Enabling Sustainable Public Transport in Smart Cities through Real-time Decision Support

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Short Paper

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Abstract

The growing consumption of fossil fuels and its negative environmental consequences have been a major concern during the last few decades. In line with that, public transport operators face global pressure to replace diesel buses by battery-electric buses (BEBs) in many countries. However, BEBs need to be recharged several times throughout the day to avoid running out of energy due to their limited driving range and slow charging rate. Accordingly, operating BEBs is substantially more sensitive to unanticipated delays and excess energy consumption, which raises serious challenges with respect to charging schedules. Moreover, BEBs are only a truly sustainable alternative if they are powered by renewable energy generators (REGs), which have intermittent and uncertain generation. Thus, we design and propose a real-time decision support system to overcome these uncertainties and maximize the utilization of REGs and minimize the impact on the grid while guaranteeing a feasible operation for the BEBs.

Keywords: Sustainable public transport, Electrified transit bus networks, Battery electric buses, Renewable energy, Real-time decision support system

Introduction

Although the industrial and technological progress of the last decades has often significantly improved people's daily lives, it also had negatively impacted the global environment. For instance, the continuously growing consumption of fossil fuels increased the global levels of carbon emissions substantially. As a result, many negative environmental issues, such as global warming and air pollution, have intensified significantly (IPCC 2018). Cities and urban centers around the world are major contributors to global emissions, and also the places where the impact of climate change and pollution will often be felt the most. According to Dodman (2009), urban areas cover only 2% of the land, and yet contribute up to 75% and 80% to global energy consumption and greenhouse gas emissions, respectively. These alarming numbers show the urgent need to take serious action to transform urban areas into more sustainable regions powered by

renewable energy sources. To achieve this objective, recent international agreements impose restrictions on various economic sectors to limit their fossil fuel consumption and switch to clean and renewable sources of energy.

Incorporating and integrating distributed renewable energy generation within cities offers many new and highly promising opportunities (Kammen and Sunter 2016). However, the limited land space available to install renewable energy generators as well as the intermittency and uncertainty of renewable energy sources represent big challenges to that integration. Moreover, planning for operations within smart cities incorporate several complexities and affects various private and governmental parties with potentially many conflicts of interests. Namely, some decisions might be more beneficial or disadvantageous to some parties compared to others. Accordingly, the planning should aim for maximizing the sustainability of operation while guaranteeing certain levels of benefits for all the involved parties within the process. Thus, it is required and expected from operations research to be intensified within the next few years and benefit from the emerging big data and Internet of Things (IoT) technologies to help solving this important challenge and contribute to the various levels of planning to facilitate the transition to a sustainable smart cities (Qi and Shen 2019). In line with that, the emerging Smart City paradigm—including the infusion of public services and infrastructure with digital technologies and advanced information systems—presents various opportunities to address these challenges.

One of the greatest challenges is faced by energy-dependent economic sectors, which will have to adapt their services to new operational needs and restrictions imposed by the intermittent and uncertain nature of renewable energy generation. One of the most important sectors is transportation, which is estimated to require investments of 15.7 trillion USD in order to limit the temperature increase to 2°C by 2050 (International Energy Agency. 2012). Therefore, we focus on urban mobility since it is an important driver of various emissions and pollutants. Within urban areas, public transportation plays a critical role in creating greener and more sustainable cities. Having a fully electrified efficient public transportation network would reduce greenhouse gas emissions within smart cities. Thus, we specifically focus on the problem of electrifying transit bus networks of public transportation services within smart cities.

We specifically investigate the challenges that public transport operators (PTOs) face in replacing their diesel bus (DB) fleets with battery electric buses (BEBs) that are integrated with renewable energy sources. BEBs have a limited driving range and much longer charging time compared to DBs. As a result, BEBs need to recharge their batteries throughout the day during their layovers in between trips to avoid running out of energy. Accordingly, operational delays and uncertainties highly affect the BEB operation as they disrupt the during-day-charging schedule. Moreover, this charging process would ideally be fully handled by renewable energy generators (REGs) which are also highly susceptible to uncertainties. Thus, in this work we investigate how smart cities' real-time data collected from different sources and online information systems can be used to ensure the feasibility of BEB operation and maximize the utilization of REGs. This could be done by a BEB real-time decision-support system (BRDSS) that monitors the random operating conditions and optimizes the charging schedule accordingly. Our BRDSS incorporates real-time data, prediction algorithms, and optimization methods.

In the next sections, we provide an overview of the previous research on transportation and its integration with renewable energy resources within smart cities. Then, we describe the details of the problem, and present our BRDSS. Afterwards, we introduce a real-world case study on the transit bus network in a big European city. Finally, in the last section, we present preliminary results and provide an outlook on the next steps within this project.

Related Work

Previous research has investigated how advanced information systems can leverage the performance and efficiency of decision making in various fields. Within the energy field, Watson et al. (2010) provide an extensive overview of how energy informatics can have a big influence on reducing the energy consumption, CO_2 emissions and increasing the efficiency of matching the supply and the demand. Bichler et al. (2010) underline the benefits and opportunities of adopting real-time intelligence in highly dynamic energy markets. Brandt et al. (2018) highlight how information systems can improve cyberphysical systems, focusing on smart grid applications. Moreover, Valogianni et al. (2014) present a charging algorithm for smart electric vehicles that leverages learning agents to effectively reduce the induced peaks due to charging

demand. Hence, although various studies have examined the potentially high value of information systems in various smart city-related applications, no previous studies investigated how it can be also beneficial in enhancing the energy transition process in public transport sector.

Transit bus networks used to run for decades operating conventional DBs which represent a significant source of air pollution and greenhouse gas emissions in urban areas and city centers. Electrifying transit bus networks by replacing DBs with BEBs raises many new challenges due to BEBs' shorter driving ranges and slower rates of charging. As a result, BEBs should recharge their batteries throughout the day during their stops to avoid running out of energy. Furthermore, previous studies show that there is substantial uncertainty regarding energy consumption of BEBs and its dependence on several factors such as route type and topologies, driving behavior, and number of stops (Kontou and Miles 2015). Moreover, the vehicle's size and the heating and air ventilation system are proven to have a significant effect on the BEBs' energy consumption (Zhou et al. 2016). As a result, the operation of BEBs is less robust against uncertainties when compared to its conventional counterparts, as an unexpected delay that causes a missed charging event or excess energy consumption may lead to operational infeasibility.

Moreover, electrifying the transit bus network without using sustainable renewable energy for charging BEBs would only imply shifting the emissions geographically outside city centers. Thus, ideally all the energy provided to the transit bus network would be provided by renewable energy resources. Due to their intermittency, employing renewable energy resources for charging BEBs adds more uncertainty to the operation of electrified transit bus networks. Various previous studies investigated how to optimally coordinate electric vehicles (EVs) charging and renewable energy generation. Schuller et al. (2015) use mixed integer programming to minimize the usage of energy generated from conventional sources to charge EV fleets. Their result show that the yearly average utilization of the renewable energy resources can be more than doubled with coordinated charging compared to the uncoordinated one. Yang et al. (2015) present a review of the different techniques used to solve that problem. They conclude that the conventional optimization techniques can be sufficient to provide good solutions in normal settings. However, they have limitations in dealing with more complicated problems with multiple objectives or stochasticity. Finally, Mwasilu et al. (2014) and Hu et al. (2016) conclude in their studies that the complete integration between EV and smart grid operations would only be possible through advanced real-time information and communication technologies. This emphasizes the notion that such an information system that uses live data to integrate energy generation and bus operations and regularly re-optimizes both systems is critical to the success of complex smart city applications.

Naturally, previous studies that leveraged real-time optimization with EVs, renewables, or the smart grid in general yielded better results than offline systems. In the general field of smart grids and renewables, Gan et al. (2013) use a real-time load control technique to shift the loads to the periods of renewable energy generation by minimizing the expected variance between the updated predictions. Their results show the superiority of the real-time algorithm compared to the static one. Mohamed and Mohammed (2013) propose a real-time energy management algorithm to charge an energy storage system with online prediction for wind energy generation and load power. They use an energy storage system that can be used during peak times to feed power to the grid to increase its reliability. In the specific field of EVs, Deilami et al. (2011) propose a real-time energy management technique that is used to charge plug-in EVs to minimize the total generating and loss costs. Ardakanian et al. (2014) develop a real-time algorithm to coordinate EV charging given the available capacity in the grid. Their results show that the coordinated strategy can charge ten times the number of EVs compared to the uncoordinated one.

Within the transportation field and public transit bus network studies, various previous studies tackled the problem of optimizing the charging schedule. Pelletier et al. (2018) use a mixed integer linear formulation to minimize the charging costs under varying electricity prices for electric freight fleets while modelling the battery degradation process. Their results show that the tradeoffs between various factors such as grid restrictions, charging costs, and maximum power demand. Leou et al. (2017) develop a mathematical formulation to minimize energy charging costs in transit BEB networks under varying electricity prices. The results of these studies show the importance of optimizing charging schedules of large EVs fleets. However, none of the previous studies investigated the problem of optimizing the charging schedule while integrating with renewable energy resources under uncertainty. In order to deal with that stochasticity arising from operational delays, contingencies, unplanned excess energy consumption, or generated renewable energy

randomness, we propose a real-time decision support system that monitors the transit BEB network and renewable resources operating conditions to regularly re-optimize both systems.

A Real-time BEB Decision Support System for Sustainable Public Transport

A transit bus network consists of service lines which are defined by origin-destination pairs of terminal stations. The frequency of the trips at each line is determined by passengers' travel demand throughout the day. With the electrified transit network, BEBs need to recharge their batteries during their layovers in between the trips at the terminal stations. Thus, the trip schedule should grant sufficient layovers for all the buses at those terminal stations that have charging facilities. Afterwards, a charging schedule is required in order to decide where, when and for how long each BEB is going to charge its battery. We develop the charging schedule with the objective of ensuring the feasibility of all BEBs' operation and maximizing the utilization of REGs. At the end of day's operation, all BEBs go the central garage for overnight charging in order to fully recharge their batteries before the beginning of the next day's service.

Ideally, all charging of the BEBs in the transit network would be handled by REGs. However, that might not be possible due to the huge load of charging BEBs, and the limited and intermitted generation of REGs. As a result, in the critical situation of anticipating a BEB to run out of energy with no sufficient renewable energy generation to recharge it in time, we allow for conventional charging from the grid. In order to minimize the additional strain that is experienced by the grid, the BRDSS attempts to charge from the grid at those times and locations at which it aligns well with the general demand-supply patterns. We use online pricing signals from the grid as a proxy for the grid situation at different locations throughout the day.

In addition, due to unforeseen operational delays, BEBs may miss some planned charging events. Unanticipated delays and weather conditions may also lead to unplanned excess energy consumption. Therefore, it might be needed to modify the charging schedule during the day to take corrective actions and compensate for that lost charging. Real-time online adaptation of the charging schedule is also required to redistribute the locations and the times of the charging events according to the varying and hardly predictable conditions of the REGs and the grid. Finally, we propose using energy storage system (ESS) to mitigate the effect of these uncertainties and increase the utilization of the REGs and minimize the impact on the grid.

To handle this large and sophisticated system, we propose designing an IS artifact (Hevner et al. 2004) to control the various components within the system and optimize the operation. Figure 1 shows the framework of our proposed BEB real-time decision support system. Before the start of each day's service operations, the charging strategy is optimized based on the predicted REGs' output, BEBs' delays and energy consumption, and the status of the grid at different times throughout the day. During the day, real-time information is collected from the various sources within the system. Real-time data of the state of charge (SoC) and delay data from the BEBs, the SoC of the ESS at different locations, the REGs' output, the status of the grid, and weather data are gathered by the BRDSS. Afterwards, the BRDSS uses the real-time weather data to make better predictions of the REGs' output during the next few hours. It also uses the real-time BEBs' operational delays data to enhance the predictions of future delays during the rest of the day. Then, the BRDSS optimization algorithm runs to optimize the charging schedule to make the decisions about each BEB's charging location, duration and time, as well as the ESS charging and discharging times and durations.

In the extreme cases of uncertainties, the BRDSS is also responsible of sending warning signals to the traffic control operators in the network in case of anticipating a BEB is expected to run out of energy under the current circumstances. Hence, the traffic control operators are responsible for making the decision of pulling-in that BEB and replace it with a fully charged one. Based on that decision, the BRDSS then re-optimizes the charging schedule. Finally, the central BRDSS shares the updated charging schedule to all the charging facilities at different locations in the network.

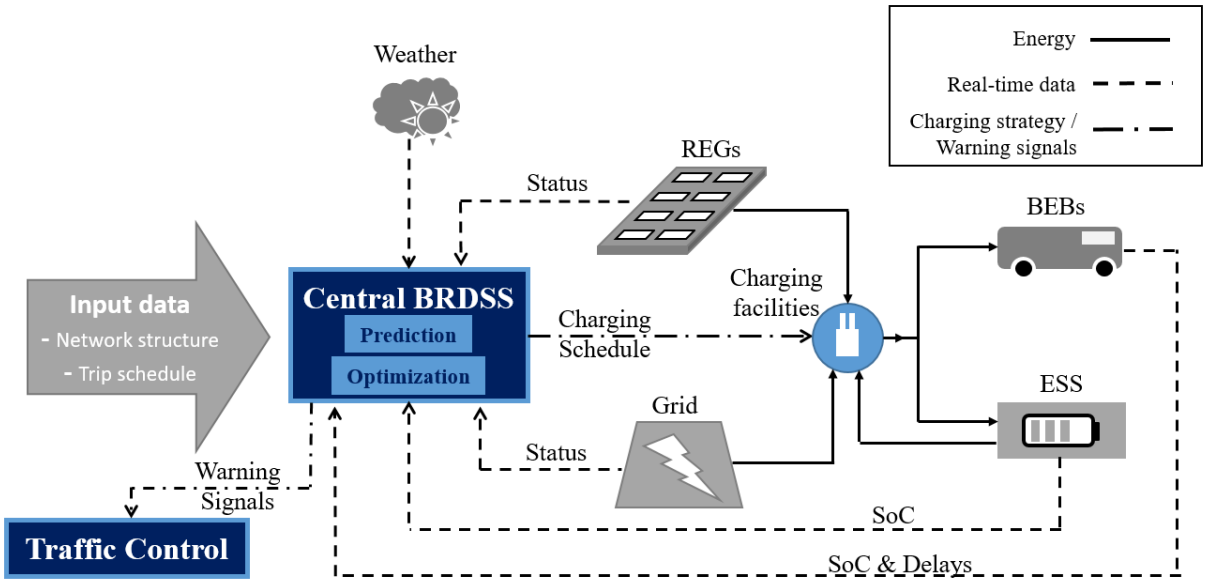

Figure 1. BRDSS general framework

Methodology

To evaluate the proposed framework, we develop a discrete-event simulation using Python's SimPy library. Moreover, the simulation is integrated with an optimization model that is responsible for optimizing the charging schedule by solving a mixed-integer linear programming problem using the CPLEX solver. As shown in Figure 2, the simulator is used to evaluate the network while incorporating different charging strategies under stochastic operating conditions. The simulator takes as an input the network structure, charging locations, numbers and power of chargers, and the trip assignment schedule. The simulator's output is our main performance measures which are how well the BEBs' charging schedule is integrated with the grid and coordinated with the renewable energy generation, and the reliability of the network's operation. Our main charging strategy is the smart online optimized (SONO), which adjusts and re-optimizes the charging schedule each hour based on the real-time data collected from the network. To assess the benefit of our proposed real-time system, we compare to the SONO strategy to an offline optimized and two heuristic charging strategies. The offline optimized (OFO) charging strategy sticks to the day ahead optimal plan regardless of any deviations that may occur due to uncertainties. The two heuristic charging strategies are first-in-first-serve (FIFS) and lowest-charge-highest-priority (LCHP). The FIFS arranges the BEBs in the queue according to their arrival time. On the other hand, the LCHP arranges them according to their SoC. Thus, a BEB with a lower SoC has a higher priority to charge. Replacing a BEB that is charging with another arriving one with a lower SoC is also allowed, if the charging BEB's current SoC is above a certain threshold.

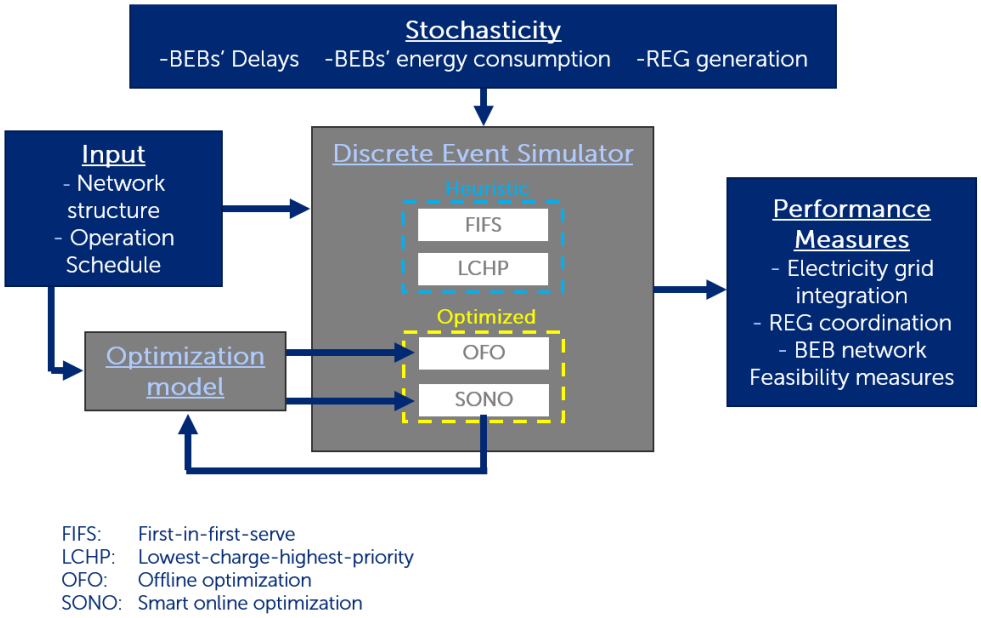

Figure 2. The layout of the simulation/optimization tool

Practical Case Study and Primarily Results

To evaluate our proposed BRDSS framework, we carry out this study in cooperation with the main PTO in a large European city. The city has a wide transit bus network that consists of 61 lines, which are going to be fully electrified within the next couple of years, while seven two-way essential lines are going to be electrified before 2020. Eleven terminal stations serve these lines, with charging facilities installed at six of them with a charging power of 240 kW. Forty-seven BEBs are going to operate on these lines with a battery capacity of 240 kWh each. Five additional BEBs are going to be kept as backup in case of contingencies. All the BEBs are going to charge during the night at the central garage using chargers with 50 kW charging power.

We assume an average energy consumption of 1.5 kWh/km. We also assume that a delayed trip would consume more energy and vice versa. To make our simulation results more realistic, we also consider the passive energy consumption, which is the energy consumed at the layovers due to the heating, ventilation, and air conditioning systems. We also consider the setup time, which is the time required to connect the BEBs to the chargers, and which is set to one minute in our study. Finally, we add a minimum charging time of one minute after excluding the setup time. Thus, a BEB does not charge if its layover at a station is shorter than this time.

It is worth mentioning that for all the strategies we test, we do not allow for the start of a trip to be delayed to allow for charging. Thus, the priority of starting a trip on time is always higher than charging. We add that restriction as there is a predetermined trip frequency per line, based on the agreement between the PTO and the municipality, which must be realized. Due to the less efficient charging beyond the 90% SoC, we add an upper limit for the SoC and do not allow for charging beyond that limit during the day. For the optimal strategies, we also add a lower limit SoC. Thus, the optimized schedule keeps all the BEBs' SoC during the day above that limit in the deterministic settings.

In our preliminary analysis, we do not include the REGs and the ESS. Hence, we analyze the network under stochasticity in the trip delays for three weeks. We carry out the analysis with the maximum number of chargers at the terminal stations which corresponds to the maximum number of simultaneously located BEBs at each location. Thus, in the deterministic settings, any BEB arriving at a terminal station with charging facilities will be able to find a free charging slot. Our preliminary results show the potential value of the BRDSS and its higher ability to maintain the operational feasibility. Figure 3 shows the overall energy costs. Given that energy costs are higher if there is excess demand, lower costs correspond with our charging

schedule being better integrated with the energy grid's needs. The results show that the SONO strategy outperforms the FIFS and is able to reduce the impact on the grid by around 20%.

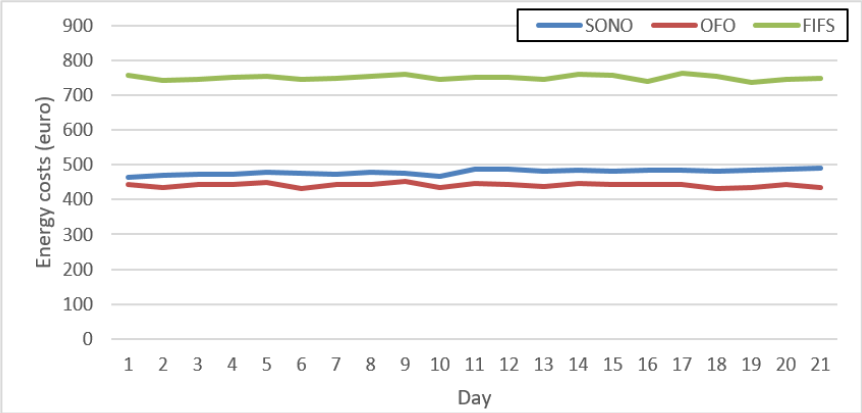

Figure 3. Impact on the grid with the different charging strategies

Figure 4 shows the lowest SoC occurring during the day among the whole fleet, which is a measure for the reliability. The results show that the FIFS has the highest reliability. This happens in the case of having the maximum number of chargers, so the FIFS will charge all the BEBs whenever they are at terminal stations with chargers. Although this yields higher levels of reliability, it has a substantial negative impact on the grid as shown previously in Figure 3, and result in potentially unnecessary charging during the day. The results also show the superior reliability of the SONO compared to the OFO strategy. Figure 4 also shows an infeasibility occurring to a BEBs on the 18th day with the SONO strategy. However, that should not be a problem with the presence of backup BEBs and the real-time monitoring system. The option of replacing a BEB, which is expected to run out of energy within the next few hours, with a fully charged one from the garage will be added to our final system with the SONO strategy.

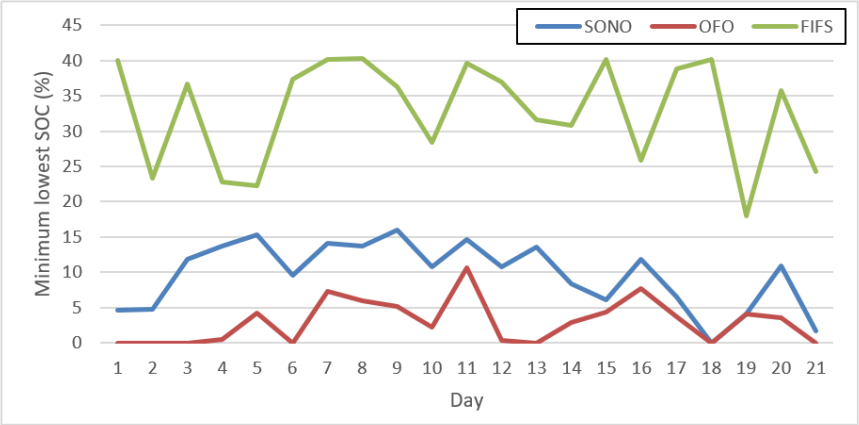

Figure 4. The lowest SoC among the BEB fleet

Conclusions and Future Work

Our preliminary results show the high potential benefits of the BRDSS. The results show its higher ability in balancing the tradeoff between the operational feasibility and the impact on the grid. Thus, the real-time optimized strategy yields higher levels of reliability compared to the offline one, and is better aligned with the grid compared to the greedy heuristic strategy. In our final complete study, we will include the REGs and their uncertainty as well as the ESS, at which we also expect a superior performance from the real-time

SONO compared to the other strategies. Thus, it is expected from the SONO strategy to reach better coordination between the charging events and the actual renewable energy generation periods due to the online updates of the predicted REGs' output. Accordingly, it is also expected that the SONO will be smarter in making the decisions regarding charging and discharging the ESS. Thus, it should charge it either when there is an excess renewable energy generation or if needed when the grid's energy prices are very low. Finally, the SONO should realize all of that while ensuring higher levels of reliability as our primarily results show. We expect to finish our study by October 2019 and present the final results and findings at ICIS in December.

However, beyond the scope of this project, there are several additional paths for future research. At the operational level, we consider the trip schedule as an input to our problem. Thus, in case of predicted infeasibility during the day, we assume having enough standby BEBs to replace the infeasible ones for the rest of the day operation, and we do not consider fixing the problem by adapting the trip schedule. Additionally, due to the lack of data, we are also unable to assess the value of predicting the operational delays in the trips. We also do not consider the option of selling the renewable energy generated to the grid. Moreover, it is worth mentioning that the BEB fleet could be integrated even more tightly with the management of the power grid. BEB fleets, with their large amount of energy stored in the batteries, could be regarded as a virtual power plant that can be used to actively balance the grid at peak times. Previous studies in the field of EVs have shown the potential advantages of applying that two-way integration (Kahlen et al. 2018). At the strategic level, our study further illustrates how separate infrastructures and service systems become more and more entangled as cities become smarter. Information systems will play a critical role in facilitating this integration by allowing for communication between these systems, leveraging advanced analytics techniques to minimize the impact of uncertainty, and enabling automated control of the overall harmonized system.

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