PREDICTING THE IMPACT OF ELECTRIC BUS CHARGING ON DISTRIBUTION POWER GRIDS

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ABSTRACT

As a major DSO in France, Enedis is interested in assessing the Grid impact of high development of Electric Mobility of different ranges and in various areas: rural or urban. For this purpose, this paper establishes a methodology for DSO to predicatively assess the peak electric power required at different locations in a transport network under various charging strategy hypothesis. The analysis uses publicly available data from existing transport networks.

A high charging power may impact the grid at the vicinity of depot or opportunity charging stations. This impact may trigger expensive connection costs and potential reinforcement expenses on the distribution network. Statistical tools were created to provide an estimate of the absorbed electric power throughout a normal operation day. Uncertainties around the exploitation of urban transport networks were taken into account.

Simulation on three networks across France proved that an overnight charging could have a significantly reduced impact when compared to an opportunity charging on these specific cases of study. Furthermore, a power control strategy enforced at a depot could help further mitigate its impact through a substantial reduction of its peak power. Results also showed that the use of a gathering of opportunity charging stations have a lower impact on the electrical grid thanks to a better control of bus operational stochasticic effects.

INTRODUCTION

Urban public transports is often seen as an efficient way to reduce greenhouse gas emissions or to improve air quality in city centres [1]. Most of these, however, are powered by diesel engines, still causing greenhouse gas emissions or lowering air quality.

Electric passenger cars have already shown satisfactory environmental performances. Their ecologic life cycle was proved 32 % better then combustion engine cars in the British market [2]. Penetration of electric vehicles amongst passenger cars have been stimulated by incentives, either political, legal or financial [3].

Advances in battery technologies have made the use of electric buses possible, leading to the possibility to start an energy transition in public transports. Some countries, such as France, have taken legal incentives to encourage urban bus renewal to cleaner technologies [4]. These include a wide range of possibilities, among them battery-electric buses. Jwa has shown a significant eightfold reduction in life cycle greenhouse gas emissions using electric buses [5].

Urban transport electric vehicles are used in city centres, leading to an increased demand for electrical power and energy at their depot or at opportunity charging stations.

Opportunity charging often requires a high power over a short duration whereas depot charging is a slow, “low-power” charging. This charging could further benefit from a Smart-Charging strategy, to help mitigate the impact on the distribution grid [6, 7].

Vehicles’ charging requires a wide spectrum of considerations, including charging cost optimisation [8], auto-consumption of renewable energy [9] and uncertainties over the consumption [10].

Pelletier introduces that freight vehicle journeys can be forecasted and that it is acceptable not to leave the depot with a fully charged battery [11]. G. Zhang suggests the benefits of a flat power demand curve and a subsequent lower peak power [7].

So the energy transition in an urban transport network is successful, it is paramount to accurately understand its specific requirements. For example, a vast majority of bus stops are seldom or never crowded while a few others are at all times [12]. That creates the need to identify main stations in the network. H. Zhang applied a methodology to identify hubs in Xiamen, China, and found that less than 3 % of stations are widely connected to the rest of the network while nearly half of them are solely connected to the next and previous stations on the same bus line [13].

Under the hypothesis that a stop at a station is observed if and only if there is at least one passenger willing to board or unboard the bus, then it is important to identify the stations where this rarely occurs: an opportunity charging at those would be impossible.

Transport networks also show a high amount of operational uncertainties. They can be related to the bus schedule [14], the vehicle’s energy consumption [10], the use of an air conditioning system [15], traffic [16], and variability in the vehicle’s routing [17], among others. Gallet has shown consumption of electric buses on different routes may vary between 1.1 kWh/km and 2.2 kWh/km. However, high variations in the distance travelled each day (typically from 60 to 350 km) makes the overall vehicle consumption range from 100 kWh to 550 kWh [18].

Extreme consumptions may require different charging strategies due to battery weight limitations in buses.

This paper integrates all aforementioned constraints and objectives to study the impact of a given transport network on the distribution grid. The methodology used includes the conversion of public data into a replicable standard and the analysis of a depot charging and of an in-exploitation charging. A software was created to analyse data from a French one million inhabitant city [19], a French regional hub (few hundred thousand inhabitants) [20] and a countryside city (a few dozen thousand inhabitants) [21].

METHODOLOGY

Modeling an actual network based on publicly available data

The first step towards understanding and predicting the power consumption in an urban transport network and therefore its impact on the grid is to define it in a standard, replicable format. To meet that purpose, it was decided to use publicly available data from the internet [19, 20, 21]. They were last accessed in December 2018.

The three sources show an explicit definition of bus route topologies, bus schedules and bus network organisation. Urban bus networks are fully defined by this set of information.

The three networks have been chosen based on the availability of required data, the size and location of the networks. They correspond to the three different network scales existing in France. The network in the biggest city shows a high geographical spread and therefore requires the use of many depots. Smaller networks use fewer if not one. Table 1 shows each network's key figures.

In this study, the bus consumption has been randomly assigned to a constant for each line. It was set to follow a normal distribution (mean: 1.5 kWh/km, standard deviation: 20% - 0.3 kWh/km).

It is then helpful to determine when each bus enters or leaves the depot. It helps give an estimate of the time spent driving. To do so, bus schedules for each line were studied. The hypothesis was made that a bus must go back to the depot before changing lines, making possible to calculate the time spent driving by all buses on a line each hour in accordance with the bus schedules as shown on table 2.

Table 1 - Key figures corresponding to each network

	Marseilles	Orleans	Valence
Nb. Buses	639	169	124
Nb. Lines	102	41	28
Nb. Depots	4	2	1
Distance per day (km)	68,000	36,000	19,000
Travelers per year	74.8M	11.6M	12.2M

Table 2 - Extract of a bus schedule

Gustave Eiffel	09h03	09h14	09h25	09h37	09h47	09h58
Saint-Jean-de-Braye	09h50	10h00	10h11	10h23	10h33	10h44

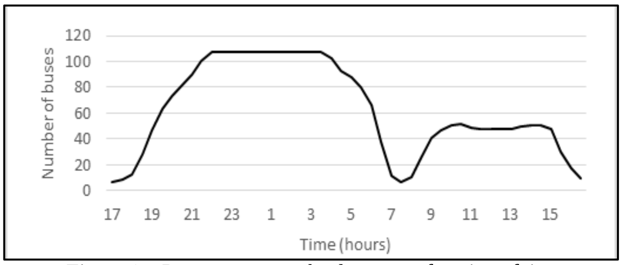

Figure 1 – Bus presence at the depot as a function of time

Applying this method to all lines and every hour gives knowledge of how many buses are required at all times during a normal operation day, their driven distance and an estimate of their energy consumption. A suitable treatment was applied to have a consistent and smooth data. The chart on figure 1 shows how many buses are present in one of the studied depots as a function of time.

This completes the definition of the networks. So far, bus line topology, usage as well as depot organisation were defined. It is therefore possible to study a realistic use of electric power at different locations in the network.

Several scenarios have been studied, including the use of the depot as the only locations where to recharge the batteries and the use of opportunity charging as the main charging mode.

Modelling power consumption at a depot.

This section aims at studying the impact of a single bus depot on the distribution grid, where overnight charging occurs. It uses power for long durations and depots gather an important number of buses. They are located inside or near city centres [19, 20, 21].

Two types of charging strategies may be proposed. The first one consists in plugging the bus as it enters the depot and wait until charging is complete or the bus is required to leave the depot. Figure 2 gives the algorithm used to simulate this charging strategy at the depot.

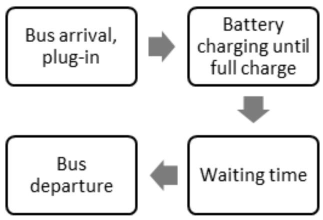

Figure 2 - Intuitive charging algorithm

This shall be compared to an optimised charging aiming at diminishing the maximal power required during the day. This is an optimisation problem, where the cost function is given in equation 1.

$$U = -\max_{t \in [0,24]} \sum_{i=1}^{n} P_i(t) \quad [1]$$

where U is the utility value, $P_i(t)$ is the charging power for bus i at a given t moment and n is the number of buses at the depot.

Maximising this utility function will consist in obtaining a low volatility load curve, aiming at reducing the load peak. Zhang gave insights into the potential negative impact of a peaking electric demand on the distribution grid [7].
However, this problem must be solved acknowledging constraints in the depot. The most important constraint is that each bus must always be able to complete its journey. This constraint is modelled using a status of charge requirement when the bus departs on a new service. Equation 2 can be used.

$$SOC(t_0) = C \quad [2]$$

where t_0 is the departure time of the bus, C is the energy consumption of the next journey and SOC(t) is the bus's status of charge at a given *t* moment.
Another charging constraint is the need to supply a power which is at most equal to the maximum the bus may charge (typically 50 to 150 kW for a slow charging) showed in equation 3.

$$P(t) \leq P_{max} \quad [3]$$

where P(t) is the electric power received by a bus at a given *t* moment, P_{max} is the maximum power admissible.
This problem was solved by calculating each of the buses' energy requirement throughout the day, sampling it and attributing the power using a priority system: a bus able to charge only during the transport network's peak-time is given full priority whereas a bus able to charge most of the time is given lower priority. Figure 3 summarises the algorithm used to calculate the power to supply to each bus at each moment of the day to reduce the peak electrical demand.

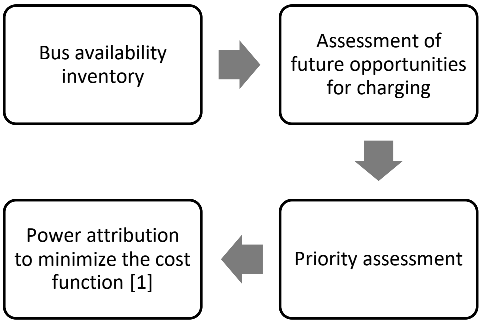

Figure 3 - Optimal charging algorithm

Modelling power consumption at opportunity charging stations

The next step is to understand the impact of opportunity charging on the distribution network. The case of study is extracted from realistic situations from the selected example networks. A fictitious bus line was created, following the specifications given on figure 4.

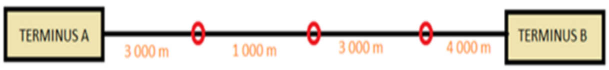

Figure 4 – fictitious bus line used to study opportunity charging

This was used to assess the rated power of charging stations to be integrated at the different charging locations. Charging times were set to 20 seconds for in-line opportunity charging and to 10 minutes for charging at terminal stations.
Stations' rated power is then calculated to ensure that enough energy is transferred to allow the bus to connect the current station to the next one without any risk for traffic disruption. This is determined by equation 4, where c_{km} is the mean consumption per kilometre, $d_{A\text{-}B}$ is the distance from A to station B to the next station and $c_{A\text{-}B}$ is the required energy to travel from station A to station B.

$$c_{A-B} = c_{km}.d_{A-B} \quad [4]$$

In this model, it is considered the charging duration may not be shortened. Even though a bus is late, charging times shall always be respected.
The exploitation of several bus lines was therefore simulated. All lines are considered to go through the same set of stations, either at terminal or in-line stops. The aim of this study is to assess the statistical use of the station to analyse the power taken from the distribution grid at all times.
The simulation takes into account uncertainties over arrival time at the stations. However, no uncertainty was acknowledged with regards to the departure time, since the charging time is fixed.
Data required include a realistic simulation of line lengths, charging station powers and service frequency. The values have been set in accordance with the calculations carried-out on the bus line presented in figure 4 and with the data obtained from example networks.
Cases of study are chosen in accordance with the topology of the example networks. They include: three terminal charging stations, three in-line charging stations and a mix of five terminal and two in-line charging stations.

RESULTS AND DISCUSSION

Power consumption at an electric vehicle depot

Figure 5 (next page) presents the energy demand at a depot for natural and optimised charging strategies. It displays the most relevant example amongst the 7 depots studied. Precise figures are given on table 3. They correspond to the depots where the optimisation has been most successful, least successful and to the median depot, relatively to the optimisation power reduction.
When vehicles are charged with a "plug as you arrive" strategy, a power peak occurs when the last ones enter the depot. This peak may be a major contributor to the depot's impact on the distribution network depending on its location and neighbouring electricity consumptions. It is also determinant to the electric connection to establish.

Table 3 – Simulation result at several depots

	Most Successful	**Median**	**Least Successful**
Nb. Buses	107	114	110
P. per bus (no optimization)	56 kW	67 kW	68 kW
P. per bus (optimized)	21 kW	29 kW	49 kW

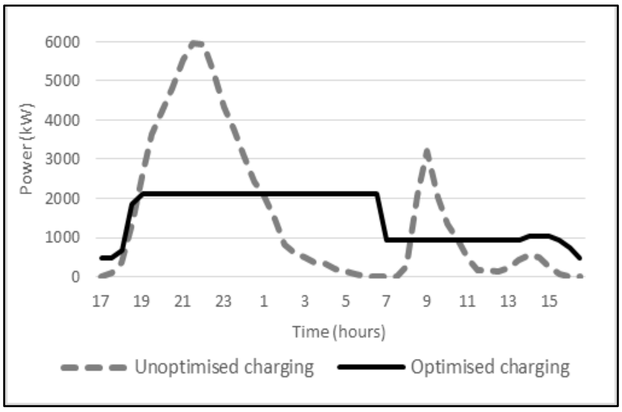

Figure 5 - Charging control at a depot

Load optimisation proved very efficient to diminish the maximum power consumption. A median peak power reduction of 57.9 % was observed (ranging from 28.0 % to 63.3 %). Optimised power consumption also makes a better use of the available subscribed power. Thanks to the optimisation, time spent consuming over 90 % of the subscribed power go up from 8.3 % to 50 % on the median depot.

It will generally be considered that the impact of depot charging on the distribution grid is low comparatively to other charging strategies. This is the consequence of a relatively low call for power (a simulated average of 56.7 kW per bus, inclusive of yields, without optimisation) and near-deterministic bus schedule at the depot. Thanks to the load optimisation process, the average maximal supplied power was reduced to an average 27.2 kW per bus over the 7 depots.

Power consumption at opportunity charging stations

Figures 6 to 8 show the power consumption at opportunity charging stations. Figure 6 consists in three charging stations at terminal bus stops, figure 7 in three in-line charging stations and figure 8 (next page) represents a mix of both types of charging stations.

These show evidence of important stochastic effects in the use of in-exploitation charging stations. Indeed, power may be called for at all times, when the buses arrive at the stations. Power must therefore be available at all times with little room for forecasting.

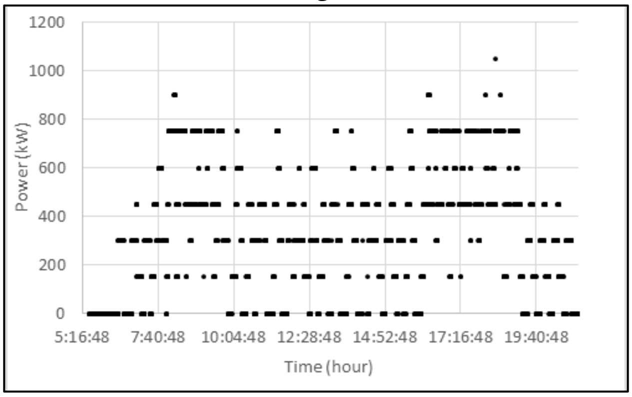

Figure 6 - Use of three terminal charging stations

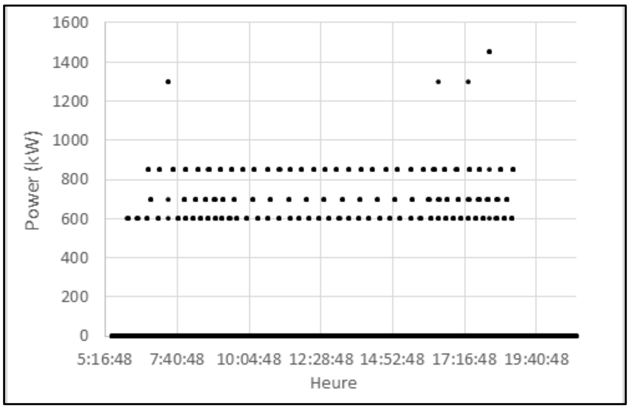

Figure 7 - Use of three in-line charging stations

In addition to this, simulation showed that the power to be made available is much greater in the case of in-line charging stations (peak at 1,450 kW for three stations) as opposed to terminal stop charging stations (peak at 1,050 kW for three stations). High stochastic effects, together with the higher power required, make terminal stop stations the preferred type of opportunity charging stations with regards to the distribution network.

However, figure 8 shows that the use of many charging stations at one location implies a seldom reach of the rated power (2,400 kW). This is due to a very low probability for stations to all be used simultaneously. Considering that the battery is able to withstand exceptionally not using the charging opportunity, it is possible to potentially reduce the electrical connection power. Figure 8 shows a 2,350 kW peak power when using 5 terminal stop stations together with 2 in-line charging stations.

For example, 950 kW (59.6 % curtailment) is called for less than 10 % of the time and 1,650 kW (29.8 % curtailment) is called for less than 1 % of the time.

Charging at in-exploitation stations may therefore benefit from a power control limiting the simultaneous use of charging stations.

A comparative analysis of the charging power per bus however puts into evidence that even with the use of a very restrictive power control at the mix of the 7 stations, the rated power per bus to charge is 135.7 kW, to be compared to the 27.2 kW obtained at the depot. In-exploitation charging may therefore require up to five times as much peak power as depot charging, triggering higher connection costs and potential impact on the grid.

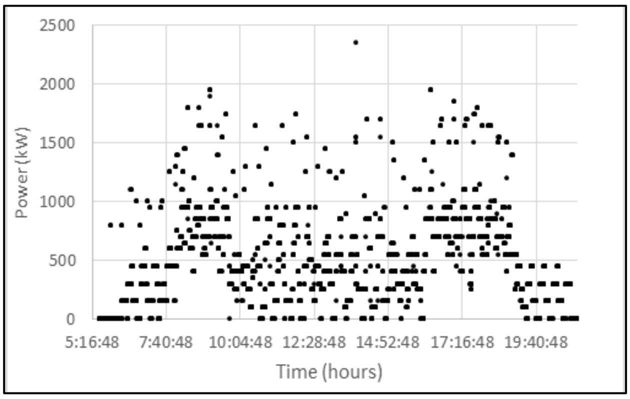

Figure 8 –Use of a mix of charging stations

In addition to this, calls for power at opportunity station have a volatility of 394 % for in-line charging, 78 % for terminal charging and 77 % for mixed charging. This sould be compared to the 121 % and 42 % volatility obtained at the depots respectively without and with charge control.

CONCLUSIONS

Urban mobility in electric buses is developing quickly and requires attention to be optimally integrated to the distribution network. Different charging strategies will each have a specific impact on the electricity grid.

This study reveals that overnight depot slow-charging should be preferred from a distribution grid perspective. It indeed may be a key factor in keeping the electrical connection fees as well as potential electrical distribution gird reinforcement expenses minimal. This is the consequence of a regular, schedulable power consumption. Together with a charging station control to limit power demand at certain times of the day, this charging could help keep network reinforcement minimal.

However, constraints over battery size might require some opportunity charging stations to be installed. They could have a greater impact on the distribution grid due to important stochastic effects and a higher peak power per bus and should therefore be kept minimal from a distribution grid perspective.

Simulation shows a great preference for the use of terminal stop charging stations over in-line charging stations. Opportunity charging should be used only if depot charging fails to meet the battery size constraint.

Charging control may also be beneficial when using opportunity charging to limit the use of available power during the distribution network's peak time.

Further studies should include the study of current and voltage quality in a depot. Overall current and voltage quality may indeed be damaged by the use of AC/DC and DC/DC converters in charging stations [22].

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