CHARGING STRATEGIES FOR ELECTRIC BUSES BASED ON DETERMINISTIC AND STOCHASTIC OPTIMISATION APPROACHES: A DUTCH CASE STUDY

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ABSTRACT

The potential of different charging strategies for electricity cost reductions of electric buses is investigated while accounting for uncertain operational factors in electricity consumption such as ambient temperature, wind speed, and day of the week. A model is developed that calculates the total electricity costs for five different charging strategies by employing deterministic and stochastic optimisation approaches that are able to deal with uncertainty. The developed model is applied to a case study based on an operational area of a Dutch bus operator. The simulation results for the tested charging strategies indicate a significant potential for total electricity cost reduction up to 35% and peak power reduction up to 58% on a monthly basis, given the input data and assumptions. The analysis provides insights on various charging strategies for electric buses and potential operational cost reduction, which outweigh the high capital cost, and supports future applications.

INTRODUCTION

Transportation in the E.U. is responsible for about one-quarter of all greenhouse gas emissions, with over 90% of the fuel utilised for transportation being oil-based [1]. To achieve the ambitious goals of the Paris Agreement [2], and improve the air quality in urban areas, it is important to consider low-carbon solutions for public transport [3]. Electric vehicles are promoted for environmental reasons, and research on the integration of electric vehicles in power distribution systems spans more than a decade. The literature covers a variety of topics: from the reduction of network losses [4], mitigation of power quality phenomena [5], and the planning of the charging infrastructure [6], to market optimisation [7], and contribution to system resource adequacy [8]. In 2019, the Dutch transport sector emitted 40 Mton CO_2, constituting 23% of the total CO_2 emissions (172 Mton) in the Netherlands [9]. The Dutch Climate Agreement describes a set of measures that aim for 49% CO_2 emission reduction by 2030, compared to 1990 levels [10]. Electric buses hold considerable potential in reducing CO_2 emissions associated with the transport sector. In [11], the authors reviewed various performance features of electric buses and concluded that battery-electric busses coupled with renewable energy sources is arguably the best solution that provides zero net emissions. However, this is highly dependent on the mix of electricity generation per country. Furthermore, electric busses introduce many new parameters and interactions that could influence the quality of the service, e.g., system design, procurement of assets [12]. To compensate for the high capital costs of electric buses, the application of smart charging strategies can result in lower operational costs without compromising the quality of service. Charging costs can be reduced by shifting electricity demand from relatively high to low price periods or by minimising the cost of purchased energy volumes at the wholesale market while accounting for imbalances during operations and by applying peak shaving for minimising the grid fees.

Previous studies on smart charging for electric buses have focused on deterministic approaches and assuming perfect forecasts as optimisation inputs, e.g., the authors in [13] assumed perfect solar forecasts. However, the electricity demand for charging purposes of electric buses depends on several uncertain factors related to the bus type, the route type, the driver type, weather conditions, and the day and time of operation. Inaccurate electricity consumption forecasts may result in large imbalance volumes. Studies devoted to forecasting the electricity consumption of electric buses while accounting for uncertain factors have focused on specific cases studies, e.g., in Singapore [14] and Finland [15], suggesting that the electricity consumption may be dependent on the geographic location, e.g., because of varying climate conditions. Studies investigating the effect of uncertain factors on the electricity consumption of electric buses specific to the Netherlands lack in the existing literature. This research aims to calculate the Total Electricity Costs (TEC) based on different charging strategies for certain and uncertain electricity consumption and compare the TEC reductions relative to the current charging strategy for a Dutch case study. The case study is performed in collaboration with Dutch bus operator Qbuzz. It concerns the operational area Drechtsteden-Molenland-Gorinchem (51.82N, 4.8E), with a 100% share of electric buses (38 buses of the same type operating in the area). For Qbuzz and other bus operators, it is of interest to explore the application of smart charging to minimise the TEC. The following section presents the methodology, the tested charging strategies, and the data collection, followed by the results and future research recommendations. The paper ends with conclusions.

METHODOLOGY

The methodology consists of four methodological steps. In the first step, desk research was conducted to explore the uncertain operational factors that affect the electricity consumption of electric buses, whereas in the second step, an impact analysis was performed to identify the most important of those factors, specific to the case study for the Netherlands. In the third step, a model was developed, consisting of five sub-models. Each sub-model calculates the TEC corresponding to a different (smart) charging strategy. In the fourth step, the model was applied to the Dutch case study to calculate the TEC for the different (smart) charging strategies. For the impact analysis of the different factors identified in the first step, the specific electricity consumption (C_i) in (Wh/m) was calculated for the electric buses of the case study. The historical trip dataset (I) provided by Qbuzz was used for calculating the C_i based on the distance driven (D_i) in (m) and the electricity consumed during trip i (E_i) in (Wh), as follows:

$$C_i = \frac{E_i}{D_i} \qquad \forall\, i \in I \qquad (1)$$

Based on the impact analysis, the critical uncertain factors for the case study were selected and serve as input for the next steps. TEC C_{tot} generally consist of five components:

$$C_{tot} = C_{elec} + C_{imb} + C_{grid,var} + C_{grid,fix} + C_{tax} \qquad (2)$$

with electricity costs C_{elec}, imbalance costs C_{imb}, variable grid fees $C_{grid,var}$, fixed grid fees $C_{grid,fix}$, and taxes C_{tax}. Variable grid fees in the Netherlands consist of two types: 1) grid fees for peak power consumed which is charged on a monthly basis in (€/kW), and 2) grid fees for peak power *contracted* in (kW) are applicable for large consumer and are charged in (€/kW). In the case that the maximum consumed peak power exceeds the contracted peak power, the maximum consumed peak power value defines the new contracted peak power value and cannot be adjusted downwards for the coming twelve months. Due to the application of a smart charging strategy, the peak power demand may be lowered, whereas a lower peak power demand also enables a lower contracted peak power, thus resulting in lower TEC via reduced variable grid fees. The fixed grid fees cannot contribute to TEC reduction by the application of a smart charging strategy, and the following four types exist in the Netherlands: 1) transport-independent fees in (€/month) which are fixed and charged per month, 2) periodical connection fee in (€/month) paid to the regional Distribution System Operator (DSO) for maintaining the grid, 3) transport fees dependent on the amount of electricity consumed in (€/kWh), and 4) metering fees in (€/connection/month) charged for metering services. In the Netherlands, electricity taxes are charged for each unit of electricity consumed. By applying a smart charging strategy, it is assumed that the electricity consumption remains the same. Thus, lowering the TEC via taxes by using a smart charging strategy is not possible.

Approaches that may reduce the TEC include smart charging strategies that minimise the electricity costs, the imbalance costs and/or the variable grid fees [13]. In this work, five charging strategies are considered: the naïve strategy, used as a reference, in which the charging pattern is not controlled, and four smart charging strategies where the charging pattern, i.e., the timing and the charging power rate, is controlled. In this work, the following smart strategies are tested. The charging strategy DAMdet is about deterministic economic optimisation based on the day-ahead market (DAM) prices [16] while assuming that the electricity consumption can be perfectly forecasted. The charging strategy DAMstoch, is about stochastic optimisation based on the DAM prices while accounting for uncertainty and potential imbalance costs. DAM optimisation is performed while considering that the decrease in electricity costs is not outweighed by the increase in variable grid fees due to peak power increase. In DAMdet and DAMstoch, the electricity consumption was deterministic and stochastic, respectively. For DAMstoch, the amount of electricity consumption is determined based on ninety runs (i.e., ten times for each of the nine sets of scenarios) of Monte Carlo simulations with different values assigned to the random variables, i.e., the imbalance price and the electricity demand. For the latter, uncertain operational factors that affect the electricity consumption of electric buses, based on an impact analysis specific to the case study, were taken into account (see next section; Table 2). The charging strategy FIXdet is about minimisation of both electricity costs and grid fees, based on deterministic economic optimisation with fixed peak and off-peak prices as input. The peak shaving charging strategy focuses solely on deterministic optimisation for minimising the variable grid fees by shifting electricity demand from peak demand periods to off-peak periods, but without accounting for the change in electricity costs. The decrease in grid fees due to peak shaving has also been assessed and proven to be effective in [17].

The developed model consists of five sub-models that represent the (smart) charging strategies: 1) the naïve charging strategy, 2) DAMdet, 3) DAMstoch, 4) FIXdet, and 5) peak shaving. The model calculates the TEC for all historical transactions within a specific selected period for overnight charging at the bus depot. The calculated TEC corresponding to the naïve charging strategy serve as a reference, as this is the currently employed charging strategy. The mathematical formulation of the model has been documented in [18]. The model was applied to a Dutch case study, and the input data, provided by Qbuzz, included historical trip (i.e., distance driven, electricity consumed, day and time) and transaction (i.e., charging start/end time, maximum charging power, total electricity charged, total electricity used during charging, and State of Charge) datasets for the entire year of 2020, as well as the supplier's monthly profiles of fixed peak and off-peak price in (€/MWh). The latter was used as input for the naïve, FIXdet, and peak shaving strategies. The ratio between the monthly average fixed peak and off-peak prices was about 1.22. After filtering the datasets for removing erroneous values, the historical trip dataset included 134,337 trips, whereas the historical transaction dataset included 10,401 transactions. For the DAMdet and DAMstoch strategies, the 2020 DAM prices were used as input [19], whereas for DAMstoch also the imbalance prices from 2020 were used within the scenario-based stochastic optimisation [20]. Daily average ambient temperature and wind speed data from 2020 from the Royal Dutch Meteorological Institute (KNMI) were also utilised as input [21]. Since the bus depot of the case study is situated in Dordrecht, which is in the grid area operated by Stedin DSO, the applicable variable and fixed grid fees were also used as input [22]. **Figure 1** provides an example of the electricity prices and model-generated charging patterns for the four (smart) charging strategies for one day in December 2020. Note that the charging pattern for DAMstoch is not included in the graph as the charging pattern differs between all ninety Monte Carlo simulations.

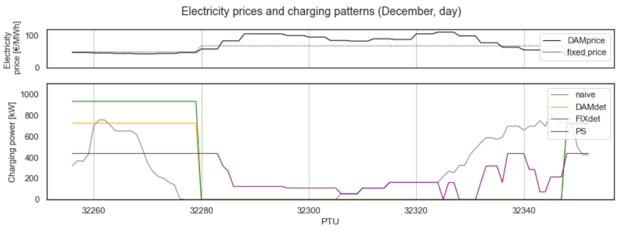

Figure 1. Electricity prices and charging patterns for the four (smart) charging strategies for one day in Dec. 2020.

RESULTS & ANALYSIS

Extensive desk research was conducted to identify uncertain operational factors that affect the electricity consumption of electric buses. In this research, the electricity consumption is the net electricity consumption and therefore includes both electricity consumption and potential electricity (re)generation due to braking. The identified factors were ordered in four categories, adapted from [23] (see **Table 1**): 1) the vehicle type, 2) the route type, 3) weather conditions, 4) the bus driver type. For the impact analysis, the specific electricity consumption was calculated, based on equation (1), and the results in terms of deviation (%) from the average electricity consumption are listed in **Table 2**, for the following factors: 1) ambient temperature, 2) wind speed, and 3) day of the week. These factors were considered critical and were taken into account in the development of the demand scenarios for the DAMstoch charging strategy. The relative reductions in TEC and peak power for the investigated case study are listed in **Table 3**. Overall, the TEC for the naïve charging strategy are the highest, meaning that all smart charging strategies have the potential to reduce the TEC. The main reason for the high TEC for the naïve charging strategy is the relatively high fixed electricity prices compared to the hourly DAM prices and also due to the relatively high peak power demand resulting in high variable grid fees.

Table 1. Overview of uncertain operational factors affecting the electricity consumption of electric buses.

Category	Factor (Unit/identifiers)
Vehicle type	Bus type (e.g., bus size/capacity) Passenger mass (kg) Curb weight (kg) Total vehicle weight (kg) Battery self-discharge rate (%) Motor efficiency (%) Auxiliary systems (e.g., heating, air conditioning, lightning) Regenerative breaking
Route type	Route type (e.g., urban, sub-urban, inter-city) Elevation (m) Average speed (km/h) Number of stops (e.g., a bus stop or due to traffic) Day of trip (Mon-Sun.) Time of trip (0-24h) Traffic conditions (e.g., average speed, stops)
Weather condition	Ambient temperature (°C) Wind speed (m/s)
Driver type	Driver experience (yrs) Driver style (e.g., speed/acceleration/ deceleration) Driver comfort (e.g., use of hearting/ air conditioning)

Table 2. Impact analysis for critical uncertain operational factors. Results are expressed in percentages in terms of deviations from the average electricity consumption.

	Minimum	Maximum
Ambient temperature	15 °C	-1 °C
	-9%	+22%
Wind speed	0 m/s	15 m/s
	-8%	+11 %
Day of the week	Sunday	Friday
	-6%	+2%

Table 3. Main finding for all smart charging strategies. The percentages show the decrease in costs and peak power demand relative to the naïve charging strategy.

	DAMdet	DAMstoch	FIXdet	Peak shaving
TEC	-29 to -33%	-26 to -35%	-13 to -15%	-10 to -14%
Peak	-42 to -58%	-28 to -47%	-39 to -58%	-54 to -58%

The application of the peak shaving strategy resulted in the lowest TEC reductions, within the range of 10-14%, and this is mainly attributed to the relatively high fixed electricity prices, whereas the only reason for the TEC reduction is the lower peak power demand resulting in lower variable grid fees. The calculated reductions are similar to the results presented in [17], where TEC reductions of 10% due to peak power reductions of 52% are reported. Application of the FIXdet strategy resulted in TEC reductions between 13-15%, induced mainly by the lower electricity costs due to electricity consumption being shifted from peak price periods to off-peak price periods. Also, in most cases, the peak power demand was reduced, which resulted in lower variable grid fees. However, it is important to note that in some cases, the peak power demand increases at levels that the increase in variable grid fees was outweighed by the decrease in electricity costs. This was often the case in December, and in some other cases also in September, due to the relatively large difference in peak and off-peak electricity prices. This means that the TEC reductions are slightly higher for the FIXdet charging strategy, compared to the peak shaving strategy, but induces very high peak power demand at some moments. The question of whether the slight increase in TEC reductions justifies the higher impact on the power system infrastructure remains. Application of the DAMdet strategy resulted in TEC reductions between 29-37% due to the lower electricity costs attributed to the wholesale DAM prices. In the case of DAMstoch where the electricity consumption of electric buses is uncertain, the TEC reductions are between 26-35%. An important note is that the TEC based on DAMstoch are highly affected by the imbalance costs. For most selected periods, the higher the average imbalance costs over all runs, the higher the average TEC. Unfortunately, the timing of the imbalance volume is independent of the imbalance prices, which means that the imbalance volume does not relate to the imbalance costs. Comparing the results from DAMstoch to the results from DAMdet reveals that accounting for the uncertainty in electricity consumption does not result in large differences in TEC, even though the average TEC for DAMstoch were slightly lower and higher than the TEC for the DAMdet charging strategy.

Figure 2 illustrates the case study results in terms of peak power demand and TEC for all (smart) charging strategies for a period of one month, for indicative months to capture the seasonal variations. Note that the peak power and TEC for DAMstoch is the median value for all simulation runs. As can be seen in all cases, the smart charging strategies result in lower peak power demand compared to the reference naïve charging strategy. The decrease in peak power for the FIXdet strategy is related to the difference in fixed peak and off-peak electricity prices and the variable grid fees. The peak power reduction is the highest in June, followed by March and September. The peak power demand reduction is the lowest for December. The peak power reduction attributed to the peak shaving strategy is the highest because only the variable grid fees, determined by the peak power demand, were minimised. Regarding the TEC, all smart charging strategies resulted in significant cost reduction. The TEC for the naïve charging strategy are the highest since the peak power demand for this charging strategy is the highest, resulting in relatively high variable grid fees, whereas the fixed electricity prices are also relatively high, compared to the DAM prices, which result in higher electricity costs.

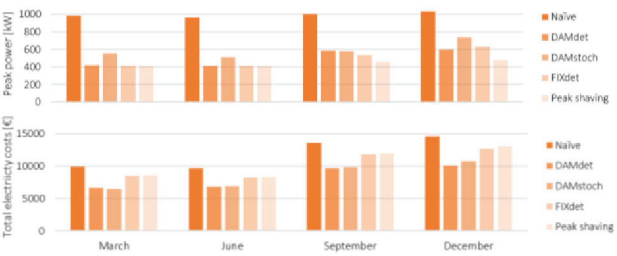

Figure 2. Peak power demand (top), and total electricity costs (bottom) for all tested charging strategies.

FUTURE RESEARCH RECOMMENDATIONS

The simulations accounted for both certain/deterministic and uncertain/stochastic electricity consumption for the charging of electric buses. Future research can account for other uncertain factors related to the DAM prices, driver type, bus type, arrival and departure times. Another suggestion is to consider an assessment covering a more extended period of several years. This would enable to address a higher number of demand scenarios, varying climate and market conditions, and also account for the COVID-19 circumstances. Both the historical trip and transaction datasets covered the reference year 2020, during which the COVID-19 pandemic was going on, and with the Netherlands going into partial lockdown as of mid-March. As can be seen in **Figure 3**, the lockdown and other restrictions affected the number of public transport passengers to a large extent, which also impacted the electricity consumption of electric buses during that period. In the second half of March 2020, the daily number of boarding (check-ins) on Dutch public transport fell by almost 90% compared to a similar day in 2019 [24].

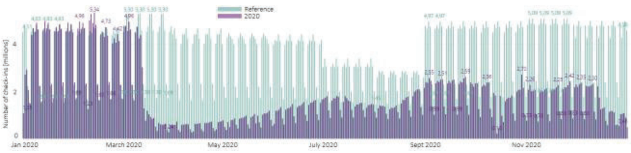

Figure 3. The number of boarding (check-ins) on public transport in 2020 and reference values, adapted from [24].

CONCLUSION

Based on extensive desk research, uncertain operational factors that impact the electricity consumption of electric buses were identified, and six of those were considered particularly important, namely the bus type, the route type, ambient temperature, wind speed, the driver experience, and the day and time. The next step was to test the effect of those factors, specific to the Netherlands, based on available datasets for a case study in collaboration with a Dutch bus operator. For the given case study, all the electric buses are of the same type, and also the set of routes, drivers, and operational times are approximately the same; therefore, the analysis focused on the remaining factors. It was found that fluctuations in the ambient temperature could result in changes of 31% in specific energy consumption, mainly due to the electricity consumption for auxiliary systems that increases with extreme ambient temperatures. An increase in wind speed was found to increase electricity consumption by 19%, due to the increased air resistance, which increases the electricity consumption for moving, acceleration, and deceleration. Finally, the average specific energy consumption varies by 8% between different days of the week. On Fridays, it is the highest due to more traffic, resulting in less favourable traffic conditions. On Sunday, it is the lowest, which is probably due to the lower number of passengers, decreasing the passenger weight and thus the total vehicle weight. Following this analysis, the factors of ambient temperature, wind speed, and day of the week were selected to be taken into account for the development of electricity demand scenarios to be tested in simulations for calculating the total electricity cost for the case study. Different charging strategies for electric buses were tested, showing significant potential for reduction of operational costs compared to the reference case of the current situation, which can outweigh the high capital cost and enable wide-scale deployments. Based on the results, the main recommendation towards the bus operator of the case study is that a peak shaving strategy is a good option in the short term for minimising the electricity costs, as it also does not require any changes in the way of purchasing electricity. In the longer term, it is recommended to further explore the potential of day-ahead market optimisation as it shows high potential for electricity cost reductions.

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