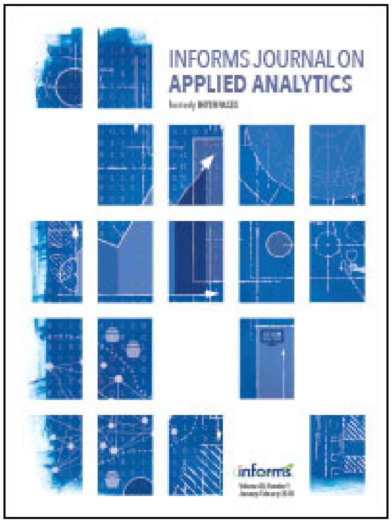

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A Boost for Urban Sustainability: Optimizing Electric Transit Bus Networks in Rotterdam

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Abstract. In 2016, the Dutch government, in pursuit of the UN's sustainable development goals, set a target that all its diesel transit bus networks should be fully electrified between 2025 and 2030. A research team from Rotterdam School of Management has since worked in close collaboration with Rotterdamse Elektrische Tram, the public transport operator in the city of Rotterdam, to accomplish this complex transition. This paper presents essential lessons learned and key practical implications derived from the project. As part of the transition process, we developed a discrete-event simulation model that can simulate the network using different settings and under uncertainty. We also formulated a mixed-integer linear programming problem to optimize the charging schedule. To mitigate the critical impact of uncertainty regarding traffic delays and energy consumption on the electrified transit bus network operation, we developed a real-time decision support system that adjusts and reoptimizes the charging schedule during the day according to the realizations of this uncertainty. We use this system to achieve better coordination between the charging schedule of the electric buses and electricity generation from renewable energy sources with the latter involving high levels of uncertainty. Our study shows the benefits of real-time optimization compared with off-line planning and other greedy strategies. We also show that even highly conservative off-line planning might not be sufficient to maintain reliability levels under extreme operational uncertainty conditions. Additionally, our results and insights have substantially contributed to the success of the first phase of the project, which involved electrifying seven essential bus lines in the city, in realizing a robust and reliable operational plan. Finally, our study shows the potential substantial positive impact of installing renewable energy generators and coordinating the electric buses' charging schedule with their output power profile. Based on our recommendations, RET developed a real-time monitoring system and is working on incorporating our charging schedule optimizer into its planning process.

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Keywords: sustainability • public transport • electric transit networks • charging scheduling • optimization • simulation

Introduction

In March 2010, the European Commission (2010) proposed Europe 2020, a 10-year strategy with an overall objective of attaining smart, sustainable, and inclusive growth. The strategy's two main objectives were reducing greenhouse gas emissions by 20% compared with 1990 levels and increasing the share of energy generated from renewables by 20%. In 2015, the Paris Agreement was signed by a global alliance, including nearly every country worldwide and the European Union, to reaffirm the importance of these objectives, which are aimed at mitigating the effects of climate change.

To meet these goals, governments have developed and implemented new regulations and laws to force organizations across various economic sectors to adapt their systems and operations to achieve these sustainability objectives. Organizations are increasingly being mandated to limit their greenhouse gas emissions and to draw a larger share of their energy needs from renewable sources. This has led to challenges for organizations in energy-dependent economic sectors. Public transportation is one of the most critical among these sectors because it emits harmful gases and consumes huge amounts of energy on a daily basis (Kammen and Sunter 2016). Although many other means of public transportation have already been electrified, transit bus networks (TBNs) still rely on diesel or other fossil fuels. In addition, TBN operations and the associated emissions are frequently centered in densely populated downtown areas, further exacerbating this problem. Thus, electrifying TBNs and replacing conventional diesel buses (DBs) with electric buses (EBs) have become an urgent building block for sustainable urban transport.

In 2016, the Netherlands set a target to have all the TBNs in the country fully electrified between 2025 and 2030. Thus, public transport operators had approximately 9 to 14 years to make all the changes necessary to meet this goal. Although this may sound like a long time, large public transport operators in major cities in the Netherlands faced an enormous challenge because of the complexity of the problem. This work presents the results, insights, and lessons learned from a collaboration between a research team from Rotterdam School of Management (RSM) and Rotterdamse Elektrische Tram (RET), the public transport operator in the city of Rotterdam. RET is responsible for operating all public transportation in this city of around one million inhabitants. The city has an extensive TBN that includes 61 lines to serve passengers in Rotterdam, its suburbs, and some neighboring towns. The RSM team has been working closely with RET since early 2017 to carry out all the necessary strategic, tactical, and operational planning needed to achieve a successful and efficient transition from a DB to an EB transit bus network.

The main practical result from this collaboration was the development of a real-time decision support system to enhance the decision-making process under uncertainty. We developed an efficient optimization formulation based on event-based discretization that can quickly reoptimize and update the charging schedule during the day given the real-time operational conditions of the network. Finally, we developed a simulation tool to evaluate the performance of our proposed models and test the network performance under any scenario and subject to uncertainty.

Our results show that optimizing the charging schedule can keep the network's reliability within the desired levels while significantly reducing the number of charging events by more than 60% compared with alternative charging strategies. We show that even conservative off-line planning is insufficient to guarantee the network's reliability under highly uncertain operational conditions. Hence, online adjustment of the charging schedule during the day is needed. Moreover, we show that using renewable energy generators in our case study can reduce the impact of electrifying the transit bus network on the grid by, on average, 71.4% in summer and 28.4% in winter. Furthermore, using real-time decision support with updated renewable energy generation predictions can increase the renewable energy utilization by 2%. Wibout van Ede, head of business operations at RET. says, "The group from RSM has worked closely together with RET to support our decision making from the early preparation till the implementation of the electric bus fleet" (van Ede 2020).

In the next section, we briefly discuss research that focuses on electrifying transit bus networks. We then present details of the project, discuss the problem, and demonstrate the models and simulation tools that we developed. Next, we describe the phases of the TBN electrification project and present our results. In the last section, we highlight the main academic and practical implications and lessons learned from the project.

Related Work

The problem of electrifying TBNs spans multiple decision levels and encompasses various subproblems. Several studies examine the strategic decision of choosing the charging method by investigating different modes of charging, such as opportunity and overnight charging, battery swapping (Li 2016, Mohamed et al. 2017), and wireless inductive charging (Chen et al. 2018), to show their advantages and disadvantages. Other studies focus on the problem of optimizing the allocation of opportunity chargers in the networks (Kunith et al. 2017, Xylia et al. 2017). Finally, several papers address the tactical problem of planning the trip and vehicle assignment schedule in electric fleet transportation networks (Paul and Yamada 2014) and the operational problem of developing the charging policy and schedule (Ke et al. 2016, Qin et al. 2016, Pelletier et al. 2018, Abdelwahed et al. 2020b). In this work, we contribute to the literature by investigating how to optimize the charging schedule of the electric bus networks and coordinating it with renewable energy generation profiles. Additionally, to our best knowledge, we are the first to study the impact of uncertainty in traffic delays and energy consumption on the reliability of the network and how to mitigate that impact via online optimization.

The Project of Electrifying Rotterdam's Transit Bus Network

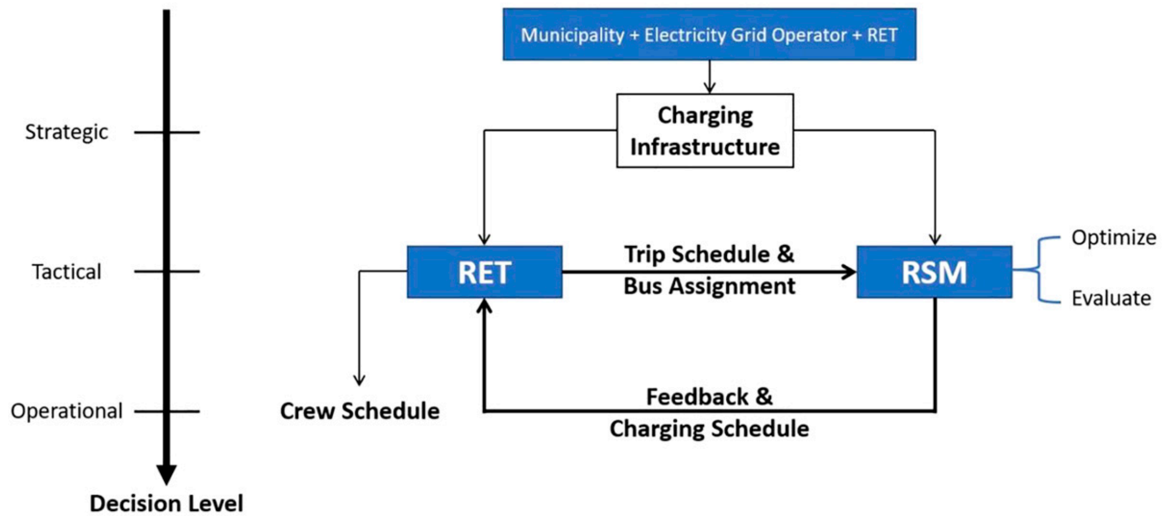
The cooperation between RSM and RET started in early 2017. At the time, the primary concern was that EBs have a limited driving range and need to have their batteries recharged frequently between trips. By replacing DBs with EBs, RET would have to redesign several planning processes. Crucial decisions had to be made at various decision levels. At the strategic level, RET needed to determine the type of chargers, the number that would be required, and their locations. Additionally, the fleet size needed to be readjusted. Moreover, if the TBN was to be fully or partially powered by renewable energy, the type and the capacity of the renewable energy generators (REGs) would need to be determined. At the tactical level, the trip and bus assignment schedules would have to be replanned to guarantee enough charging time for the EBs between trips. At the operational level, crew scheduling would have to be changed to accommodate EB recharging. Finally, a charging schedule would have to be developed to determine where and when each EB would be recharged and the time required.

In summary, electrifying the TBN meant completely restructuring the network and raised challenges at various decision levels (see Figure 1). The strategic decisions about the charging infrastructure involved several stakeholders, including RET, the municipality, and the grid operator, all of whom imposed constraints. Hence, the locations of the chargers had already been determined in the early stages of the project. Fast chargers with high charging power were to be used only at selected terminal stations to recharge EBs during layovers between trips, whereas slow chargers were to be used for overnight charging at the garage. Next, two critical and interrelated problems—developing the bus assignment and charging schedules—had to be solved to guarantee the TBN's reliability. Attempting to solve these two problems simultaneously would result in a large and multilayer optimization problem; therefore, we decided to solve this problem iteratively. Thus, we followed a closed feedback–loop structure in determining the necessary tactical and operational plans as Figure 1 illustrates. RET would be responsible for the trip schedules and bus assignments to guarantee sufficient layover time between trips at charging terminals. The RSM group would use the output as an input to the problem of developing the optimal charging schedules given varying objectives and would be responsible for evaluating the network under uncertainty to assess its reliability. Through RSM feedback, RET could make the necessary changes to the trip and bus assignment schedules. As a final step, RET developed the crew schedule based on multiple factors, such as labor law and drivers' requirements (this step exceeded the scope of the work we present in this paper).

The city of Rotterdam is split into two main sections, the northern and southern sections, separated by the Maas river (see Figure 2). Therefore, the plan to electrify the TBN was divided into phases, each focused on one part of city. The northern part (phase 1), which includes the central station, is the most vital part of the city and was electrified at the end of 2019. Plans are in place to electrify the southern part (phase 2) in the coming years. Because the two city districts have different structures and settings, they require different analyses, which we present in detail in the next sections. Figure 3 shows the approximate timeline of the phases and the project progress since 2017. We present the main findings and implications in the next sections.

During the early stages of the project (phase 0), RET's main concern was the substantial uncertainty related to the TBN's electrification process. RET needed a tool to test a range of scenarios with varying parameters, settings, and schedules. Thus, the first

Figure 1. (Color online) Multiple Decision Levels and Stakeholders Involved in the Project



objective of the RSM group was to develop a simulation tool that it could use to test any scenario in a risk-free environment. Meanwhile, RET and the other stakeholders were involved in strategic decisions about the charging infrastructure and the EB specifications. In phase 1, RET developed the trip and bus assignment schedules for the northern network, and the RSM group used these as input for a mathematical optimization model to develop charging schedules. The group implemented and compared different discretization techniques to efficiently solve the optimization problem. The optimization model and the simulator were then integrated to assess the value of using real-time monitoring and decision support systems in mitigating the effect of uncertainty and improving other performance measures. In phase 2, the RSM group advised RET about the benefits of adding renewable energy generators and energy storage systems to the network to charge EBs. We proceed by describing the methods and results for the three project phases. In Table 1, we list the acronyms used in this paper.

Phase 0: Exploring the Impact of Electrification

At the beginning of the project, RET's first goal was to investigate the possibility of electrifying the network without making substantial changes to its trip and bus assignment schedules. Thus, examining the impact of the various electrification parameters, such as battery capacity and charging power, on the feasibility of the electrification process was important. Hence, the RSM group developed a discrete-event simulation through which the network could be evaluated under various scenarios. Later, it was also used to simulate various charging strategies and to evaluate the network under uncertainty.

For this analysis, we considered the first lines that were to be electrified in the northern part of Rotterdam's TBN. To investigate the distinct impact of the trip and bus assignment schedule on the feasibility, we fixed the infrastructure effect by assuming that enough chargers are available for every arriving EB at each terminal station with charging facility. As a result, all EBs arriving at these terminal stations always start charging. Thus, the number of chargers does not have an impact on the feasibility of the network. This also results in the maximum possible state-of-charge (SoC) profile for each EB given the original DB trip and bus assignment schedule.

Because the energy consumption rate is higher in winter than in summer because of the heating system, we carried out the simulation twice with different rates. We used the expected consumption rates provided by RET of 1.93 kilowatt hours per kilometer (kWh/km) in

Figure 2. (Color online) Map of the City of Rotterdam Showing the North and South Sections

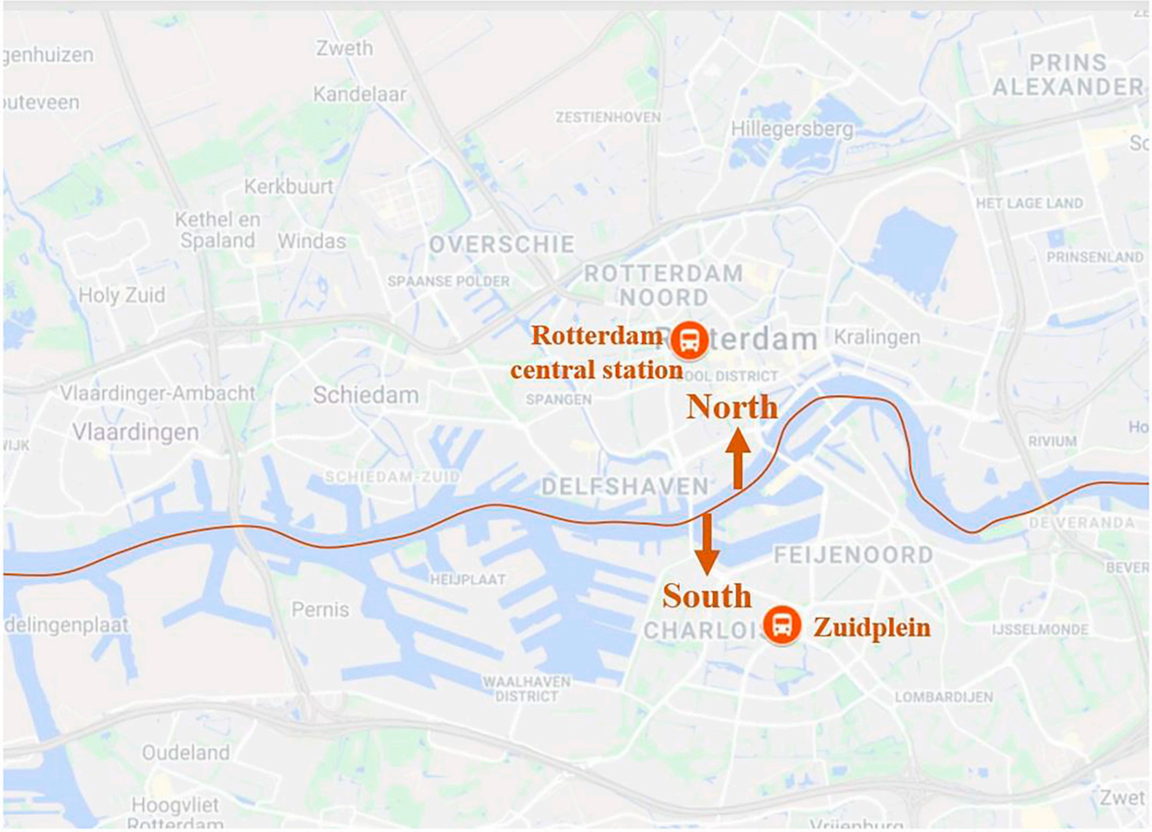
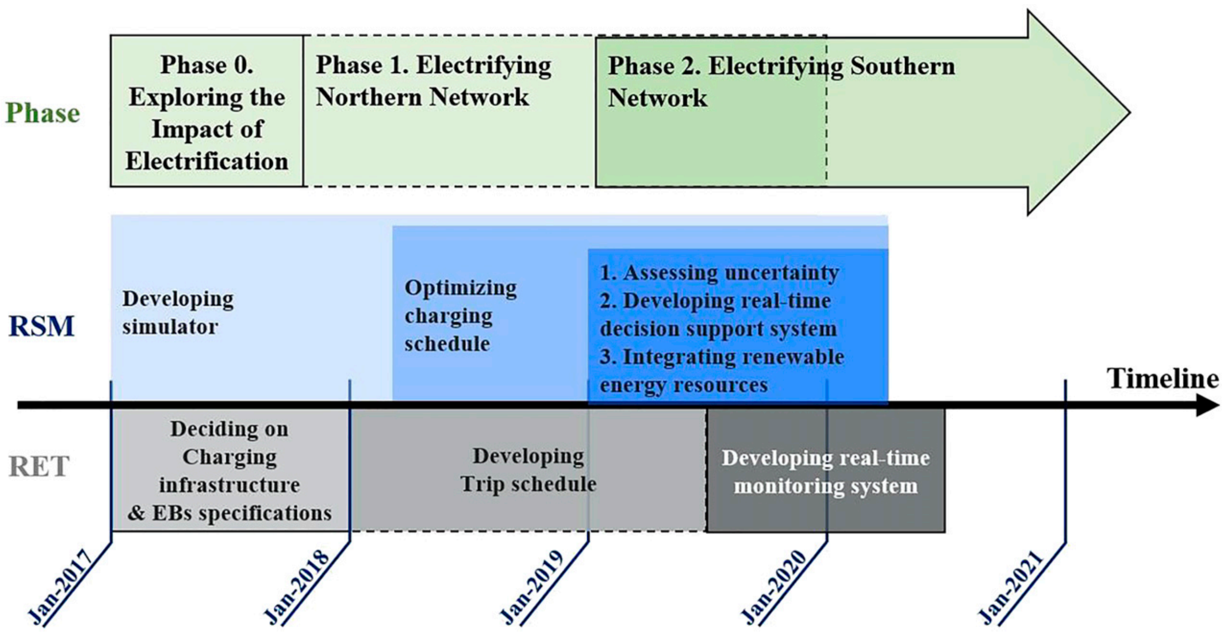


Figure 3. (Color online) Project Timeline Showing Our Progress and Our Cooperation with RET



the winter (Figure 4(a)) and 1.5 kWh/km in the summer (Figure 4(b)). Figure 4 shows the number of EBs with a SoC below the critical level of 10% during the day for varying charging power and battery capacity values. As Figure 4(b) shows, even with the lower energy consumption rate, the highest potential battery capacity of 250 kWh and charging power of 250 kilowatts (kW), three EBs' SoC levels fall below 10%. Furthermore, the original DB schedule was developed for a fleet of 74 buses, and RET was planning to use approximately 50 EBs in the electrified network. Because having fewer buses would result in greater energy consumption per bus on average, we expect that reducing the number of buses from 74 to 50 would result in poorer results

Our results from the initial exploratory phase showed that, even in the most optimistic scenario and network configurations, it is not reliable to use the DB trip schedule for the electrified TBN. For RET, these results confirmed that it is practically impossible to use the DB schedules and the necessity of taking into account the SoC levels while optimizing the trip and bus assignment schedule. van Ede (2020) says, "In the early phases, the simulation tool developed by RSM gave us the opportunity to easily evaluate the impact of different specifications regarding the battery size, the charging power, and the energy consumption. The simulation convincingly showed that significant changes had to be made to our schedule to allow for a feasible electric bus operation and that electric-specific features of the electric buses should be taken into account while designing the trip and bus allocation schedule."

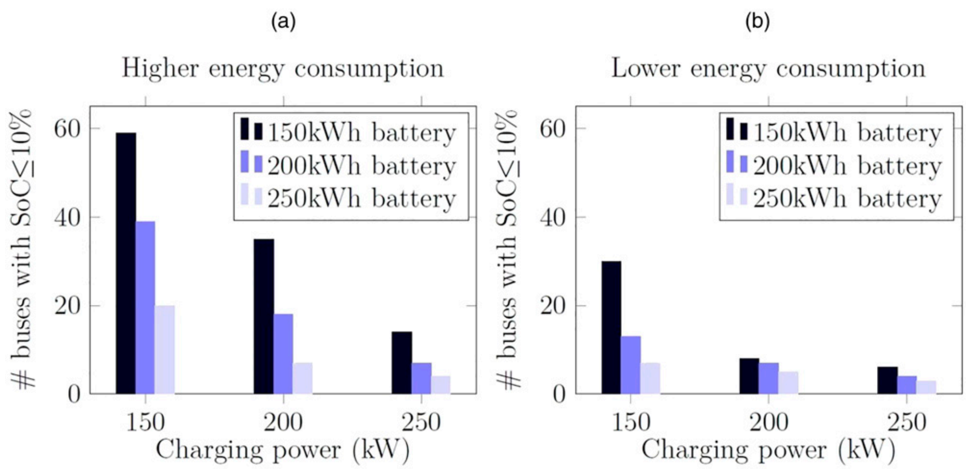
Table 1. Acronyms Used in This Paper

Acronym	Definition
DTB	Dynamic threshold–based
EB	Electric bus
ESS	Energy storage system
FIFS	First-in, first-served
LCHP	Lowest-charge, highest-priority
MILP	Mixed integer linear programming
OFO	Off-line optimization
ONO	Online optimization
REG	Renewable energy generator
SDGs	Sustainable development goals
SoC	State of charge
TBN	Transit bus network

Phase 1: Electrifying the Northern Part of Rotterdam's TBN

As a next step, phase 1 included the iterative closed-feedback approach between RET and RSM. In this process, RET generated the trip schedule and assigned trips to buses, guaranteeing sufficient layover time at terminal stations with charging facilities. The RSM group used the resulting output as an input to the problem of optimizing charging strategies with varying objectives and evaluated the network under uncertainty to assess its reliability. This feedback helped RET in planning robust trip and bus assignment schedules, which can realize higher levels of reliability in the network and mitigate impact of uncertainty.

Figure 4. (Color online) Graphs Showing the Electrified Network Performance Using the DB Schedule



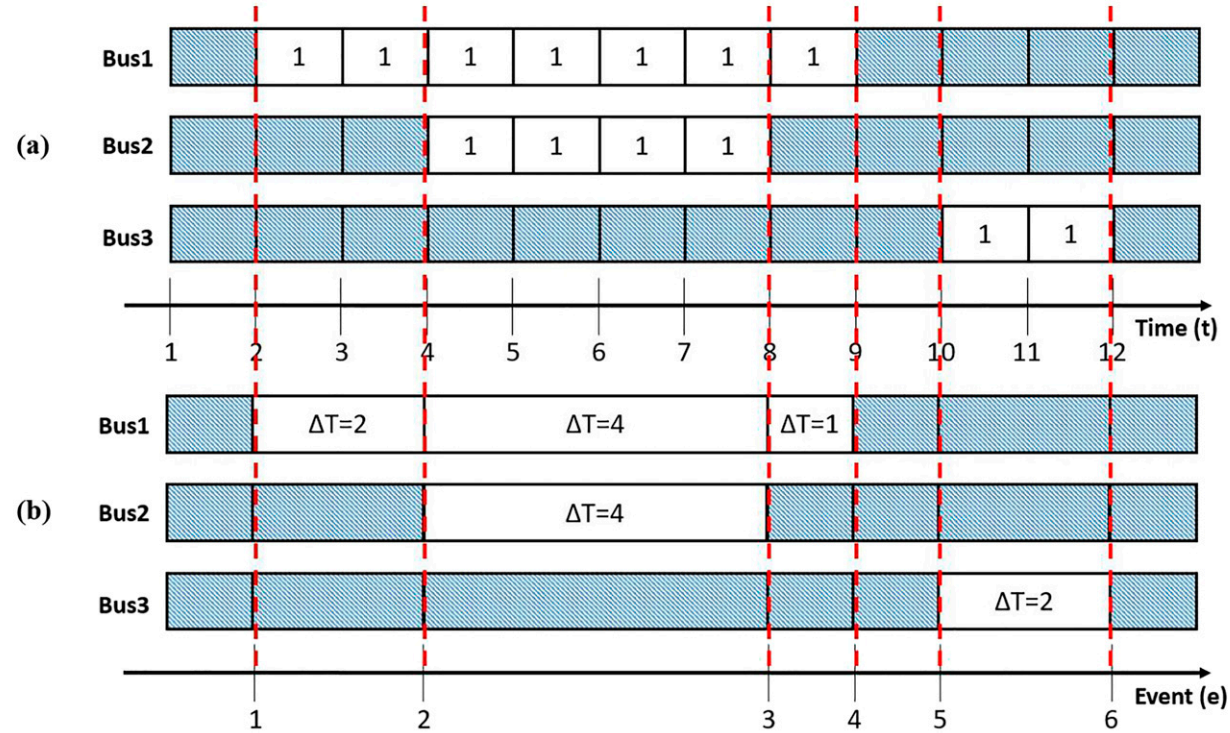
Seven two-way lines of the northern TBN of Rotterdam were selected to be electrified by the end of 2019. The central station is 1 among 11 other terminal stations that serve these seven lines. Fourteen fast chargers would be distributed among six of these terminal stations. Slow chargers would be installed at a central garage for overnight charging. Additionally, four fast chargers would be installed in the garage to charge EBs that have layovers there during the day.

Optimizing the Charging Schedule

While RET was working on developing the new trip and bus assignment schedule, the RSM group developed a mathematical model to optimize the charging schedule, which is a time-dependent problem that requires discretization. Adopting a time-expanded network at the highest practical resolution would provide the nearest to optimal solution. In our problem, this would imply using a time-based discretization with a resolution of one minute because the TBN's timetabling is developed at the minute level. However, because this problem would need to be solved in real time to mitigate the effect of operational uncertainty, we presumed that using a time-expanded network would not be the best alternative because of the large problem size and long solving time. To address this, we developed discrete-event optimization (DEO) and discrete-time optimization (DTO) models and compared them (Abdelwahed et al. 2020b). Figure 5 shows the difference between the two techniques. Although time slots are uniformly distributed in the DTO formulation, they are distributed nonuniformly based on the occurrence of events in the DEO. We developed the event-based approach to reduce the problem size and benefit from the nature of our problem, in which charging events would normally start only if a bus arrived at or departed from one of the terminal stations with charging facilities. Thus, our initial hypothesis was that the quality of the solution with respect to the resulting objective function value that the DEO provides would be close to that of the DTO but could be reached more quickly because of the reduced problem size. Accordingly, the DEO can offer a more efficient model that can be used in the online optimization, which we present in detail in the next section.

The detailed mathematical formulations of the two mixed-integer linear programming (MILP) models are described in Abdelwahed et al. (2020b), and a summary of the models is presented in the appendix. According to RET's operational requirements, our objective was to minimize the number of charging events. RET's reasoning is that more charging events have a negative impact on the battery lifetime and increase operational complexity. The main constraints in our problem are to control the minimum and maximum SoC the EBs are allowed to reach during the day, the capacity of the charging facilities, and the minimum-allowed charging time. Additionally, RET imposed several constraints to address some practical issues in day-to-day bus operations. In the analysis, we use the values provided by RET for the average active energy consumption (during driving) of 1.55 kWh/km and a charging power of 240 kW. Furthermore, we consider the passive energy consumption, which is the energy consumed by the EBs for heating, ventilating, and air conditioning during layovers, at a rate of 10 kW. Because batteries charge less efficiently beyond 90% SoC, we do not allow charging during the day beyond that limit. We consider a setup time of one minute, which is the approximate time needed to connect EBs to chargers. We carried out a comparative study between the two formulations in two networks with different sizes: a large network with 47 EBs and a smaller one with nine EBs. To ensure a comprehensive comparison, we generated 16 different instances per network with different numbers of chargers, charging efficiency, minimum-allowed charging time, and minimum allowed SoC. We used a CPLEX solver to solve the MILP

Figure 5. (Color online) An Illustration of (a) the Time- and (b) Event-Based Discretization Techniques (Abdelwahed et al. 2020b)



Notes. This table is for one station. There are similar tables for each station. The "1s" in (a) mark that this bus is at this station during that minute; therefore, it can charge at any of these one-minute slots. The dotted lines show the moments when an arrival or departure event occurs at this station. The shaded time slots show that the corresponding bus is not allowed to charge during that time slot because it is not at the station. The unshaded ones show the available time slots for charging for each bus.

problems and set the stopping criteria to a time limit of 900 seconds or an optimality gap of 0.01%. We chose the 900-second time limit for this comparison because it is a reasonable time that can be used later in online optimization.

Table 2 provides an overview of the results of the comparative study. As initially expected, the results show that the discrete-event model substantially outperforms the discrete-time model in terms of search time. In the smaller network, the DEO reaches almost the same optimal value as that of the DTO but in a significantly shorter execution time. The DEO's average execution time is around two seconds compared with 92 seconds for the DTO. For the large network, the DTO cannot reach any integer solution for any of the instances within the 900-second time limit although the DEO reaches the optimal solution in an average time of 22 seconds. Detailed results of the comparison can be found in Abdelwahed et al. (2020b).

Our comparative study demonstrates the superiority of the DEO in solving our problem. It shows that time-expanded networks are not necessary in solving our problem because of its event-based structure. It also shows the applicability of the DEO in online settings to solve the problem in real time if needed, whereas the DTO requires a substantially longer solving time.

Evaluating Under Uncertainty: Integrating the Simulation and Optimization Model

In a next step, we upgraded the discrete-event simulation to evaluate charging strategies under uncertainty in trip delays and energy consumption and integrated it with the optimization model as Figure 6 shows. Our goal was to evaluate the robustness of the various charging strategies under operational uncertainty. Specifically, (1) we tested whether the optimal charging strategy was robust enough under uncertainty to maintain the feasibility of the network, (2) we checked whether applying a real-time optimization and updating the optimal strategy during the day would improve network reliability, and (3) we compared the off-line optimal strategy (OFO) and the online optimal strategy (ONO) to a few established greedy strategies and another heuristic that we developed.

The OFO always adheres to the day-ahead optimal charging schedule regardless of any delays or unplanned excess energy consumption. In contrast, the

Table 2. Overview of Our Time- and Event-Based Formulations

	DTO		DEO	
Network	Objective (number of charging events)	Execution time, s	Objective (number of charging events)	Execution time, s
Nine EBs	53.17	92.18	53.83	1.98
Forty-seven EBs	NA	900	250	22.09

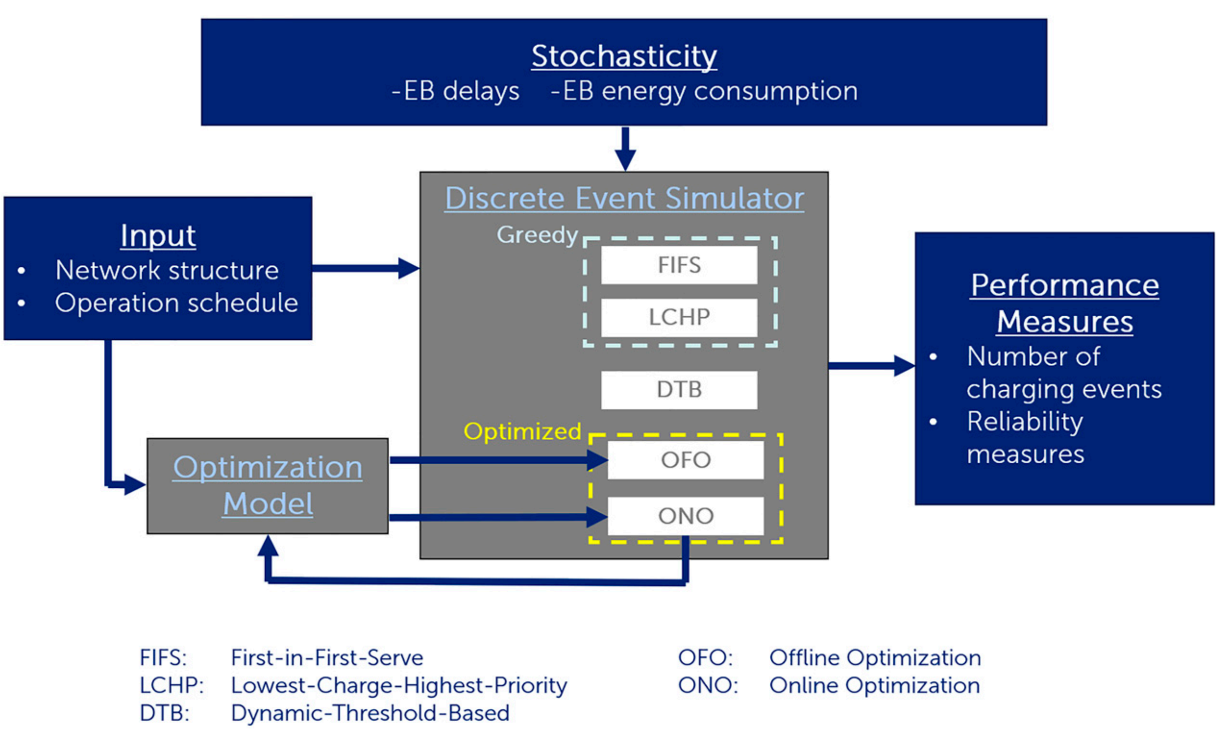
Notes. All values are averaged over all the instances. The objective is to minimize the number of charging events. The maximum allowed execution time is 900 seconds.

ONO updates the charging schedule periodically during the day to take into account any divergence between the actual operating conditions and the expected conditions. Because of this divergence, several modifications to the off-line model were required before it could be applied to the online setting; see Abdelwahed et al. (2020a) for details. We present a summary of the models in the appendix. In summary, ONO also minimizes the number of charging events during the day and aims to keep the SoC of all EBs above (or as close as possible to) the prespecified minimum limit. If maintaining the SoCs above the minimum limit is not feasible because of a substantial divergence between expected and actual operating conditions, the objective of ONO is adjusted to keep the minimum SoC of these EBs as high as possible rather than optimizing the original objective.

We compare the OFO and the ONO to two common greedy strategies: first-in, first-served (FIFS) and lowest-charge, highest-priority (LCHP). FIFS queues EBs for charging in the order of their arrival at the station, whereas LCHP arranges them according to their SoC by giving the highest priority to the EB with the lowest SoC. LCHP also allows an arriving EB with a low SoC to replace another EB that is using a charger and has a higher SoC if no other charger is available.

Additionally, we developed the dynamic threshold–based (DTB) heuristic strategy, which provides a charging schedule adapted to the operational situation without the need for a real-time communication system. Similar to the OFO, the DTB strategy is based on the day-ahead optimal schedule. Drivers are given a card that contains a suggested SoC threshold after each trip that ends at a terminal station with charging facilities. The threshold values are based on the SoC levels from the optimized schedule. If the EB's SoC is below that threshold, the driver should connect the EB to an available charger. The EB then charges during its entire layover time or until it reaches the 90% SoC limit. If enough chargers are not available at the terminal

Figure 6. (Color online) Graph Showing the Architecture of the Integration of the Optimization Model and the Discrete-Event Simulation



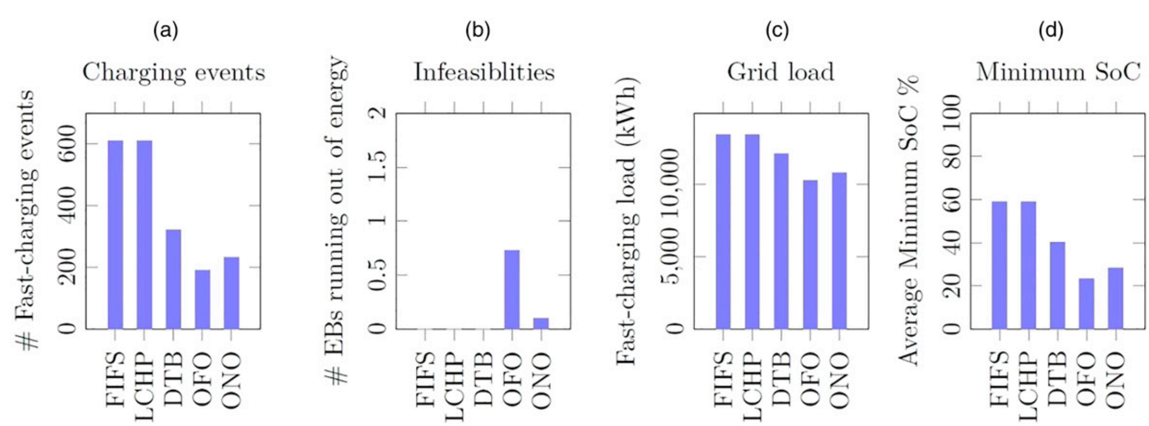
stations for all the EBs, the ones that arrive first are given priority for a charging spot (similar to FIFS). This may negatively affect the level of reliability and feasibility as the charging spots are given to the buses that arrive first and not to the more critical ones with a lower SoC.

We simulated 30 days under uncertainty in trip delays and compared the performance of the five charging strategies. We assumed that operational delays result in extra energy consumption. We used truncated normal distributions for the trip delays whose means and standard deviations are functions of trip-specific parameters, that is, time of day, trip duration without any traffic on its route, and time- and route-specific delays accounted for by RET during trip scheduling. The optimized strategies account for these anticipated delays by including them in the projected trip duration. We set the objective function of the optimized strategy to minimize the number of charging events while keeping the SoC of all the buses above a target threshold of 30%. We also calculated a range of additional performance measures, including overall feasibility, reliability, and the fast-charging load on the grid. We did not optimize for these other performance measures. However, they are correlated to our main objective function of minimizing the number of charging events in the network. A smaller number of charging events would normally result in a smaller charging load on the grid. Moreover, for the same total amount of charging, a smaller number of charging events results in longer charging events. Thus, the impact of traffic delays on the reliability becomes smaller because missing a few minutes from a planned longer charging event is not as costly as with a shorter charging event.

We carried out the comparative study for two network configurations: full and reduced number of chargers. With the full number of chargers (15), charging availability is guaranteed for every EB arriving at a terminal station with charging facilities during the day. Hence, the results between FIFS and LCHP do not differ as Figure 7 shows. FIFS and LCHP also result in the highest possible level of reliability because they achieve the maximum possible SoC profile for each EB by maximizing the amount of charging during the day. However, this also results in a considerable amount of unnecessary charging, which leads to a significantly higher number of charging events and load on the grid during the day compared with the other strategies as is evident in Figure 7. In contrast, despite the 30% SoC lower limit in planning, the OFO has the lowest reliability with an average of 0.7 EBs running out of energy per day. This implies that the day-ahead planning is not conservative enough, and the OFO cannot guarantee reliable operations. Thus, planning needs to be done with a lower limit on the SoC that is greater than 30%. However, doing so is not possible for all the buses because the layovers resulting from the trip assignment schedule cannot be long enough to grant that. On the other hand, the ONO largely addresses this issue with only 0.1 EBs running out of energy, on average, per day. It also has an average lowest SoC of 28.4%, which is the closest to the target level of 30% compared with the other strategies. Thus, although FIFS could be regarded as more reliable than ONO, this is achieved at the cost of substantial redundant charging during the day. ONO reduces the number of charging events (our main performance measure and the objective value) by approximately 62% compared with FIFS. The ONO also uses, on average, approximately 20% less fast-charging energy from the grid than FIFS uses per day.

The DTB strategy achieves a good level of reliability because it keeps the lowest SoC of almost all the EBs

Figure 7. (Color online) Graphs Comparing Charging Strategies Under Uncertainty Using the Full Number of Chargers (i.e., 15)



Note. All values are averages over 30 days.

above the 30% threshold with an average value of 40%. The results of the DTB reflect an excellent trade-off between the higher reliability of FIFS and the lower number of charging events and reduced fast-charging grid load of the ONO. On the one hand, DTB achieves higher reliability than the ONO while increasing the daily number of charging events by 38% and the load on the grid during the day by 12%. On the other hand, compared with FIFS, DTB reduces the number of charging events by approximately 47% and the fast-charging load added to the grid by approximately 10%.

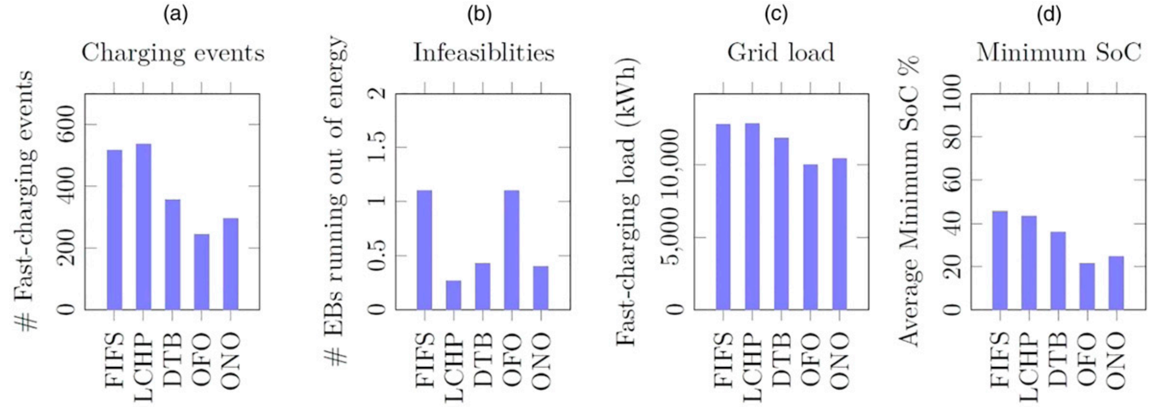
Next, we evaluate the charging strategies for a scenario with a reduced number of chargers. We specifically consider an extremely pessimistic scenario in which the number of fast chargers in the network is reduced from 15 to 6. This is equivalent to removing all chargers that are used for less than three hours during the day when following the FIFS or the LCHP strategies in the scenario with the complete number of chargers. In this case, the OFO has the lowest reliability, as Figure 8 shows, when compared with the four other charging strategies because of its inability to adapt to changing circumstances. Additionally, FIFS, with an average of 1.1 EBs running out of energy per day, is no longer the most reliable strategy. In contrast to the case with the full number of chargers, the ONO can maintain more reliable operations than FIFS. The LCHP is now the most reliable strategy with, on average, a slightly lower number of EBs running out of energy than the ONO per day. However, the LCHP still does not offer a very practical solution because it results in a considerably greater number of charging events and fast-charging load added to the grid. Thus, in the worst-case scenario, the ONO would remain the most practical and reliable option.

Practical Implications of Phase 1

Phase 1 provided us with several crucial lessons learned. First, optimizing the charging schedule can significantly reduce the number of daily charging events compared with naïve greedy charging policies (such as FIFS), which have a positive impact on battery lifetime and also result in less complex operational processes. Additionally, under more challenging operational conditions, naïve approaches cannot allocate charging slots to buses in a way that produces a feasible operation. Based on these results, RET is currently investigating how to integrate our proposed optimized charging strategy into its planning process. van Ede (2020) says, “The charging schedule optimization model has shown that we could do with fewer charging facilities and that significant improvements can be made to the charging schedule. Using this optimization model, we are able to control various parameters and compare different charging strategies. We are now in the process of implementing the model in our software so that it can be used for our day-to-day planning.”

Furthermore, the results show that operational uncertainty and unexpected delays may have a large impact on the reliability of electrified TBNs. Hence, even conservative off-line optimization might not be sufficient to guarantee feasible operations under uncertainty, and any bus may run out of energy based on the realization of that uncertainty. Thus, real-time monitoring is required to detect and predict any potential issue or infeasibility and to take the required corrective actions in time. Supported by methods and results from this project, RET developed a real-time monitoring and control system; the first version is currently in operation. van Ede (2020) says, “During the planning of the first batch of EBs, the simulation also showed the impact of uncertainty in the trip durations

Figure 8. (Color online) Graphs Comparing Charging Strategies Under Uncertainty Using a Reduced Number of Chargers (i.e., Six)



Note. All values are averages over 30 days.

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 EBs. This tool is now in operation."

Phase 2: Electrifying the Southern Part of Rotterdam's TBN

Unlike the northern part of the TBN, Rotterdam's southern TBN has a centralized structure. All charging is planned to take place at the central Zuidplein hub. Additionally, the existence of a huge nearby free area of about 15,000 square meters (m^2) offers an opportunity to install a photovoltaic solar park that can be used to provide locally generated clean energy to be used for charging EBs. The southern TBN consists of eight lines with 50 EBs planned to operate along them. Twelve 300-kW fast chargers are planned for installation at Zuidplein, sufficient to guarantee a charging spot for each bus arriving at the station under the currently suggested trip schedule. Given the 15,000 m^2 photovoltaic solar park that is scheduled to be developed and at an average peak power density of 175 watts per m^2 (W/m^2), this corresponds to a rated peak power amount of 2.625 megawatts (MW). Additionally, a central garage for the southern network will house four fast chargers for daytime charging and 50 slow chargers for overnight charging.

As part of this transition, RET, the grid operator, and the municipality faced three crucial questions:

1. What is the value of installing the solar park with respect to reducing the impact on the grid?
2. How would installing an energy storage system (ESS) affect the renewable energy utilization?
3. How can the intermittency and uncertainty of renewable energy generation be overcome to maximize its utilization?

The current electrical cables and infrastructure feeding power to Zuidplein cannot provide the entire amount of power required to charge the EBs at the newly planned charging facility; therefore, the first question was very crucial to the grid operator and the municipality. The answer would determine whether installing REGs would be sufficient to resolve this issue or whether a new electrical feeder cable would have to be extended from the nearest distribution station, which is located at a substantial distance from Zuidplein.

To answer these questions, we use 2018 renewable energy generation data from the city of Antwerp in Belgium (Elia Group 2019). Antwerp is close to Rotterdam and has a similar solar irradiation profile and weather conditions. Elia also provides day-ahead predictions for renewable energy generation as well as intraday predictions that are updated four times a day. We use active average energy consumption rates of 1.93 kWh/km in winter and 1.55 kWh/km in summer and passive rates of 18 kW in winter and 6kW in summer as suggested by RET.

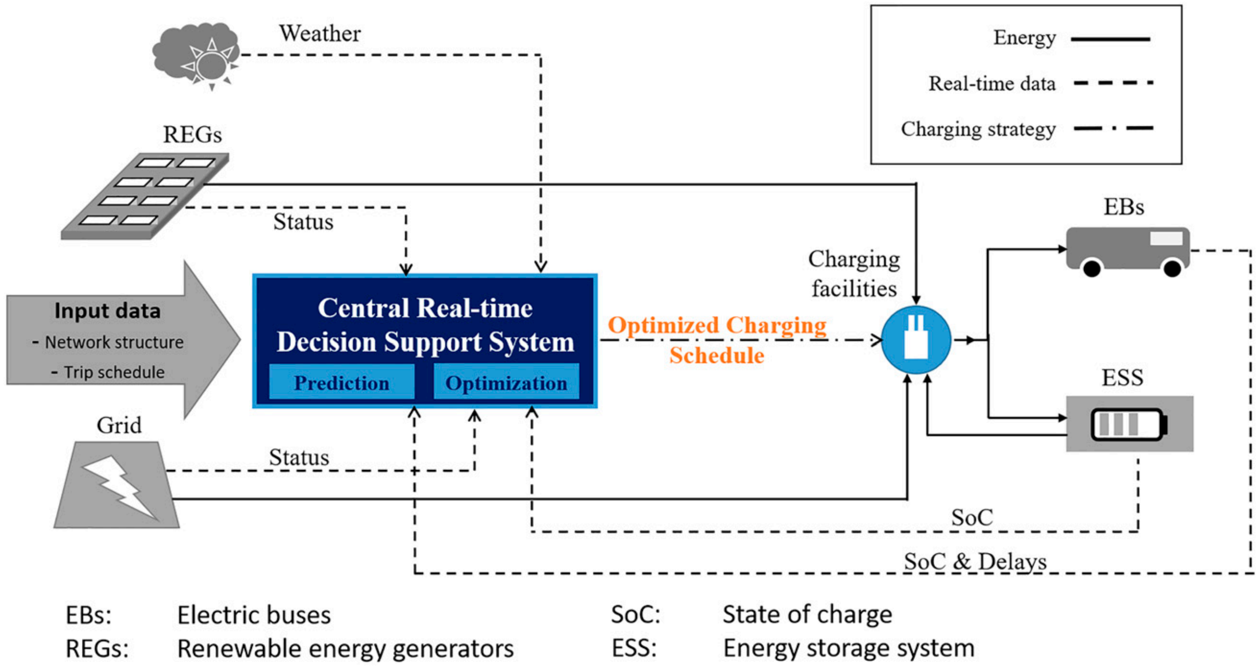
In the next section, we focus on the first two questions and investigate the benefits of adding renewable energy sources and an ESS to provide locally sourced power to the electric TBN. The benefit gained from the renewable energy sources depends on how well the charging schedule and the renewable energy generation profile are coordinated. However, this coordination can be difficult because of the intermittency and uncertainty of renewable energy generation and can reduce the benefits gained. To address these intricacies, we split the analysis into two parts. In the first part, we determine the maximum benefit that can be gained from the REGs. Specifically, we follow the FIFS charging strategy under deterministic trip-delay settings and with a sufficient number of chargers to provide energy to all the EBs during the day, which maximizes the amount of charging in the network. This approach maximizes the utilization of the renewable energy generated given the bus and trip assignment schedule. However, because of the nature of the FIFS strategy, it also maximizes the load imposed on the grid compared with the other strategies.

In the "Using a Real-time Decision Support System to Improve REG Utilization" section, we present the full structure of our proposed real-time decision support system. The real-time decision support system also uses the ONO techniques, which we presented earlier, to reoptimize the charging schedule periodically during the day. However, in the southern part of the network, we also have renewable energy generators. Thus, as Figure 9 shows, the real-time decision support system is responsible for collecting real-time weather data to update the renewable energy– generation predictions throughout the day. It also collects real-time data from the EBs to adjust to unplanned delays or changing energy consumption profiles in the updated charging schedule (similar to the study presented in phase 1 in the northern part of the network). Finally, the real-time decision support system schedules and then communicates the new charging schedules to the operators at the charging facilities.

Evaluating the Benefits of Adding Renewable Energy Generators and an Energy Storage System

As we mention, to evaluate the maximum benefit and REG usage, we follow the FIFS charging strategy using a number of chargers that is sufficient to guarantee a charging spot for each EB arriving at Zuidplein during the day. In addition to maximizing the renewable

Figure 9. (Color online) Graph Illustrating the Structure of the Transit Bus Network Using the Central Real-Time Decision Support System



energy usage, this also maximizes the reliability of the network. However, this puts the largest strain on the grid because of excessive intraday charging. We considered adding an ESS of 600 kWh capacity and 300 kW charging power. We used a straightforward (dis)-charging strategy for the ESS. It is charged whenever excess renewable energy is generated and when the output power of the REG is greater than the EB load, and it is used to provide power to the EBs if the REGs' power output is less than the EB load.

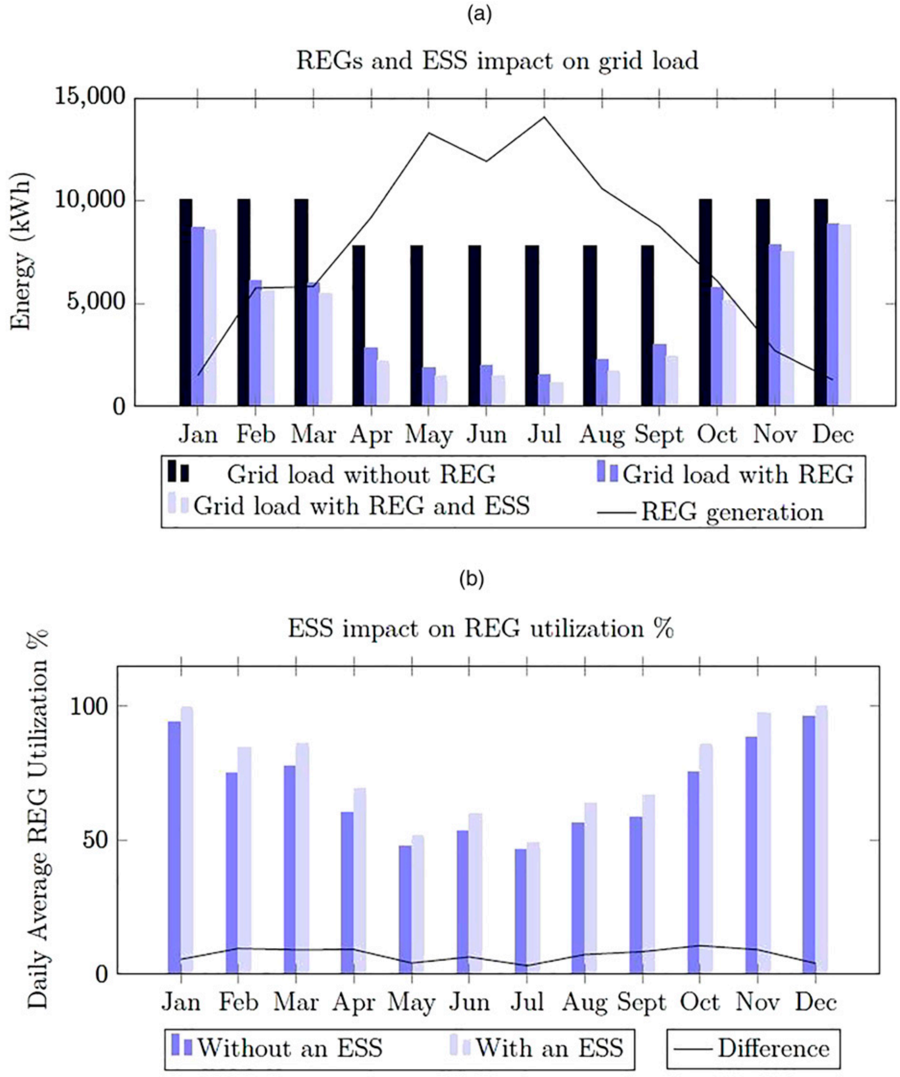
We simulated the network for a full year (2018) and calculated our main performance measures, that is, the impact on the grid and renewable energy usage during each month. Because of the different energy consumption rates in the seasons, the daily average EB charging load at Zuidplein is 10,081 kWh in winter and 7,824 kWh in summer. Figure 10(a) shows the average daily amounts of renewable energy generated and the average daily load on the grid at Zuidplein using three settings: without REGs, with REGs, and with REGs and the ESS per month. The results show that the average daily renewable energy generation is 3,846 kWh in winter and 11,305 kWh in summer. REG output is particularly low in November, December, and January with the average daily amounts falling below 2,700 kWh. In contrast, it reaches the highest levels between May and July with average daily values above 11,000 kWh. As a result, the load reduction on the grid from installing REGs at Zuidplein is much more pronounced during the summer (71.4% average reduction) compared with the winter (28.4% average reduction).

To assess the added value of installing an ESS, we conducted a simulation with an added ESS of 600 kWh capacity at Zuidplein. Figure 10(b) shows that adding an ESS can increase renewable energy usage by approximately 520 kWh and 362 kWh, on average, per day in summer and winter, respectively. This is equivalent to further reducing the amount of energy drawn from the grid by 23.5% in summer and 5.7% in winter. It also corresponds to an increase in the average daily renewable energy usage of around 7.8% in winter and 6.3% in summer as Figure 10(b) shows.

Using a Real-Time Decision Support System to Improve REG Utilization

These results illustrate the potential value of installing REGs to provide clean energy to charge EBs. However, the previous analysis is based on the best-case scenario to evaluate the maximum potential benefit from the REGs because it considers deterministic delays and does not account for uncertainty. We also used the FIFS strategy, which maximizes the renewable energy usage. However, it also causes the largest amount of fast charging load in the grid. Thus, in this section, we consider a more realistic scenario and compare the FIFS strategy to ONO and OFO under uncertainty and with a sufficient number of chargers available. We consider uncertainty in the trip durations and energy consumption resulting from

Figure 10. (Color online) Graphs Illustrating Average Daily Renewable Energy Generation and Load on the Grid per Month at Zuidplein Using Various Settings



operational delays and uncertainty in renewable energy generation. Similar to previous analyses, the FIFS performance provides an upper bound for the reliability of the system if a sufficient number of chargers is available but generates the highest impact on the grid. Once more, we use an MILP formulation to optimize the charging schedule for the optimized strategies. The OFO provides an optimized plan based on the day-ahead renewable energy generation prediction to which it adheres regardless of any unpredicted delays or weather conditions that affect the REG output. The ONO collects real-time data on delays, energy consumption, grid status, and weather, and accordingly reoptimizes the charging schedule periodically during the day. However, for the optimized strategies, we consider a different objective function than in the northern network. Because our aim is to minimize the impact on the grid by maximizing the utilization of renewable energy and shifting the load to off-peak times, we adopt that objective. We take the day-ahead hourly energy costs to serve as a proxy for the impact on the grid because these prices reflect the difficulty of balancing electricity supply and demand during different times of the day. From the grid operator's perspective, charging the EBs when the prices are lower is better because these are the off-peak hours and vice versa. Furthermore, we assume zero costs for charging from the REGs. Thus, the objective of minimizing the charging costs implies minimizing the impact on the grid as well as maximizing the renewable energy usage. However, some modifications to the MILP, which we discuss in Abdelwahed et al. (2020b), are needed to incorporate the REGs and/or the ESS into the system. Abdelwahed et al. (2020a) presents the details of the modified formulation. We also present a summary of the models in the appendix.

We simulated the two months of January and July 2018 and applied the higher winter rates for active and passive energy consumption for January and the summer rates for July. Table 3 summarizes the outcomes of the comparative study for July. The results show that, as with the northern network, the OFO cannot guarantee the reliability of the network under uncertainty. In contrast and as expected, the FIFS strategy has the highest reliability levels because it keeps all the EBs' SoC above 30%. The ONO can also maintain the reliability of the system with no EBs running out of energy and approximately one EB with a SoC dropping below 10% every few days, on average. Furthermore, the FIFS strategy can utilize, on average, 5.5% more renewable energy generated than the ONO. However, the ONO reduces the amount of day charging in the network (at the garage and at Zuidplein) by around 41% and reduces the impact on the grid (proxied by the charging costs) by 17.5%. Finally, compared with the OFO, the ONO uses, on average, an additional 280 kWh (2%) of daily renewable energy.

In the winter, none of the three strategies can ensure the reliability of the system under the current trip and bus assignment schedule, thus uncovering a weakness in the assignment schedule, providing RET with critical insights and highlighting the need to resolve this issue. The development of the final trip, bus assignment, and charging schedules is still ongoing as a close collaboration between RET and RSM continues.

Practical Implications of Phase 2

During phase 2, we examined the value of installing renewable energy generators to provide clean energy to the southern part of Rotterdam's TBN. We carried out the feasibility analysis to answer critical questions regarding the value of installing REGs and an ESS at Zuidplein. The results from this phase provide the stakeholders (i.e., the RET, the grid operators, and the municipality) with critical input for the next rounds of strategic decision making.

Our results show that integrating REGs can significantly reduce the impact of the TBN's electrification on the power grid. In addition, we investigated the benefits of installing an ESS to increase the utilization of renewable energy generated. We showed that, in this particular case, the additional benefit of installing an ESS is limited because of the current trip schedule. The schedule allows a sufficient number of layovers with charging slots to use almost all the renewable energy generated. Finally, the benefit of a real-time decision support system to enhance the reliability and the performance of TBNs was once more confirmed. In addition to handling bus delays, it can improve the renewable energy utilization by incorporating real-time renewable energy predictions.

Summary: Lessons Learned and Managerial Implications

This study has examined the close collaboration between RET and RSM in a project to electrify Rotterdam's TBN during the three-year period from 2017 to 2020. In addition to its essential contribution toward the successful realization of the first phase of the electrification process in late 2019, the collaboration provided RET with important directions for future improvements. It has also resulted in more lessons learned, models, formulations, and frameworks that can support other public transport operators worldwide in the transition toward sustainable electric bus networks.

Our analysis shows that an existing diesel-based TBN cannot be replaced by electric buses without setting up an entirely new structure and replanning the whole network. This is mainly a result of the need to

Table 3. A Comparative Study Summarizing Online and Off-line Optimization and FIFS in the Southern Network

		Charging strategies		
Performance measure	Metric (per day values)	ONO	OFO	FIFS
Summer (July 2018)				
Impact on the grid	Average charging costs, €	451.72	428.90	548.20
	Maximum charging costs, €	588.22	584.16	746.78
	Average day load, kWh	2,442.34	2,001.40	4,158.95
Renewable energy utilization	Average renewable energy generation, kWh		14,079.17	
	Average renewable energy utilization, %	39.47	37.37	45.14
Reliability	Maximum number of infeasible EBs	0	3	0
	Average number of infeasible EBs	0	0.58	0
	Average number of EBs with 0 < SoC% ≤ 10	0.55	1.62	0
	Average number of EBs with 10 < SoC% ≤ 20	1.61	5.27	0
	Average number of EBs with 20 < SoC% ≤ 30	9.16	12.42	0
	Average number of EBs with SoC% > 30	38.68	28.19	50.00
	Average lowest SoC%	36.73	35.13	59.59

recharge electric buses several times during the day to maintain a feasible operation. Because of the complexity of the problem, which involves interdependent strategic, tactical, and operational decisions, we executed an iterative approach using a closed-feedback loop among the subproblems at the various decision levels. Although this approach might not yield the globally optimal solution for the entire system, we demonstrate its practicability and efficiency in planning TBN electrification. Additionally, we illustrate the substantial benefits resulting from optimizing the charging schedule compared with following easier naïve charging policies such as FIFS or LCHP. We demonstrate that day-ahead off-line optimization might not be sufficient to ensure the feasibility of operations under uncertainty. Online monitoring and control systems are required to supervise the network in real time and to take corrective actions by adjusting the operational schedules to avoid the negative impact of uncertainty. We introduce the DTB strategy, an efficient heuristic that yields a good trade-off between the maximum reliability and the minimum number of charging events in the TBN. Key advantages of the DTB strategy are its easy implementation and reduced costs because implementing it does not require sophisticated online communication or a real-time decision support system. Our analysis shows the potential value of installing REGs to provide green energy to TBNs and how these clean decentralized energy sources can significantly reduce the impact of electric TBNs on electricity grids. Additionally, a real-time decision support system can enhance renewable energy usage by updating renewable energy predictions during the day. Finally, our results show that the value of adding an ESS to increase the renewable energy usage at a specific station is limited by the load profile of the EBs charging there.

From an academic point of view, our research contributes at several levels. We develop and compare two MILP formulations based on different discretization techniques to solve the problem of optimizing the electric TBN charging schedule. We demonstrate how choosing an appropriate event-based discretization can reduce the size of the problem and the run time compared with the time-expanded network without having any significant impact on the quality of the solution. We also show that even conservative off-line optimization approaches might not be enough to guarantee the reliability of a system whose feasibility is sensitive to operational uncertainty. Thereby, we demonstrate how real-time decision support systems can use real-time data gathering, monitoring, improved predictions, and online optimization to mitigate the impact of uncertainty and improve performance measures in similar problems.

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Appendix. Summary of Mathematical Formulations and Models

We develop an MILP formulation to solve the charging scheduling problem. In Abdelwahed et al. (2020b), we develop and compare two formulations using two discretization techniques: DTO and DEO. The former discretizes the problem to uniform one-minute time slots, and the latter discretizes it to nonuniform time slots depending on bus arrival and departure events in the trip schedule. Equations (A.1) and (A.2) show the objective function of minimizing the charging events in the two formulations, respectively,

$$\min\left(\sum_{t\in T}\sum_{b\in B} I_{bt}\right), \tag{A.1}$$

$$\min\left(\sum_{e\in E}\sum_{b\in B} I_{be}\right). \tag{A.2}$$

In the previous equations, the decision binary variable I is set to one if bus b started charging at time slot t (in the DTO formulation) or time slot e (in the DEO formulation). Set B includes all the buses in the network, and T and E are the sets of the time slots in the two formulations, respectively.

The decision variable I in the two formulations depends on the main decision variable in our problem, which is X_{bt} (at the DTO) or X_{be} (at the DEO). The variable X is a binary variable that is set to one if bus b is charging at the corresponding time slot. Thus, if bus b is charging for more than one successive time slot, the variable I is set to one at the first time slot.

Our model has several input parameters. The main one is the trip and bus assignment schedule, which indicates the location of each bus at each time slot. A bus location could be at the garage, driving, at a terminal station with no chargers, or at a terminal station with a charging facility. The latter case is the one at which a bus can recharge its battery. In addition to the trip and bus assignment schedule, we take as an input the number of chargers at each terminal station, the setup time, the minimum charging duration, and the required SoC lower and upper bounds. The setup time is the time needed for a bus to be connected to a charger. The following constraints are added to our formulations to

- Calculate the SoC of each bus at each time slot given the energy consumed to perform trips and the decision variable that indicates if a bus is charging during this time slot.
- Keep the SoC of each bus within a prespecified range during the entire day. Thus, it does not fall below or exceed beyond the prespecified lower and upper limits.

- Ensure that the number of charging buses at each station never exceeds the number of chargers.
- Evaluate the value of the decision variable I from the decision variable X.
- Prevent buses from charging for less than the prespecified minimum charging duration.
- Prevent buses from being connected to the chargers for overnight charging more than once. Thus, buses cannot be connected and reconnected to the chargers during overnight charging.

In Abdelwahed et al. (2020a), we use the same DEO model to optimize the charging schedule in the online settings. However, we consider charging from various sources at this work: the grid, renewable energy generators, and an energy storage system. We adopt an objective function of minimizing the total charging costs, which aligns with minimizing the impact on the grid and maximizing the renewable energy utilization as Equation (A.3) shows:

$$\min\left(\sum_{e\in E}\sum_{s\in S}(\Pi^{G}_{se}P^{G}_{se}+\Pi^{R}_{se}P^{R}_{se}+\Pi^{Q}_{se}P^{Q-}_{se})\left(\frac{T_e}{60}\right)\right). \quad \text{(A.3)}$$

The parameters Π^G, Π^R, and Π^Q represent the charging cost per kWh at each station s and time slot e from the grid, the renewable energy generators, and the energy storage system, respectively. The corresponding decision variables P^G, P^R, and P^{Q-} are the charging power from each source at each station and time slot; T_e is the length of time slot e in minutes. We proxy the impact on the grid by minimizing the charging costs because charging at off-peak times is less expensive than charging during peak times. We consider zero charging costs from the renewable energy generators. Hence, minimizing the total charging costs aligns with maximizing the renewable energy utilization.

The optimization problem is solved periodically during the day to reoptimize the charging schedule according to the realizations of uncertainty and the updated renewable energy generation predictions. However, the main complication in this rolling horizon setting is the lower bound constraint on the SoC of the buses. Because of uncertainty in energy consumption or traffic delays, which may lead to missing planned charging events, it might not be possible to maintain the SoC of all the buses above the prespecified threshold. Hence, when this occurs, we relax this constraint and replace it at each bus based on an algorithm that redistributes the available charging slots to the buses according to their SoC status. For simplicity, we assume that the charging schedule is reoptimized at the beginning of each hour. Our proposed algorithm attempts to redistribute the charging events to the buses within the next hour such that the most critical buses (i.e., buses with the lowest SoC) are assigned more charging slots. We present a summary of the algorithm steps that are executed at each reoptimization event during the day.

- Estimate the minimum future SoC of each bus that occurs during the time remaining this day given its current SoC, the trip schedule, and the previous charging schedule after excluding all the previously planned charging events during the next hour.
- If the minimum future SoC of a bus is above the minimum threshold, a constraint is added to it to keep it above that level.
- For the remaining buses, we classify them into groups based on their level of criticality. For example, buses with an estimated future SoC that is below 10% are grouped into the most critical group, followed by buses with a value between 10% and 20%, and so on.
- We start with the most critical group and attempt to make all the buses in this group charge such that they reach the 10% estimated future SoC by maximizing the charge added to them. If a bus can reach the 10% threshold, we move it to the next group. If not, we add a constraint to keep its SoC above the maximum value that we realized from the previous solution.
- We repeat the process for all groups

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