# Centralized Scheduling Approach to Manage Smart Charging of Electric Vehicles in Smart Cities

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Abstract: Electric vehicles (EVs) are emerging as the future of individual mobility systems in smart cities since they reduce greenhouse gas emissions and fossil fuel dependence. However, the deepening penetration of battery EVs forecasted for the incoming years could cause significant stress on distribution networks (DNs), as well as the need to address the growing energy demand. In order to limit the negative drawbacks associated with EVs charging demand, the paper proposes a centralized approach for the EVs smart charging, and its performance are compared with the uncontrolled charging approach. An optimization framework is formulated in order to reduce both the overall peak power demand and the EVs charging cost according to the electricity prices during the day. Finally, several Monte Carlo simulations are carried out to evaluate the benefits introduced by the proposed scheduling strategy on a real case study, in terms of charging cost for EVs' users, satisfaction of EVs charging needs, and flattening of the load profile.

## 1 INTRODUCTION

Electric vehicles (EVs) are becoming a very interesting option to reduce both fuel consumption and greenhouse gas emissions in the transportation sector for the near future, (IEA, 2016). Therefore, world governments are pushing more and more electric mobility in the smart cities. As a result, EVs penetration is expected to reach an amount between 10% and 25% of the overall circulating vehicles in the 2010-2030, (Mukherjee, 2015). Unfortunately, lithium batteries of EVs still ensure a limited range of only 150-200 km, and they often need to charge, (Nissan, 2015). For these reasons, significant EVs charging activities will mostly take place in users' car garages, public or corporate car parks and dedicated charging stations (You, 2017 – Yu, 2016). However, a deep penetration of EVs could increase both average and peak load in the distribution networks, where the charging stations are usually connected, with a potential reduction of its reliability due to the overloads, (Hao Xu, 2016 – Veldman, 2015). Several studies showed that smart charging strategies could contribute to support a deeper penetration of EVs within distribution networks, (de Hoog, 2015 – Hao Xing, 2016). Thus, the need for optimal charging scheduling algorithms is becoming a relevant issue to face with future power system planning and management actions, (Kumar, 2015 – Qi Kang, 2016). Scheduling strategies, also, aim to optimize EVs charging cost introducing charging options based on real-time and/or day-ahead price information, (Cao, 2012 – Vandael, 2015).

The smart charging problem is well studied, and many approaches are proposed in the technical literature. Among them, it is possible to discern two main categories based on centralized or decentralized approaches, (Bina, 2015 – Esmaili, 2015). Decentralized scheduling assumes there is no central controller and all individuals decide or optimize their own charging profiles. Since smart grids are large-scale systems, centralized algorithms may be unfeasible due to lack of scalability, requirement for global information, and expensive implementation cost, while decentralized control algorithms are deemed as a promising alternative, (Jiang, 2014). The algorithms proposed in (Gan, 2013) require each EV reporting its power demand to an aggregator. The aggregator then broadcasts a few messages from which each EV makes locally based and binary charging decisions (charge or not charge). In (Wen, 2012), Authors consider a multi-layer hierarchical power network in which each sub-aggregator can decide the states of its associated EVs locally. On the other hand, the centralized scheduling algorithms



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provide a higher EV integration level in the existing grid, (Wanrong, 2014 – Zhou, 2014): in fact, a single operator controls precisely time duration and rates of all charging actions. Each EV submits detailed information to a central processing unit, which produces the charging schedule for each EV, considering various objectives, such as power loss and/or load variance minimization, or maximization of the EVs penetration level (Veldman, 2015 – Qi Kang, 2016). Within the literature, (Rezaee, 2013) presents a global scheduling optimization problem in which the charging events are chosen to minimize the total EVs charging cost during the day. (Cao, 2012) proposes optimized EV charging strategies in response to time-of-use (ToU) prices in a regulated market. Finally charging scheduling algorithms present an opportunity also to provide electric energy storage (EES)-based ancillary services, e.g., smoothing intermittency due to renewable energy sources (RESs) and supporting grid-widefrequency stability, (Zhang, 2014 – Falahati, 2016).

Here, we want to hightlight that a centralized approach to manage the scheduling of EVs, represents a good solution for two important aspects: i) by means of adequate optimization strategies it is possible to take into account the requirements of users, distribution systems, and aggregators; ii) in perspective, more different aggregators can represent controlled buses for a smart grid, and a centralized approach allows using the potentiality of the bus as generator, load or storageto support the distribution systems.

In order to highligth these potentialities, we propose a contribution that mainly consists of two parts: i) a formulation of an optimization problem to centralize the management of EVs charge, by flattening the demand load profile and minimizing the EVs charging costs, according to the electricity prices during the day; ii) the assessesment of the impact of EVs on a real microgrid to evaluate the benefits introduced by the proposed smart charging method.

The management proposal is tested by using measured data and identifying typical load cluster for the EVs charging demand.

The remainder of paper is organized as follows: Section 2 describes the data acquisition and clustering methods employed in the CO.S.MO. research project. Section 3 points out the mathematical formulation of the proposed scheduling problem, while results of several simulations based on the case study represented by the University of Salerno (UniSA) campus are discussed in Section 4. Finally, Section 5 ends the paper with concluding remarks.

# 2 MODELING AND PROBLEM FORMULATION

Here we describe the charging stations (CSs) model, the proposed approach to the centralized EVs smart charging and some details on its implementation.

## 2.1 Charging Mode

According to the Nissan Leaf specifications (Nissan, 2015), we consider two values of CSs' rated power for the incoming EVs in the parking areas: AC1 (230 V, 3.3 kW) for domestic use charging and AC2 (230 V, 6.6 kW) for public use charging, (de Hoog, 2015). However, the proposed methodology can be applied even in the case of other types of charging stations. For each $CS_i$, given the residual SoC value of the EV connected to it, $SoC_i(t)$, its variation at time $t+dT$ is described as follows:

$$\begin{aligned} &SoC_i(t+dT) = SoC_i(t) + \frac{P_i^{Batt}(t)\cdot dT}{3600\cdot C^{Batt}} \\ &P_i^{Batt}(t) = \eta \cdot P_i^{CH} = V_i(t)\cdot I_i(t) \end{aligned} \tag{1}$$

Where $dT$ is the time-step, $P_i^{CH}(t)$ represents the charging power at charging station $CS_i$, and $\eta$ is the charging efficiency. $P_i^{Batt}(t)$, $V_i(t)$ and $I_i(t)$ are the battery charging power, voltage and current, respectively, computed according to the constant current (*ccm*) and constant voltage (*cvm*) charging mode of the EV battery, (Cao, 2012): they are approximated by (2) and depicted in Figure 1.

$$\begin{cases} I_i = I_i^{cc}\cdot u_i^{SoC} + I_i^{cc}\cdot \exp\left(-\dfrac{t}{T_i^{cc}}\right)\cdot\left(1-u_i^{SoC}\right) \\ V_i = V_i^{cv}\cdot\left(1-\exp\left(-\dfrac{t}{T_i^{cv}}\right)\right)\cdot u_i^{SoC} + V_i^{cv}\cdot\left(1-u_i^{SoC}\right) \end{cases} \tag{2}$$

Here $I_i^{cc}$ and $T_i^{cc}$ represent the current values and the duration, respectively, of the battery in *ccm*, while, $V_i^{cv}$ and $T_i^{cv}$ represent the minimum voltage, the maximum voltage and time constant of the battery, respectively, in *cvm*. Finally, $u_i^{SoC}$ is a binary variable and its value is defined by the SoC value. In particular, we assume the *ccm* for SoC values below 80% and thus we set $u_i^{SoC}$ = 1, while $u_i^{SoC}$ = 0 in the *cvm* where SoC > 80%.

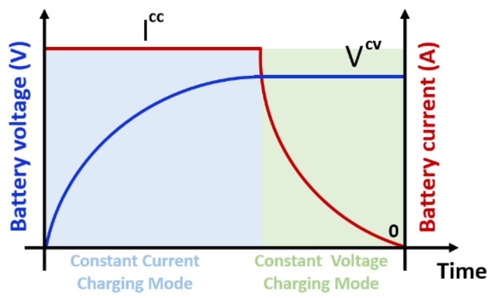


Figure 1: Charging modes of the battery pack.

We define the effective charging time $t_i^{CH}$ for the EV user connected to the $CS_i$ as the minimum value between the expected parking time $T_i^{PARKING}$ and the required time to fully charge the EV, $T_i^{CHARGE}$. If $T_i^{PARKING} < T_i^{CHARGE}$, then $t_i^{CH}$ is set to the time required to the $CS_i$ to bring the SoC to such a value as to allow the EV user coming back to its departure site. In this case, it is necessary to wait for an extra time before the charging session is complete.

To address the worst case in terms of additional load required at the point of common coupling (PCC), we assume the number of available CSs equal to the capacity of the considered parking areas.

## 2.2 Scheduling Optimization Problem

The main idea of the proposed scheduling approach is to break the required charging time into many small charging intervals within the parking time, (Rezaei, 2014). In each scheduling-slot, $\Delta t$, if enabled, a CS can charge the EV connected to it only for the duration of the scheduling-slot providing a charging packet. During each $\Delta t$, the algorithm assigns the starting time of each charging packet for all EVs in the parking areas minimizing the peak demand and the charging cost at the same time. Each EV is charged according to a FCFS - first come first serve - service policy. The proposed scheduling technique is mathematically formulated as follows:

$$\begin{cases} \min\limits_{t_{i,j}^{START} \in \Re} J \\ J = \sum\limits_{i=1}^{N_{CS}} \int\limits_{T_i^{PARKING}} \sum\limits_{j=1}^{N_i^{PACK}} c(t - t_{i,j}^{START}) \cdot \left[ p^{BASE}(t) + p_i^{CHARGE}(t - t_{i,j}^{START}) \right] dt \end{cases} \quad (3)$$

The problem (3) is subject to the constraints (4):

Where NCS is the number of CSs, represents the number of charging packet for the EV at CSi (it is the first integer greater than /Δt). Moreover, c(t) represents the electricity unit price depending on the hours of day, is the starting time of the j-th charging packet related to the EV connected to the CSi. Finally, (t) is the forecasted base load including production from RES whereas (t) is the charging power supplied by CSi to the EV.

Finally, $p^{BASE}(t)$ is the forecasted base load including production from RES whereas $p_i^{CHARGE}(t)$ is the charging power supplied by $CS_i$ to the EV.

$$\begin{cases} t_{i,1}^{START} \geq t & \forall t, \forall i = 1,\dots,N_{CS} \\ t_{i,j+1}^{START} \geq t_{i,j}^{START} + \Delta t & \forall i = 1,\dots,N_{CS} \\ & \forall j = 1,\dots,N_i^{PACK} \\ t_{i,N_i^{PACK}}^{START} + \Delta t \leq T_i^{PARKING} & \forall i = 1,\dots,N_{CS} \\ \int\limits_{T_i^{PARKING}} p_i^{CHARGE}(t)dt = (1 - SoC_i^{START})C^{Batt} & \forall i = 1,\dots,N_{CS} \\ 0 \leq p_i^{CHARGE}(t) \leq \dfrac{P_i^{Batt}(t)}{\eta} & \forall i = 1,\dots,N_{CS} \end{cases} \quad (4)$$

In (4), $SoC_i^{START}$ and $P_i^{Batt}(t)$ are the residual SoC values of the EV at the $CS_i$ and its required charging power, respectively.

## 2.3 Method of Solution

A heuristic algorithm based on genetic algorithm (GA) is proposed to solve the scheduling problem. The GA based scheduler for each EV in the parking areas computes the scheduling-slot sequence in which each EV is enabled to receive a charging packet. We use a binary chromosome changing its length according to the $T_i^{PARKING}$ value, for each EV in the parking areas. Thus, they are aggregated into a single 2-dimensional chromosome representing the scheduling solution.

The structure of the scheduling chromosome composed by several EV-chromosome with different length is shown in Figure 2. The scheduling is a

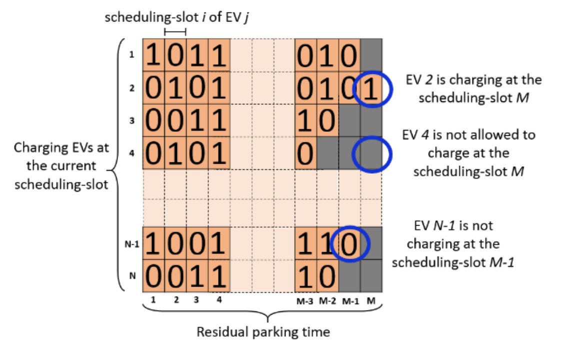


Figure 2: Genetic representation of the scheduling.

is a 2-dimensional matrix having number of row equal to the EVs in the parking areas, *N*, and number of column depending on the maximum parking time (in scheduling slot), *M*, among all the EVs. The number and the length of the scheduling chromosome also affects the simulation speed performance and the reliability of the final solution. Therefore, we impose a limit of 10.000 iterations and a population of 20 scheduling chromosomes.

In Figure 3 is shown the proposed scheduling architecture: a central controller (CC) is assumed receiving the forecasted base load and the production from RES for the day. Each charging station communicates with a local controller (LC) - one for each parking area - to send the charging update/request of the EV connected to it. LCs acquire and aggregate data sent by the CSs located in their parking area and transmit them to the CC. According to data provided by LCs, CC performs the scheduling optimization deciding when to allow each CS to charge the EV connected to it.

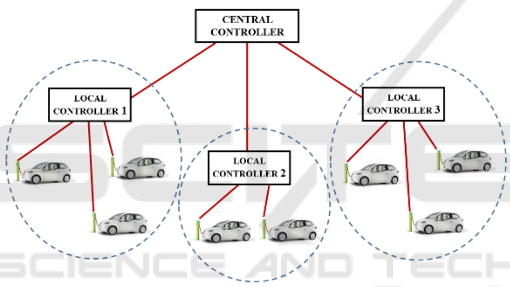


Figure 3: Architecture of the coordinated scheduler.

In the following, the CC and LC routines, performed on a daily base, are shown.

```
Initialize: The CC forecasts the base
load for the current day.

Loop (for each scheduling slot):
   Begin LC routine
      1. Receive the scheduled charging
         sessions for the current time slot
         from the CC.
      2. Acquire new charging request.
      3. Update charging vehicles status.
      4. Send data to the CC.
   End
   Begin CC routine
      1. Receive the new charging request
         and the charging vehicles status
         for the current time slot.
      2. Run the EVs scheduling strategy
         to all the vehicles in the parking
         areas.
      3. Update base load profile
         addicting in charge EVs.
      4. Update the base load forecast,
         including the RES
      5. Send data to the LCs.
   End
End
```

## 3 SIMULATION AND RESULTS

To show the effectiveness of the presented methodology, a Monte Carlo simulation framework is implemented to calculate the EVs charging needs starting from given statistical distribution of incoming EVs, their parking times and residual SoC values, (Calderaro, 2014). We use real data acquired during the fulfilment of CO.S.MO. research project, and processed through clustering operations.

### 3.1 Case Study

The UniSA microgrid is a 12 bus 20 kV distribution system with two feeders configured in closed loop. Connected to the grid, there are several distributed generators (DG): two cogeneration (CHP) units, with a rated power of 580 kW each one, and eight photovoltaic (PV) power plants for a total PV rated power of 1076 kW installed on the roof of the campus buildings. CHP units produce both electricity used to supply the loads and thermal energy used to heat water of the campus sport facilities.

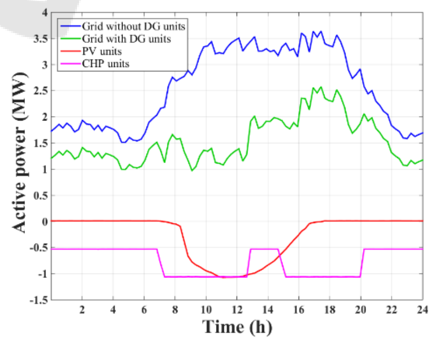


Figure 4: Active power drown from the UniSA microgrid.

In Figure 4 is shown the typical daily profiles of the net active power drown from the main external PCC by the UniSA network. Blue and green lines depict the active power absorption with and without internal PVs and CHPs, respectively. Finally, red and pink lines show the average (calculated every 15 minutes) active power generated by the PV and CHP units.

Table 1: Daily price of the electricity cost.

| Price category | Hours | Days |
|---|---|---|
| F1 – Peak | 10:00 - 15:00 / 18:00 - 21:00 | Monday to Friday |
| F2 – Mid-level | 07:00 - 10:00 / 15:00 - 18:00 / 21:00 - 23:00 | Monday to Friday |
| | 07:00 -23:00 | Saturday |
| F3 – Off-peak | 23:00 - 07:00 | All the week and holidays |

Table 1 shows the three hourly price categories for the electricity cost in the UniSA campus. Adopting the actual prices of peak, mid-level and off-peak load period in the city are 0.18 €/kWh, 0.14 €/kWh and 0.10 €/kWh, respectively, (Enel Distribuzione, 2017).

## 3.2 Data Acquisition

CO.S.MO. (Cooperative Systems for Sustainable Mobility and Energy Efficiency) was a 32-months pilot project co-founded by the European Commission involving the installation of advanced intelligent transportation system (ITS), in three pilot sites: Göteborg (SE), Vienna (AT), and the UniSA campus in Salerno (IT), (Alcaraz, 2013). The scope of CO.S.MO. was to prove and quantify the benefits of cooperative mobility services for increasing the energy efficiency of infrastructures and vehicles.

Figure 5: Parking areas at UniSA - Google Maps view.

Several cameras and antennas systems were installed at both entrances and exits of UniSA parking areas (outlined in Figure 5), in order to record data related to their occupancy level. They were able to read vehicles plates, date, time and parking time: all data was stored in a database. It consists of more than 200.000 parking events over a one-year period of observation. The collected data are representative of the parking areas used by a significant number of students with their own car.

## 3.3 Data Clustering Results

In order to assess the different state of charge (SoC) values for trips made with EVs, we evaluate the origin-destination routes of students enrolled at the UniSA. The data analysis allows classifying all different paths to reach UniSA campus from different departure points in terms of urban, extra urban and highway routes. According to the studies published by the Idaho National Laboratory, (INL, 2015) real users of EVs show a strong preference to charging in the evening and driving during the day. Thus we assume the students' EVs leaving fully charged from each departure point (e.g., students' homes), and we derive the arrival residual SoC by using Eq. 5.

$$SoC_a = SoC_d - \frac{(c_U \cdot d_U) + (c_E \cdot d_E) + (c_H \cdot d_H)}{C^{Batt}} \qquad (5)$$

Where $SoC_a$ e $SoC_d$ are the arrival and departure SoC values, respectively, and $C^{Batt}$ [kWh] is the EV's battery capacity. Here, $c_U$, $c_E$, $c_H$ [kWh/km] represent the energy consumptions coefficients, whereas $d_U$, $d_E$, $d_H$ [km] are the distances covered in the urban, extra urban, and highway route, respectively.

We compute the electric energy consumption of the EVs associated to each travel, assuming as reference EV the Nissan Leaf model, having battery capacity of 24 kWh. The manufacturer provides the average consumptions for different route types and they are shown in Table 2, (Nissan, 2015).

Table 2: Nissan Leaf Energy Consumption.

| Route Type | Value [kWh/km] |
|---|---|
| Urban | 0.160 |
| Extra urban | 0.126 |
| Highway | 0.185 |
| Mixed | 0.169 |

By analysing the departure points of the UniSA students considering the shortest path to reach the campus, 50 clusters are derived, each one with a different residual SoC value at the arrival in the parking areas (Figure 6). The average residual SoC value of EVs arriving at the UniSA is approximately equal to 70%.

Figure 7 illustrates the statistical distribution of the average EVs parking time. In particular, the most of the students arrive at the UniSA campus around the 8:30 a.m. and they are characterized by an average parking time of 4 hours. This fact leads to an expected peak demand for charging between 9:00 a.m. and 12:00 a.m. that can be flattened by the scheduler according to the parking time declared by each EV.

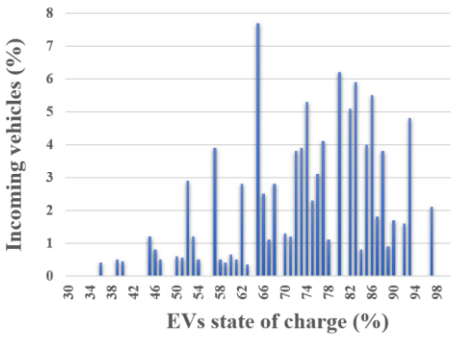


Figure 6: Residual SoC of incoming EVs.

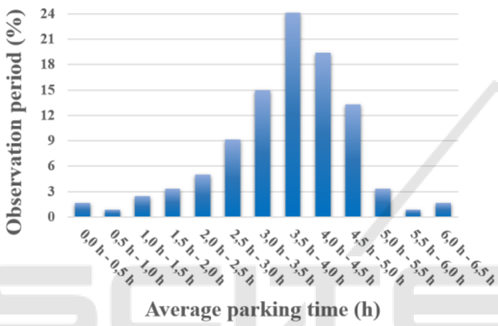


Figure 7: Average parking time of incoming EVs.

Data related to the parking areas occupancy and hourly rate of incoming EVs, collected during the observation period, on a day-by-day base, are analysed in order to find common features concerning the days of the week, months, and seasons. Thus, they are taken into account by splitting the observation period into different clusters.

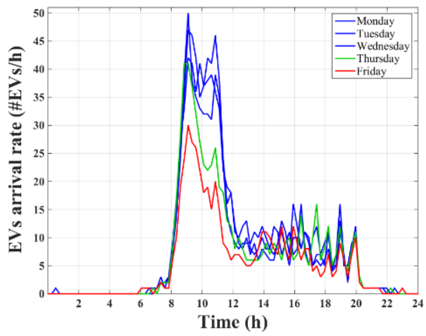


Figure 8: Arrival rate of incoming EVs (courses period).

The clustering function is implemented by using the *k-means* algorithm because it ensures a very quick convergence and it minimizes the total intra-cluster variance. All the observed days are divided in two main clusters: the first one concerning the institutional courses period and the second one related to the examination period. The courses period cluster is characterized by days in which the EVs' arrival rate is significantly greater than those are in the examination period cluster. It is possible to subdivide the first main cluster in three other different sub-clusters: from Monday to Wednesday, Thursday and Friday respectively. In Figure 8 is shown the EVs' arrival rate cluster to one parking area for each day of the week, during the institutional courses periods. The examination period is considered as a single cluster, because of the absence of relevant differences among the weekdays. Thus, four different daily clusters are assumed adequate to describe arrival rate concerning the three parking areas.

### 3.4 Scheduled Ev Charging Results

Figure 9 and Figure 10 show the comparison between the uncontrolled charge and the proposed scheduling strategy assuming AC1 and AC2 charging stations, respectively. It is worth to note a flattened load profile and a significant reduction of the peak power absorption in the hours between 8:00 a.m. and

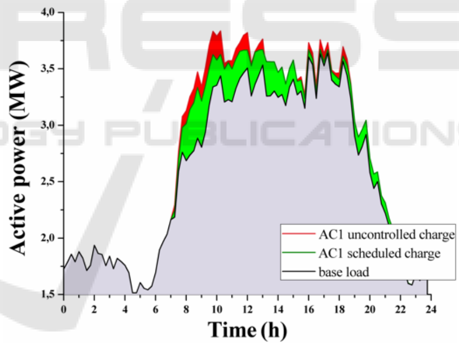


Figure 9: Comparison between uncontrolled and scheduled charging (AC1 CSs).

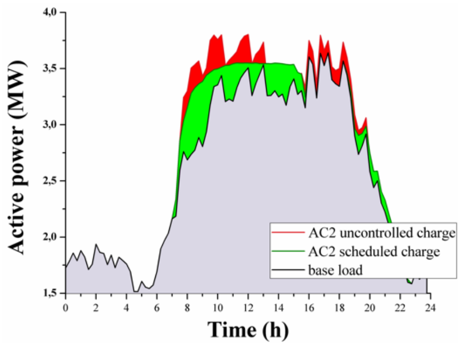


Figure 10: Comparison between uncontrolled and scheduled charging (AC2 CSs).

12:00 p.m. compared to the uncontrolled charging Specifically, the proposed scheduling algorithm shows, at 9:45 a.m., a peak reduction of 232 kW and 326 kW for AC1 and AC2 charging stations, respectively. On the other hand, the scheduler significantly increases the load profile during the hours of low charging demand assuming the uncontrolled charging, e.g. between 2:00 p.m. and 4:00 p.m. The charging peak demand by using AC1 CSs is slightly higher than the peak of the base load (at 17:00 p.m.) while it is always lower by using AC2 CSs. Furthermore, Table 3 shows the comparison on battery SoC level reached by EVs between AC1 and AC2 CSs. In particular, the number of EVs having battery SoC level able to get home the user, and the number of fully charged EVs compared to the overall EVs are assumed as performance indices.

Table 3: SoC level (AC1 and AC2 CSs).

| **Residual SoC [%]** | **Number of EVs** | |
|---|---|---|
| | **AC1 mode** | **AC2 mode** |
| SoC ≥ 80 | 100 (87) | 100 (94) |
| 65 ≤ SoC < 80 | 100 (74) | 100 (83) |
| 50 ≤ SoC < 65 | 92 (50) | 99 (92) |
| 30 ≤ SoC < 50 | 62 (41) | 80 (72) |

By using the AC1 CSs the scheduler ensures to all users with residual SoC value higher than 65% to come back to their departure point, but not to fully charge their vehicle. For users with residual SoC value less than 65% (about 20% of all EVs in a single day), the performance indices are higher than 70%. However, AC2 CSs ensure that all incoming EVs in a day are able to come back to their starting point, but only 90% can fully charge their vehicle. Table 4 shows the comparison concerning the charging extra time by using the proposed scheduling strategy between AC1 and AC2 modes. The average extra time required to complete the EVs charge is considered when $T^{PARKING} < T^{CHARGE}$: it is due to EV user expected parking time and it is minimized by scheduling operations. By using AC1 CSs, EVs with the lowest residual SoC value have to wait an average extra-time of about 2 hours, whereas AC2 CSs lead to an average extra-time less than 1 hour.

Table 4: Charging extra time (AC1 and AC2 CSs).

| **Residual SoC [%]** | **Average extra time [min]** | |
|---|---|---|
| | **AC1 mode** | **AC2 mode** |
| SoC ≥ 80 | 45 | 18 |
| 65 ≤ SoC < 80 | 74 | 30 |
| 50 ≤ SoC < 65 | 99 | 46 |
| 30 ≤ SoC < 50 | 121 | 52 |

Finally, Table 5 shows the comparison concerning the average charging cost by using the proposed scheduling strategy. In particular, EV user benefits of a slightly reduction in the average charging cost because the chronological shift of the charging packets allow to obtain a lower electricity cost. In particular, the average charging cost is reduced by 16.2% and 18.5% compared to uncontrolled charge and considering AC1 and AC2 CSs, respectively.

Table 5: Charging cost (AC1 and AC2 CSs).

| **PEV charge** | **Average charging cost [€]** | |
|---|---|---|
| | **AC1 mode** | **AC2 mode** |
| Uncontroled | 1.78 | 1.62 |
| Scheduled | 1.49 | 1.32 |

## 4 CONCLUSIONS

The paper presents a centralized scheduling algorithm for optimizing EVs charge in smart grids in order to minimize the EVs charging costs and reduce the peak power demand. The UniSA parking areas are characterized in terms of incoming EVs rate and hourly occupancy level, according to a large measured database, in order to evaluate the EVs charging demand. Several Monte Carlo simulations are performed to test the proposed scheduling algorithm. Obtained results confirm the effectiveness of the proposed scheduling algorithm: by using AC1 CSs, it ensures up to 75% of users the minimum charge required to come back to their departure point, whereas by using AC2 CSs it ensures the fully charge to over 90% of users. Finally, the EV user's further benefits by a lower charging cost compared to the uncontrolled charge. In conclusion, the obtained results proof that by means of optimization strategies it is possible to take into account the requirements of users, distribution systems, and aggregators; furthermore, with regard to distribution system impact, the results show that an aggregator is a potential smart bus that can bring many benefits to distribution systems.

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# REFERENCES

International Energy Agency (IEA), 2016. World Energy Outlook. Available on line at url http://www.worldenergyoutlook.org /weo2016/

Mukherjee, J.C., Gupta, A., 2015. A Review of Charge Scheduling of Electric Vehicles in Smart Grid. In *IEEE Systems Journal*, vol. 9, pp. 1541-1553.

Nissan, 2015. Nissan Leaf prices and specifications. Available on-line at: <http://media.nissan.eu/content /dam/pes/GB/leaf/prices_and_equipment/pdf/New-LEAF-Tech-Spec-and-Pricesv3.pdf>, pp. 1-7.

You P., Low S. Tushar W., Geng G., Yuen C., Yang Z., Sun Y., 2017. Scheduling of EV Battery Swapping, I: Centralized Solution. In *IEEE Trans. on Control of Network Systems*, vol. PP.

Rong Yu R., Zhong W., Xie S., Yuen C. Gjessing S., Zhang Y., 2016. Balancing Power Demand through EV Mobility in Vehicle-to-Grid Mobile Energy Networks. In *IEEE Trans. on Industrial Informatics*, vol. 12, pp. 79-90.

Hao Xu, Fan Ouyang, Haifeng Liu, Shihong Miao, Haiguo Tang, Wenwu Liang, Hui Li, Dongyuan Shi, 2016. A probability load modeling method for the charging demand of large-scale PEVs accounting users' charging willingness. In *International Journal of Electrical Power & Energy Systems*, vol. 82, pp. 331-338.

Veldman, E., Verzijlbergh, R.A., 2015. Distribution Grid Impacts of Smart Electric Vehicle Charging From Different Perspectives," *IEEE Trans. on Smart Grid*, vol. 6, pp. 333-342.

de Hoog, J., Alpcan, T., Brazil, M., Thomas, D.A., Mareels, I., 2015. Optimal Charging of Electric Vehicles taking Distribution Network Constraints into Account. In *IEEE Trans. on Power Systems*, vol. 30, pp. 365-375.

Hao Xing, Minyue Fu, Zhiyun Lin, Yuting Mou, 2016. Decentralized Optimal Scheduling for Charging and Discharging of Plug-In Electric Vehicles in Smart Grids. In *IEEE Trans. on Power Systems*, vol. 31, pp. 4118- 4127.

Kumar K.N., Sivaneasan B., Lam So, P., 2015. Impact of Priority Criteria on Electric Vehicle Charge Scheduling. In *IEEE Trans. on Transportation Electrification*, vol. 1, pp. 200-210.

Kang, Q., Wang, J., Zhou, M., Ammari, A.C., 2016. Centralized Charging Strategy and Scheduling Algorithm for Electric Vehicles Under a Battery Swapping Scenario. In *IEEE Trans. on Intelligent Transportation Systems*, vol. 17, pp. 659-669.

Cao, Y. Tang, S., Li, C., Zhang, P., Tan, Y., Zhang, Z., Li, J., 2012. An Optimized EV Charging Model Considering TOU Price and SOC Curve. In *IEEE Trans. on Smart Grid*, vol. 3, pp. 388-393.

Vandael, S., Claessens, B., Ernst, D., Holvoet, T., Deconinck, G., 2015. Reinforcement Learning of Heuristic EV Fleet Charging in a Day-Ahead Electricity Market. In *IEEE Trans. on Smart Grid*, vol. 6, pp. 1795-1805.

Bina, T., Ahmadi, D., 2015. Stochastic modelling for scheduling the charging demand of EV in distribution systems using copulas. In *International Journal of Electrical Power & Energy Systems*, vol. 71, pp. 15-25.

Esmaili, M., Goldou, A., 2015. Multi-objective optimal charging of plug-in electric vehicles in unbalanced distribution networks. In *Int. Journal of Electrical Power & Energy Systems*, vol. 73, pp. 644-652.

Jiang, T., Putrus, G., Gao, Z., Conti, M., McDonald, S., Lacey, G., 2014. Development of a decentralized smart charge controller for electric vehicles. In *International Journal of Electrical Power & Energy Systems*, vol. 61, pp. 355-370.

Gan, L., Topcu, U., Low, S.H., 2013. Optimal decentralized protocol for electric vehicle charging. In *IEEE Trans. on Power Systems*, vol. 28, pp. 940-951.

Chao-Kai Wen, Jung-Chieh Chen, Jen-Hao Teng, Pangan Ting, 2012. Decentralized energy management system for charging and discharging of plug-in electric vehicles. In *Wireless Communications & Signal Processing Int. Conference*, pp. 1-6.

Wanrong T., Suzhi Bi, Y.J.A. Zhang, 2014. Online Coordinated Charging Decision Algorithm for Electric Vehicles without Future Information. In *IEEE Trans. on Smart Grid*, vol. 5, pp. 2810-2824.

Kan Zhou, Lin Cai, 2014. Randomized PHEV Charging Under Distribution Grid Constraints. In *IEEE Trans. on Smart Grid*, vol. 5, pp. 879-887, March 2014.

Rezaee, S., Farjah, E., Khorramdel, B., 2013. Probabilistic analysis of plug-in electric vehicles impact on electrical grid through homes and parking lots. In *IEEE Trans. on Sustainable Energy*, vol.4, pp. 1024-1033.

Tian Zhang, Wei Chen, Zhu Han, Zhigang Cao, 2014. Charging Scheduling of Electric Vehicles with Local Renewable Energy under Uncertain Electric Vehicle Arrival and Grid Power Price. In IEEE Trans. on Vehicular Technology, vol. 63, pp. 2600-2612.

Falahati, S., Taher, S.A., Shahidehpour M., 2016. A new smart charging method for EVs for frequency control of smart grid. In *International Journal of Electrical Power & Energy Systems*, vol. 83, pp. 458-469.

Alcaraz, G., Galdi, V., Trapuzzano, A., 2013. Cooperative Systems for Energy Efficiency and driver behaviour change: University of Salerno Pilot Site Results. In *ITS European Congress*, pp. 1-6.

Idaho National Laboratory (INL), 2015. Plugged In: How Americans Charge Their Electric Vehicles. Available on-line at: <https://avt.inl.gov/sites/default/files/pdf/ arra/SummaryReport.pdf>.

Rezaei, P., Frolik, J., Hines, P.D.H., 2014. Packetized Plug-In Electric Vehicle Charge Management. In *IEEE Trans. on Smart Grid*, vol. 5, pp. 642-650.

Calderaro, V., Galdi, V., Graber, G., Massa, G., Piccolo, A., 2014. Plug-in EV charging impact on grid based on vehicles usage data. In *IEEE International Electric Vehicle Conference*, pp. 1-7.

Enel Distribuzione, 2017. Price categories for the electricity cost. Available on-line at: <https://www.enelservizio elettrico.it/itIT/tariffe/altriusi/bta-6-trioraria>.