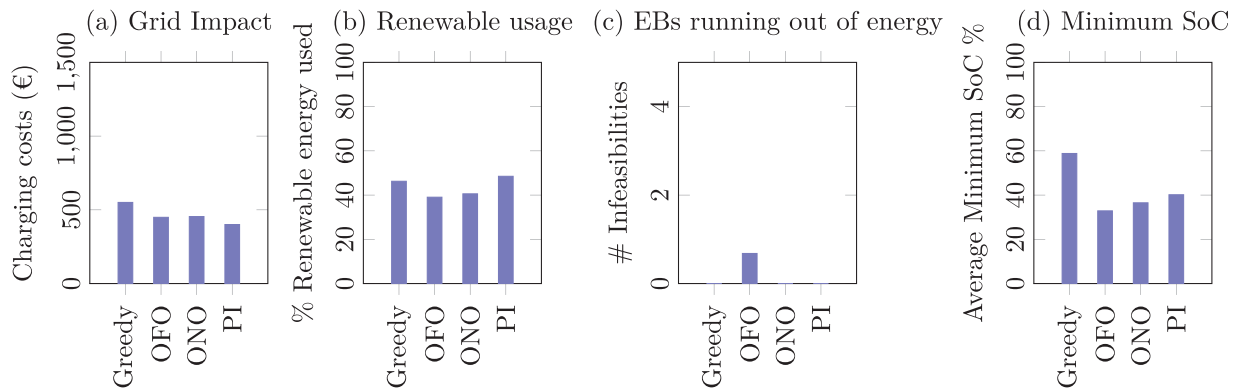
- *Option 1:* Replan the bus trip schedules to allow for more potential charging slots for the buses such that the ONO strategy becomes able to achieve the same reliability level as the greedy strategy. It is also highly likely that it will reduce the impact on the grid, similar to the summer results, compared to the greedy strategy which has the maximum impact on the grid.
- *Option 2:* Implement the greedy strategy, which is the most conservative scenario, and accept the significantly higher grid impact (Figure 11a) and unnecessary day charging (Figure 11d).
- *Option 3:* If there are available backup buses, the PTO may decide to adopt the ONO strategy and dispatch the backup buses to replace buses which are about to run out of energy. This would require the PTO to have at least three backup buses, which is the maximum number of infeasibilities occurring in a single day based on the simulation results.

In general, it is advisable to follow Option 1 as it is highly likely to reduce the impact on the grid and eliminate any



**FIGURE 10** Comparative study between the charging strategies under uncertainty in July. EBs, electric buses; OFO, offline optimized; ONO, online optimized; PI, perfect information; SoC, state of charge.

Note: All values are averages over a month.



**FIGURE 11** Comparative study between the charging strategies under uncertainty in January. EBs, electric buses; OFO, offline optimized; ONO, online optimized; PI, perfect information; SoC, state of charge.

Note: All values are averages over a month.

unnecessary day charging during peak hours. However, if practical or operational constraints prevent the replanning of the bus trip and assignment schedules, then the PTO should decide between Options 2 and 3 based on the available resources, ease of implementation, and cost analysis.

### 5.3 | The value of the ESS

In the final analysis, we examine the potential advantages of deploying an ESS at the central station to enhance the utilization of renewable energy when the ONO strategy is applied. This study follows the same setup as the one described in Section 5.2, including the network operation with random trip delays. As indicated before, the ESS considered has a capacity of 600 kWh and a charging/discharging rate of 300 kW, in line with the PTO's recommendations. Moreover, in the optimized strategy, the ESS is permitted to draw power from the grid, potentially charging during off-peak periods and discharging during peak demand times.

As summarized in Table 3, the incorporation of an ESS leads to a mean increase in renewable energy utilization by approximately 1.4% in summer and 7.9% in winter. This corresponds to an average daily rise in renewable energy usage of around 191 kWh for summer and 118 kWh for winter. In addition to augmenting renewable energy consumption, the ESS can facilitate a shift in charging demand away from peak periods by storing energy from the grid during low-demand periods and subsequently supplying it to the EBs at times of high demand. Consequently, the introduction of an ESS can lead to an average reduction in grid impact of about 1.7% in winter and 3.2% in summer.

It is crucial to acknowledge that the effectiveness of the ESS may differ if it were positioned at a different station. If an ESS is installed at a site where the generated renewable energy is consistently consumed for EB charging due to the trip schedule, the benefits of an ESS may be negligible. Hence, the strategic placement of an ESS at a station with a less consistent EB charging demand throughout the day could potentially amplify its value.



**TABLE 3** The value of adding an energy storage system (ESS) to the system while following the online optimized (ONO) strategy.

Performance measure	Winter (January 2018)		Summer (July 2018)	
	ONO without ESS	ONO with ESS	ONO without ESS	ONO with ESS
Impact on the grid (proxied by charging costs in €)	985.04	968.06	454.29	439.87
Renewable energy generation (kWh)	1488.79		14,079.17	
Renewable energy utilization (%)	88.62	96.51	40.56	41.92

## 6 | CONCLUSION AND PRACTICAL IMPLICATIONS

In this work, we addressed two essential research gaps related to the problem of electrifying TBNs: studying the impact of operational uncertainty and coordinating the charging schedules of electric TBNs with renewable energy generation profiles. We studied how real-time decision support systems, through online optimization, can mitigate the impact of uncertainty on the operational reliability and improve the renewable energy utilization. Our study has several important academic and managerial implications and findings, which are summarized below.

- **Importance of optimizing charging schedules.** Optimizing the charging schedule can result in an enhanced coordination with the renewable energy generation profiles and minimize the impact on the grid by reducing charging during peak times. Furthermore, optimization improves the reliability of the network compared to greedy strategies, particularly when there is a limited number of chargers.
- **Renewable energy integration.** More sustainable operations for electric TBNs can be achieved through powering bus charging from renewable energy resources. Using locally generated renewable energy can also reduce the impact on the grid and cut down the infrastructure costs required to power the EBs.
- **Opportunity fast-charging electric bus networks can be critically impacted by operational uncertainty.** If an EB misses a few minutes of a charging event due to an unexpected delay, its operational feasibility may be threatened since a considerable amount of energy was planned to be added during that short time frame. Moreover, the impact of traffic delays is amplified by severe weather conditions as more energy is consumed by the EBs for longer unplanned periods to operate the HVAC systems.
- **Online decision support can mitigate the impact of operational uncertainty in opportunity fast-charging bus networks.** Online optimization that leverages real-time data to take corrective actions in the charging schedules based on the actual unexpected events can improve the operational reliability of the network. In addition, it can also increase the degree to which renewable energy is used to charge the buses by using updated and improved renewable energy predictions.
- **Extreme weather could be a challenge.** EBs' HVAC systems may need to operate for longer periods under extreme

weather conditions. This results in significantly higher energy consumption for the buses. This impact is amplified by an increase in travel delays in the network as this results in partially or fully missing the preplanned recharging sessions for the buses. Accordingly, buses may require more recharging slots and longer charging durations during the day to avoid running out of energy, which cannot always be guaranteed because of the trip schedules. Thus, it might be necessary in these cases to adapt the EBs' trip assignment and charging schedules to such severe weather conditions. If such modifications to the trip assignment schedule are not possible, these effects can be mitigated by charging the buses at every given opportunity, which is in line with the greedy charging strategy.

- **The value of ESSs.** Installing an ESS to store locally generated renewable energy can help in improving renewable energy utilization as well as shifting the TBN's load on the grid to the less straining off-peak times.

Our work contributed to the successful implementation of the first phase of the TBN electrification in the city of Rotterdam. Based on our analyses and results, the PTO has taken actions to build a real-time monitoring tool and in implementing charging scheduling optimization in their planning system.

*“During the planning of the first batch of electric buses, the simulation also showed the impact of uncertainty in the trip duration on the feasibility of the schedule. It showed that even a conservative charging schedule would result in a few buses that will run into problems during the day. These results confirmed that real-time monitoring is an absolute must. We used the ideas of the RSM team in the development of a real-time monitoring tool for the electric buses. This tool is now in operation.”* Wibout van Ede, Head of Business Operations at RET

Nevertheless, the electrification of TBNs and the integration with renewable energy generation to create smart and sustainable cities still requires further research and our work should be perceived as a starting point in that context. While we focused only on optimizing the charging schedule, our results have shown that the input trip schedule fundamentally affects the feasibility of the network if it does not grant enough charging time for the EBs under uncertainty. Thus, it

is important to acknowledge the implications of operational uncertainty on strategic decisions and to further study the interdependencies between trip schedule and charging schedule. An important direction of future research would be to study how to integrate optimizing the trip assignment and charging scheduling. Although this would increase the computational complexity of the problem, it can lead to a more efficient and robust network. Further avenues for future work also include the explicit modeling of EBs that run out of energy during operations to assess the precise operational impact, the role of battery degradation for ESS costs, and a more extensive integration of the bus batteries and the ESS into energy markets as a virtual power plant (Kahlen et al., 2018).

## ACKNOWLEDGMENTS

This research has been conducted as part of EU Horizon 2020 project RUGGEDISED and received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no 731198. Tobias Brandt was supported by the State of North Rhine-Westphalia's Ministry of Economic Affairs, Industry, Climate Action and Energy through the Exzellenz Start-up Center.NRW program at the REACH EUREGIO Start-Up Center. The authors thank partners at RET for providing data and feedback during the research project.

## NOMENCLATURE

Acronym	Definition
EB	Battery electric bus
ESS	Energy storage system
FIFS	First-in-first-served
HVAC	Heating, ventilation and air conditioning
LCHP	Lowest-charge-highest-priority
MILP	Mixed-integer linear programming
OFO	Offline optimized
ONO	Online optimized
PI	Perfect information
PTO	Public transport operator
RDSS	Real-time decision support system
REG	Renewable energy generator
SoC	State of charge
TBN	Transit bus network

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**How to cite this article:** Abdelwahed, A., van den Berg, P.L., Brandt, T. & Ketter, W. (2025) A real-time decision support system to improve operations in electric bus networks. *Decision Sciences*, 56, 193–212. <https://doi.org/10.1111/deci.12633>

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