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***Abstract*—Due to sustainability concerns raised by the transportation sector, still relying mostly on oil as main energy source, urban mobility is quickly shifting towards the adoption of electric vehicles (EVs). The EV charging process should heavily rely on Renewable Energy Sources (RES) and be smartly scheduled to promote sustainability and pollution reduction. In this context, renewable powered Battery Swapping Stations (BSS) represent a promising solution to enable sustainable and feasible e-mobility. Focusing on a BSS powered by photovoltaic panels, we investigate the issue of properly dimensioning its capacity (in terms of number of sockets) and the renewable energy supply to satisfy the battery swapping demand, trading off cost, Quality of Service and feasibility constraints. In addition, we analyse the potential benefits of smart scheduling strategies for battery recharging. Our results show that considerable cost saving of up to almost 40% can be achieved with a local RE supply to power the BSS. Furthermore, a proper tuning of the scheduling strategy configuration parameters is required to better trade off cost and Quality of Service, based on the desired performance targets.**

***Index Terms*—Battery Swapping Stations, e-mobility, Renewable Energy**

I. Introduction

Currently the main energy source for the transportation sector is still represented by oil, satisfying more than 90% of the sector energy demand. According to [1], road transportation alone is responsible of the largest oil consumption among all sectors, with a share of almost 50%. Furthermore, whereas in other sectors oil consumption has not been significantly increasing in the past decades, the total final oil consumption of road transportation has almost triplicated in less than five decades, currently amounting to almost 2000 Mtoe per year [1], a trend which is clearly not sustainable.

Besides sustainability, especially in urban environments, traditional transportation raises also concerns related to air pollution. In this context, urban mobility is quickly shifting towards the adoption of electric vehicles (EVs). However, the positive impact of e-mobility on pollution reduction is sustainable in the medium to long term only if EV charging is carefully managed through energy supply systems which heavily rely on Renewable Energy Sources (RES) and schedule and plan recharging in a smart way.

A promising solution that facilitates the adoption of sustainable and smart charging is Battery Swap technology, which consists in EVs equipped with batteries that can be quickly changed, so that a discharged battery can be substituted with a fully charged one in a short time. In this way, the need for mobility is decoupled from the battery charging process that is managed by independent companies through Battery Swapping Stations (BSS) that operate in a similar way to a fuel filling station. This has a number of advantages over EVs with standard batteries. First, the time for a battery swap is comparable to refueling an Internal Combustion Engine vehicle and this, in its turn, reduces the users' range anxiety (fear that a vehicle has insufficient range to reach the destination) which is one of the major obstacles to the large-scale adoption of all-electric cars [2], [3]. Second, new convenient business models are possible. The user or the car sharing company owns the EVs, whereas batteries are owned and managed by a centralized provider, which is in charge of battery maintenance. This lowers the EV prices and relieves the burden on users to cope with exhausted batteries. Third, smart scheduling of battery charging is possible. The time constraint for recharging is relaxed and the recharging process can adapt to the RES production and be activated when RES energy is available. In addition, the charging process can respond to Smart Grid requests in a beneficial interaction that schedules battery charging in periods of low price, or when RE is available or to prevent peak loads of electricity.

Some studies from the literature investigate optimal battery charging schedule approaches aiming at minimizing the operational cost. Authors in [4] proposes a mathematical model to schedule the battery charging process. This approach optimizes an objective function that considers: (i) the number of batteries taken from the BSS to satisfy the demand for EV battery replacement, (ii) the potential damage due to high-rate charging, and (iii) the varying electricity cost. The work presented in [5] focuses on deploying a mathematical model to optimally operate a BSS considering the random demands of fully charged batteries, and exploiting demand shifting and energy sellback to reduce the BSS operational cost. The study in [6], based on a Monte Carlo simulation approach, shows that optimal schedule for the charging process contributes to satisfy more EV swapping and charging requests maximizing the service capacity. Regarding renewable powered BSSs, forecasting models based on statistics and machine learning techniques can be integrated in the scheduling approaches to

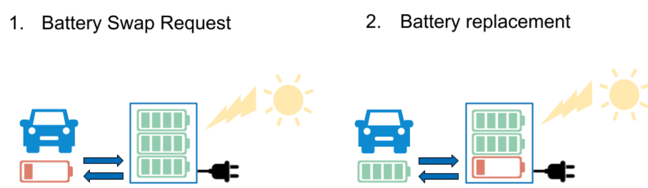


Fig. 1: Renewable powered Battery Swapping Station.

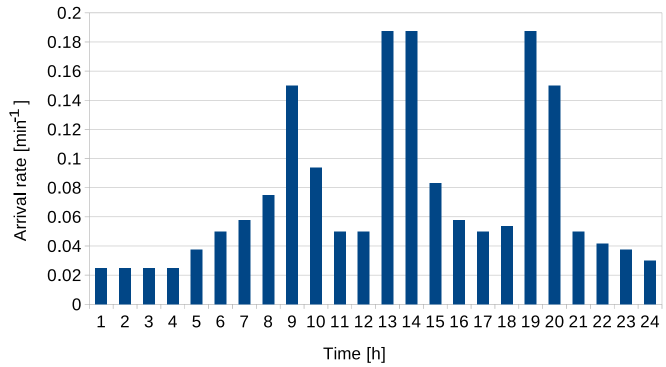


Fig. 2: Daily profile of EV arrival rates.

address the uncertainties related not only to traffic load and swapping demand, but also to renewable energy generation and weather conditions [7], [8]. In [9], a charging strategy is designed with the purpose of improving self-utilization of renewable energy.

In this paper, we focus on urban e-mobility based on battery swap technology, considering a renewable powered BSS. We investigate the issue of properly dimensioning the BSS capacity and the renewable energy supply to trade off cost and Quality of Service. In addition, we analyse the potential benefits of smart scheduling strategies for battery recharging. The main contributions of the paper are the following:

- We analyze the performance of Battery Swap technology in terms of cost and grid energy consumption when BSS make use of solar panels;
- we discuss the dimensioning of the BSS in terms of number of sockets, to satisfy the battery swapping demand trading off cost and service loss probability;
- we investigate the dimensioning of RE supply to trade off cost saving and feasibility constraints;
- we propose some simple smart scheduling strategies and observe the benefits of adapting charging schedules to energy availability and electricity prices, investigating the proper tuning of the strategy parameters settings.

II. Sustainable urban mobility scenario

We consider a scenario with a fleet of EVs owned by a private company either offering goods delivery service or car sharing service over a city and its suburban area. EVs are equipped with a specially designed battery unit that, in case of low charge level, can be replaced by a fully recharged battery at a Battery Swapping Station (BSS), as shown in Fig. 1. The swap takes a very short time and once the discharged battery is replaced its recharging at the BSS can start. The battery units have 20 kWh capacity. Due to the nonlinear charging power of lithium-ion batteries, it is difficult to exactly estimate the final charging time of each storage unit [3]. Nevertheless, according to [10], a constant current can be used to quickly recharge the battery from 0% to approximately 80%, whereas the charging power in the remaining stage is significantly lower. In our study, we assume a constant charging rate of 10 kW, allowing to charge half the battery capacity per hour.

A number of BSSs are distributed in the city to provide battery charging service to the fleet of EVs. In our paper we focus on a single BSS, featuring a number of sockets that is denoted by N_S. Besides being powered by the electric grid, the BSS is equipped with a set of photovoltaic (PV) panels that locally produce renewable energy (RE) that is used to recharge the battery units, as depicted in Fig. 1. Given a unitary capacity of 1 kWp, and assuming one of the most efficient crystalline silicon technologies, with efficiency 19%, the physical area occupancy of the corresponding PV modules is about 5 m^2 per kWp [11], [12]. Real RE generation profiles are obtained from the PVWatts tool [11] for a city in Northern Italy during the typical meteorological year. To evaluate the BSS operational cost, we consider real electricity prices derived from the Day-Ahead Market, provided by *Gestore dei Mercati Energetici* (GME), the Italian company responsible for the electricity market management [13]. EVs are assumed to arrive at the BSS to replace their discharged battery according to an inhomogeneous Poisson process, characterized by average arrival rate λ varying with the time of the day on an hourly basis, according to the daily traffic profile reported in Fig.2. Taking inspiration from typical models of EV arrival rates that are adopted in the literature [14], this pattern reflects traffic variations during the day, showing traffic peaks at the beginning of the working day, during lunchtime, and in the evening.

The battery charge level of the EVs that arrive at the BSS is denoted $L \cdot C_B$, with L representing the fraction of the total battery capacity, denoted by C_B. L is assumed to be uniformly distributed according to $\mathcal{U}_{[0.2,0.4]}$. This assumption allows to take into account the Maximum Depth of Discharge (DoD) of the battery, that is set in this case to 0.8, in order to limit the battery degradation. Furthermore, under this assumption the risk of fully running out of battery is avoided, allowing the EV to reach another BSS in case no battery units are currently ready to replace the EV battery.

III. Smart scheduling strategies

When an EV arrives at the BSS, if at least a fully recharged battery is available, this battery is used to replace the discharged battery of the EV, and the EV battery takes its place at the corresponding socket in the BSS, to start its recharge process. In case no fully recharged battery is currently available at the BSS, the EV cannot be served by the considered BSS and another BSS must be reached. The described operation corresponds to the *Baseline Strategy (BLS)*. In addition, we design different smart scheduling algorithms aiming at more efficiently exploiting the produced RE, when available, and at reducing operational cost. The proposed strategies represent variants of the BLS and are based on the additional possibility to periodically postpone the charging of a fraction of the batteries currently under charge at the BSS. The postponing decisions are based on predictions about the future renewable energy generation and the electricity cost. In this paper, we assume that prediction errors are negligible. The three proposed approaches are detailed hereafter.

A. Renewable Energy based Postponing Strategy (REPS)

According to this strategy, the charging of a subset of batteries plugged to the BSS can periodically be suspended by an amount of time that facilitates the recharging with renewable energy so as to decrease the consumption from the electric grid. Let us denote by F the maximum number of batteries under charge in the BSS whose charging process can be postponed by a period of time T_{max} and let $e^G(t)$ be the energy requested by the electric grid if recharging starts at time t. When a new EV arrives at the BSS or one of the batteries under charge at the BSS achieves the target charging level, an algorithm is triggered to select up to F batteries, whose charge is postponed by a period t_r, with $t_r \leq T_{max}$, as long as the following condition holds:

$$e^G(t+t_r) = \min_{\forall i \in (0,T_{max}]} e^G(t+i) \tag{1}$$

$$e^G(t) > e^G(t+t_r) \tag{2}$$

where (1) identifies the best choice of the postponing time t_r and (2) verifies that the best option for postponing is better than non-postponing. The value of $e^G(t)$ depends on the initial charge level of the battery and on the RE that is produced during the period in which the battery remains under charge.

B. Renewable Energy and Energy Price based Postponing Strategy (RE-EPPS)

Based on the algorithm implemented by this strategy, the charge of some batteries at the BSS can be postponed by up to T_{max} if the cost for the energy drawn from the grid is expected to be more convenient in the next future. In particular, when a new EV arrives at the BSS or one of the batteries under charge at the BSS achieves the target charging level, an algorithm is triggered to select up to F batteries at the BSS, whose charge is postponed by a period t_r, with $t_r \leq T_{max}$, as long as the following conditions hold:

$$c^G(t+t_r) = \min_{\forall i \in (0,T_{max}]} c^G(t+i) \tag{3}$$

$$c^G(t) > c^G(t+t_r) \tag{4}$$

where $t+t_r$ corresponds to the time between t and $t+T_{max}$ at which the battery charge, once postponed at time t, must be resumed to observe the minimum value of the cost for the energy drawn from the grid that is required to recharge the considered battery to the desired level. The value of $c^G(t)$ depends on the initial charge level of the battery, on the RE that is produced during the period in which the battery remains under charge, and on the time-varying electricity prices.

IV. Key Performance Indicators

The following Key Performance Indicators (KPIs) are defined to evaluate the system performance under the different smart scheduling strategies:

a. *Average Service Loss probability* - P_l: it is the average daily probability that an EV arrives at the BSS and cannot be served, since no battery is immediately ready to be swapped with the EV battery.

$$P_l = \frac{1}{D}\sum_{i=1}^{D} \frac{V_i^a - V_i^s}{V_i^a} \qquad i = 1,2,...D \tag{5}$$

where V_i^a is the number of EVs arrived at the BSS during day i , V_i^s is the number of EVs served by the BSS on day i, and D is the number of days in the observation period.

b. *Average Energy Demand from the Grid* - E^G: it is the average daily BSS energy demand drawn from the electric grid.

$$E^G = \frac{1}{D}\sum_{i=1}^{D} E_i^G \qquad i = 1,2,...D \tag{6}$$

where E_i^G is the energy drawn from the grid on day i to recharge the batteries of EVs that are served during day i.

c. *Average Total Cost* - C^T: it is the average daily cost to operate the BSS.

$$C^T = \frac{1}{D}\sum_{i=1}^{D} C_i^T \qquad i = 1,2,...D \tag{7}$$

where C_i^T is the cost spent on day i to operate the BSS. A low value of C_T does not necessarily reflect a desirable system performance, since a high value of service loss probability may contribute to decrease the total cost at the price of Quality of Service impairment. We hence define also the following KPI, i.e. the *Average Cost per Service*, whose value is not influenced by the service loss probability.

d. *Average Cost per Service* - C^S: it is the average daily cost to serve an EV and replace its battery with a recharged

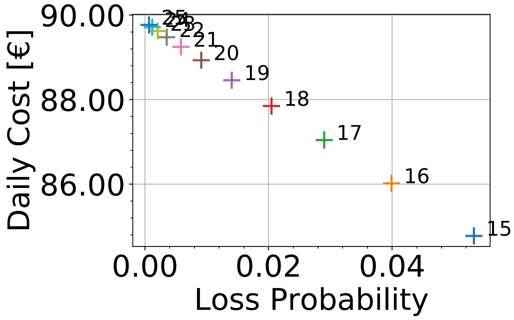


Fig. 3: Average daily total cost versus loss probability.

battery.

$$C^S = \frac{C^T D}{\sum_{i=1}^{D} V_i^s} \qquad i = 1, 2, \ldots D \tag{8}$$

V. System dimensioning

We first investigate how the system dimensioning influences the overall performance, considering both the BSS charging capability in terms of number of installed sockets and the size of the RE supply. We assume that the system operates under the BLS. An average value of 101.8 EV arrivals per day is assumed. The simulations are run over a period of one year.

A. Dimensioning the BSS

We evaluate the BSS dimensioning in a baseline scenario where no RE supply is envisioned. Fig. 3 reports the average total daily cost, C^T, versus the service loss probability, P_l, obtained under different values of the number of sockets in the BSS, N_S. For each point in the graph, a label specifies the corresponding value of N_S. As the BSS size increases, the service loss probability decreases, whereas the total cost grows larger, due to the larger fraction of EVs that can be served. However, the gain in terms of P_l reduction and the cost increase that are observed as N_S increases tends to become less relevant under higher values of N_S. For example, under values of N_S as low as 15, entailing a loss probability of about 0.05, the introduction of two additional sockets allows to almost halve P_l, at the price of less than 3% cost increase, whereas raising N_S from 22 to 23, although not very costly, does not provide significant benefits in terms of further P_l reduction, since the service loss probability results well below 0.01 in both cases.

Unlike C^T, and as intuitively expected, the average cost per service, C^S (not shown here for the sake of brevity), remains constant around 0.88 € under any BSS size. This finding confirms that the total cost reduction observed under smaller size of the BSS, i.e., lower N_S, basically depends on the lower fraction of EVs that can successfully be served, due to the higher service loss probability.

B. Dimensioning Renewable Energy supply to reduce cost

Assuming that RE can be utilized to power the BSS in addition to the energy drawn from the electric grid, we analyse

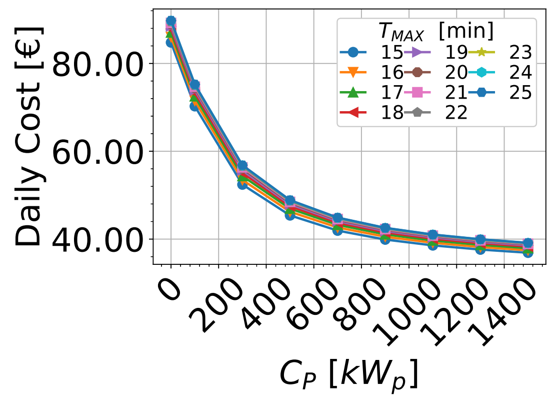


Fig. 4: Average total cost, C^T, under different settings of PV panel capacity, C_P, and number of sockets, N_S.

the contribution of the RE supply to reduce the operational cost, investigating the effect of its dimensioning on the system performance.

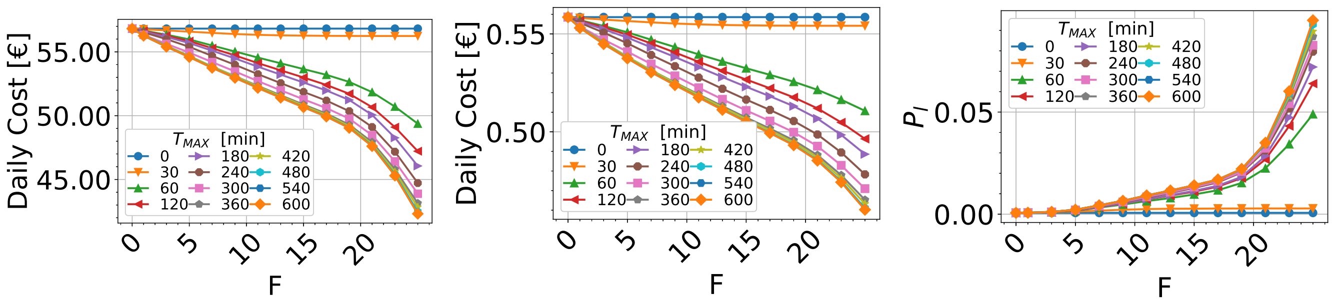
Fig. 4 depicts the average daily cost, C^T, for increasing RE generator capacity, C_P, with each curve representing a different value of the number of sockets, N_S. The introduction of a set of PV panels with capacity 300 kW_p allows to decrease the cost by up to almost 40%. If C_P is raised by 50%, the cost is further decreased by few percentage points only. Further increasing the size of the RE supply hence does not provide remarkable additional gain in terms of cost reduction. Considering that PV modules requires a surface of 5 m^2 per kW_p, a value of C_P=300 kW_p allows to trade off between the obtained operational cost saving and the need for limiting the area required to host the PV system installation due to feasibility and CAPEX constraints. To further decrease cost in the RE powered BSS, N_S can be slightly reduced, keeping in mind that it is not convenient to remarkably decrease the number of sockets, since the limited additional cost savings under lower N_S comes at the price of higher service loss probability.

VI. Smart scheduling strategies performance evaluation

The system performance is now investigated under various settings of the smart scheduling strategy parameters, to derive guidelines to properly tune the parameter configuration based on desired performance targets. Furthermore, the performance under the different strategies is compared to analyse the benefits provided by the various algorithms. A BSS equipped with 25 sockets and a RE supply of capacity 300 kW_p are assumed.

A. Tuning configuration parameters

We now assume that the charging of some batteries at the BSS can be postponed, if convenient. The system performance under REPS is considered hereafter. Fig. 5 shows the total cost, C^T, the daily cost per service, C^S, and the service loss probability, P_l, for increasing values of the maximum number



(a) Total cost, C^T

(b) Cost per service, C^S

(c) Service loss probability, P_l.

Fig. 5: Average total cost, C^T, cost per service, C^S, and service loss probability, P_l, under different settings of F and T_{max}.

of batteries whose charge can be postponed, F, for different values of T_{max}, that correspond to the various reported curves. Under T_{max} lower than 60 min, the setting of F does not significantly affect the total cost (Fig. 5a). Under higher values of T_{max}, as F becomes larger, the cost tends to gradually decrease. A steeper descent is observed for extremely high values of F. For a given value of F, the larger the value of T_{max}, the higher the cost reduction. Remarkable cost saving of up to about 26% with respect to the baseline strategy are achieved under very high values of T_{max} and F. Nevertheless, this comes at the price of higher service loss probability, as shown by Fig.5c, where P_l tends to grow as F increases, with a sharper increase when T_{max} is higher. Clearly, although providing relevant cost saving, very high values of both T_{max} and F are not advisable, since similar settings lead to a P_l increase of up to almost 10%. Conversely, limiting F to 15, the value of T_{max} can be conveniently increased to raise the cost saving up to more than 10%, still keeping P_l below 0.02. As highlighted by Fig. 5b, the cost per service, similarly to C^T, tends to decrease as F and T_{max} grow larger, although with a more gradual descent under very large values of F. This suggests that the higher cost reduction obtained under REPS when F and T_{max} are increased does not only depend on the higher service loss probability, but it also results form properly shifting the battery charge processes to periods in which more RE is available.

B. Smart scheduling based on charge postponing

The system performance under the proposed smart scheduling strategies based on battery charge postponing, REPS and RE-EPPS, is now evaluated and compared in terms of grid energy demand, operational cost and Quality of Service.

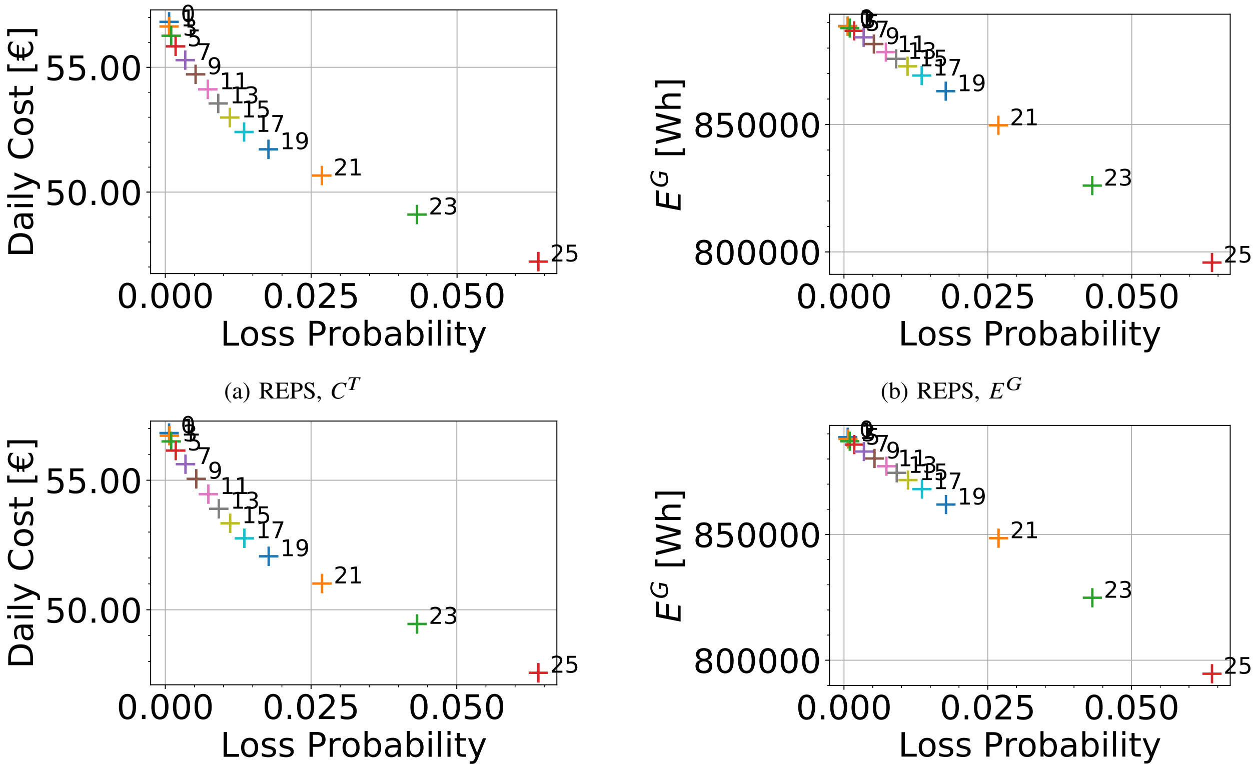
First, the different approaches are compared under different settings of F. Fig. 6 depicts the total daily cost, C^T, and the grid energy demand, E^G, versus the service loss probability, P_l, under different settings of F (whose values are indicated by the labels specified for each point in the graph), considering the operation under REPS (Fig. 6a-6b) and RE-EPPS (Fig. 6c-6d). T_{max} is set equal to 120 min. Under both strategies, as F grows larger, the cost and the service loss probability tend to decrease gradually for low values of F, and more sharply under larger values of F. Up to almost 10% of cost can be saved under the largest value of F. Nevertheless, to limit P_l below a target value of 0.02, the charge of up to no more than 19 batteries can be simultaneously postponed.

Focusing on the grid energy demand, E^G decreases as F increases, entailing higher service loss probability. Unlike C^T, the decrease of E^G is rather proportional to the P_l increase. This suggests that cost saving does not merely depend on the reduction of the total amount of energy drawn from the grid, but also on timely postponing the charge of some batteries, to take advantage of time periods characterized by higher RE availability and lower electricity prices.

No remarkable difference is observed between REPS and RE-EPPS in terms of cost saving and yielded service loss probability. This is likely due to the fact that the daily patterns of RE production and electricity prices result coupled, entailing peaks of prices that roughly overlap with peaks of RE production. Hence, in the considered scenario, a strategy that takes the decisions to postpone the charge of some batteries based on the future RE availability provides similar effects to a strategy that takes decisions based on both future RE production and electricity prices.

We now compare the performance of the various strategies under different settings of T_{max}. Fig. 7 shows the total daily cost, C^T, and the grid energy demand, E^G, versus the service loss probability, P_l, under different settings of T_{max}, considering the operation under REPS (Fig. 7a-7b) and RE-EPPS (Fig. 7c-7d). F is set equal to 17.

Under both strategies, the daily cost tends to decrease as T_{max} becomes larger, as well as the grid energy demand. Up to more than 12% cost saving can be achieved under REPS and RE-EPPS with respect to the baseline case in which none of the strategies is applied. However, under higher settings of T_{max}, REPS provides slightly lower cost, granting smaller service loss probability than RE-EPPS. This is likely due to the fact that decisions to postpone the charge of some batteries, although based on both RE future availability and electricity prices under RE-EPPS, may provide optimal cost savings in the current moment, nevertheless they may lead to additional future service losses or may prevent future operations of battery charging postponement due to lack of convenience, hence reducing the overall cost gain.



(a) REPS, C^T

(b) REPS, E^G

(c) RE-EPPS, C^T

(d) RE-EPPS, E^G

Fig. 6: Daily total cost (C^T) versus service loss probability (P_l), under different settings of F (values are indicated by the labels that are specified for each point in the graph), considering the operation under REPS and RE-EPPS.

Our findings suggest that when the target P_l value is set to a higher level, for instance $P_l < 0.02$, both T_{max} and F can be modulated to reduce cost without impairing Quality of Service, preferably adopting REPS. Conversely, under tighter constraints on P_l, like $P_l < 0.01$, it looks more effective to increase F rather than T_{max} to obtain relevant cost reduction without remarkably affecting the service loss probability, with similar performance under both strategies.

VII. Conclusion

Our work investigates the potential of renewable powered BSSs to make urban mobility more sustainable and more competitive with respect to benefits provided by non-electric mobility. Our results show that introducing a RE supply of about 12-20 kW_p per each socket provides up to almost 40% cost saving, hence contributing to make the BSS more sustainable, trading off cost and feasibility constraints. An appropriate dimensioning of the BSS in terms of number of available sockets allows to limit the service loss probability. Furthermore, properly designed smart scheduling strategies allow to more effectively exploit the locally produced RE, keeping in mind that effective policies do not aim at merely reducing the energy consumption from the grid, but at timely reducing the grid energy demand when the electricity prices are not convenient as well as enhancing the RE utilization. Finally, a convenient tuning of parameter settings is required to better trade off cost and Quality of Service, based on the desired performance targets.

Future work is required to investigate seasonal trends of the system behavior, to identify optimal parameter configurations depending on the time of the year, besides envisioning the possibility to sell back unused RE to the electric grid. In addition, further research efforts should be directed to investigate whether the strategy performance can be improved by slightly relaxing some constraints, like allowing to reduce the minimum charge level required to release a battery under charge at the BSS in case of an EV request, or assuming that EVs can wait for a short time at the BSS for a battery to become ready for swapping, in case no batteries are immediately available. Moreover, the sensitivity of the strategies to prediction errors about renewable energy production and electricity cost has also to be assessed.

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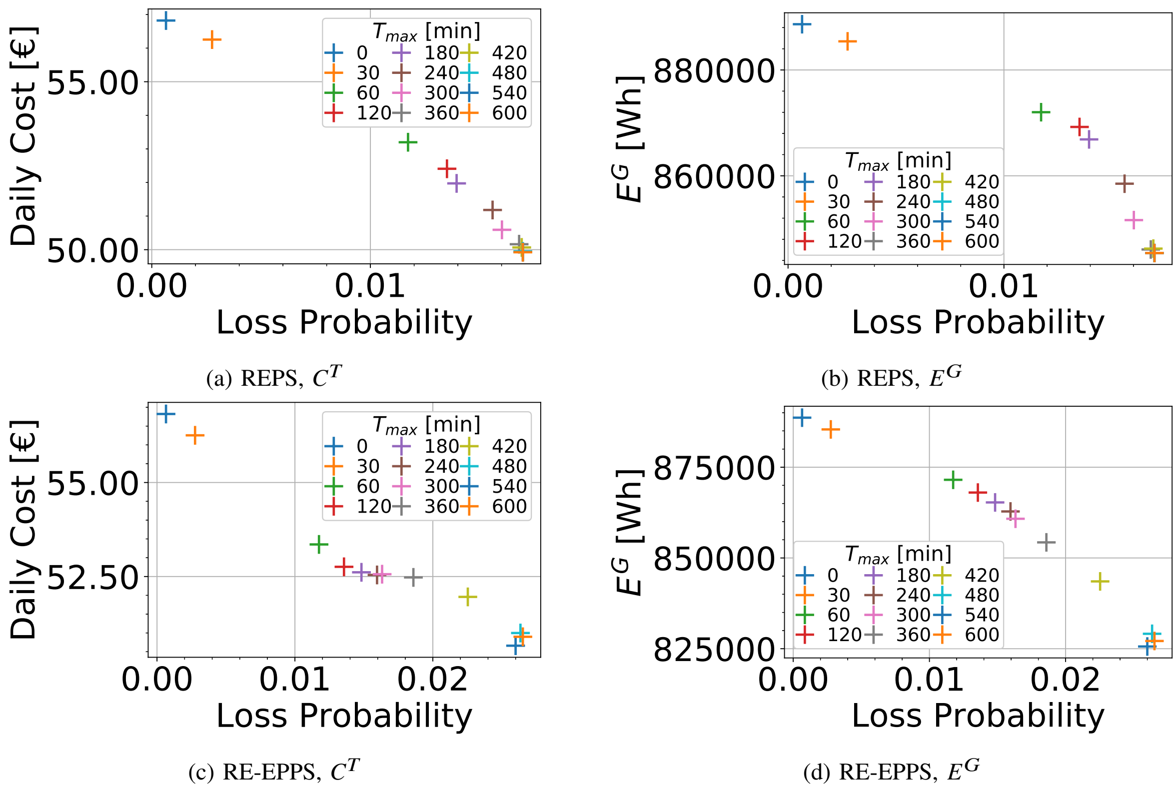

(a) REPS, C^T

(b) REPS, E^G

(c) RE-EPPS, C^T

(d) RE-EPPS, E^G

Fig. 7: Daily total cost, (C^T), and grid energy demand (E^G), versus service loss probability (P_l), under different settings of T_{max}, considering the operation under REPS and RE-EPPS.

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