Vehicle-to-Home Usage Scenarios for Self-Consumption Improvement of a Residential Prosumer With Photovoltaic Roof

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Vehicle-to-Home Usage Scenarios for Self-Consumption Improvement of a Residential Prosumer With Photovoltaic Roof

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***Abstract* — This paper proposes a procedure for the control of Electric Vehicle (EV) batteries, aiming to have an optimal matching between local renewable production, domestic loads and EV consumption. The procedure starts with the analysis of historical PhotoVoltaic (PV), EV and domestic load profiles. Load and PV profiles are forecasted using statistical based algorithms, while the expected patterns of EV usages are forecasted using a combination of statistics and clustering techniques. Then, the forecasted profiles are used to estimate future energy balances trough an optimization process. Finally, the real time management corrects the forecasting logic and checks the parameters of the EV storage to guarantee its correct and safe operation. Three different EV usage profile (obtained by the clustering of 215 real users) are shown and their impact on the energy balance of EV-PV-home systems is quantified. The results are finally compared with those obtained with a traditional rule-based logic working without forecasts, by also reporting a detailed analysis of the main aspects having an impact on the results.**

Keywords— Electric vehicles, photovoltaic systems, battery management systems, forecasting, prosumer.

I. INTRODUCTION

A. Motivations

The worldwide industrialization and the increasing demand for electricity result in problems of energy supply and environmental pollution. As an example, in 2017, the transportation sector was responsible of 24% of direct CO_2 emissions in the world [1]. Referring only to transportation sector, road vehicles (e.g. cars and trucks) accounted for 77% of both global energy demand and CO_2 emissions. Thus, the renewal of transportation sector is fundamental for an effective fight against climate change. In fact, research and industry are working for the electric conversion of the transportation sector [2][3][4], that will even more supplied by Renewable Sources (RS). Moreover, the installation cost of renewable systems, especially Photovoltaic (PV) generators faced a drop in the last years [5]. Thus, in many countries, the local electricity production is more cost-effective than the absorption from the grid [6]. Furthermore, the batteries installed in Electric Vehicles (EV) could increase the use of renewable resources and the flexibility of the electric system. As a result, a recent line of research is studying the use of EVs and their effects on the energy balance of users equipped with charging station and photovoltaic generators. This kind of research is in line with the exploitation of the concept of Power-to-X [7], which has been recently exploited for coupling different sectors with proper conversion systems (e.g., Power-to-Gas [8]). The cases investigated in this paper aim to present an application combining the concept of Power-to-Mobility (P2M) and Power-to-Home (P2H) applied to residential customer. These applications aim both to guarantee the sufficient level of charge to the vehicle, and to increase the exploitation of RS-based production. The choice to investigate the above aspects for residential customer has been driven by the issue of recent standards that already indicate as potential charging mode the one using the home plant. For example, IEC 61851 [9]) defines this kind of charging mode as Mode 1.

In line with this and considering charging points equipped with bi-directional conversion units, it is possible to exploit the presence of a battery system (installed on the car) to improve the performance of the prosumer where non-dispatchable generation (i.e., PV system), radial distribution system (the home plant), loads and a storage system (not always available, i.e., the electric vehicle) are installed. It is worth noting that the case study considers a grid (i.e., the home plant) connected to the main grid, and it is thus considered that the system operator is still responsible for guaranteeing frequency and voltage quality standards.

B. State of the art

The interaction between loads, PV and EVs is not new in literature. For example, [10] and [11] show two case studies. In both cases, real residential loads and PV production profiles are analyzed, and stochastic models are used to predict future energy flows due to the use of EVs. The results show that, thanks to EVs, an improvement in the matching between PV generation and loads is possible, with consequent energy and economic benefits for the users. In [12], the energy and the environmental performance of a PV system that satisfies the electric demand of a single EV, as well as the space heating and cooling demand of an office building in Southern Italy is analyzed. Under the assumptions made by the authors, the simulations put into evidence that, in the best case, 59% of the PV production is used by local loads and an EV. A similar work was presented in [13], where the benefit of using PV to charge EV is investigated from the point of view of electric

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grid management. As a matter of fact, the distribution system operator would reduce the negative effect of high numbers of distributed generators in the grid (such as voltage fluctuations [14], harmonic content increase [15], and the overheating of the power lines). In [13], they concluded that, despite the better matching between loads and PV generation introduced by EVs, system upgrades will be still necessary (e.g., the installation of new transformers with higher sizes and the reduction of impedance of lines).

In the above cited works, the main issue is the lack of an advanced control strategy for the optimal management of batteries. In particular, storage is simply discharged when power is required by the car, and batteries are charged when the car is connected to the charging station. A possible improvement consists of the development of a Smart Storage Management (SSM) for EV batteries, which optimizes charge-discharge cycles by pursuing a pre-defined goal. Following this logic, batteries inside the car can be used to feed residential loads (Vehicle-to-Home, V2H) or the grid (Vehicle-to-grid V2G). Obviously, the management must guarantee the correct work of the storage for traveling, by appropriate constraints.

In order to implement SSM, different possible approaches are proposed in literature. The first approach combines the management of the charge-discharge cycles of EV batteries with a real-time check of PV generation, loads and storage parameters. In literature, some energy management logics for EV/PV systems are based on the heuristic approach [16][17][18]. In such works, algorithms are based on simple logical rules to instantaneously react to new events (e.g. plugging/unplugging of an EV, increasing/decreasing of PV power). However, they use only real-time information and cannot optimize the charging pattern for a longer time period. As a conclusion, it is necessary to combine the prediction of future EV states with an efficient real-time management.

The second approach consists of a procedure, which does not perform a real time management: the optimal charge-discharge cycles are calculated by elaborating *a priori* production and EV/load profiles. The possible data elaboration algorithms are grouped in three main categories:

- *Deterministic* methods: the EV-PV-load profiles are inputs of the simulation, and they are fixed a priori. Examples of deterministic method applications for EV-PV-load systems are present in [19] and in [20]. In both cases, a linear optimization problem is solved, and a significant improvement is demonstrated. In particular, there is a better match between local PV production and loads, and the electricity cost reduction is achieved, with respect to the case without a smart storage management.
- *Stochastic* methods, which consider EV-PV-load profiles randomly generated on the base of opportune criteria. For example, Probability Density Function (PDF) for the PV production is built from historical data. Then, the PDF is used to randomly generate new profiles. The works in [21]-[23] show that the stochastic methods result in a more realistic analysis, with respect to deterministic methods.
- *Forecasting statistical* methods, which predict future EV-PV-load profiles based on historical data and analysis of trends. This forecasting method is used in [24] and [25] to predict power flows in a micro-grid, and in office buildings, respectively. Nevertheless, in the two above cited papers, the forecast is used only for PV and loads. For sake of simplicity, a deterministic approach has been used to estimate data related to electric vehicles.

By using deterministic and stochastic methods, it is not possible to evaluate the performance of a real time management system, which corrects its operation in case of differences between input information and real profiles. Finally, in [26], a forecasting statistical method based on model predictive control is proposed, which includes both the real time management and the forecast of EV usage. However, aspects related to the maximization of use of local renewable source and the maximization of energy efficiency are not addressed.

The present work is the extended version of [27]: in that paper, a heuristic algorithm had been used to define charge-discharge profiles of EV storage, whereas EV consumption profiles were based on the analysis of a survey, performed to analyze different scenarios for EV usage.

The main advancement presented in this paper consists of:

- The fully use of forecasts statistical methods for PV, loads and even EV profiles, in combination of a rule-based logic.
- The use of real data presented in [28] to choose the types of users, thus substituting in this way the survey used as data source in [27].
- The introduction of a new methodology which differs from the one presented in [27], as we now aim at improving the self-consumption acting on the charging/discharging cycles and not only at quantifying its generic improvement due to the introduction of EVs.

Furthermore, the paper presents a detailed analysis of the challenges existing when “human aspects” (i.e., the need of a sufficient level of charging for the trips) and weather conditions must be taken into account, showing results with perfectly forecasted data and data affected by forecasting error.

The remaining part of the paper is organized as follows: Section II presents the methodology, with emphasis on the different forecasting methods that are needed. Section III shows the results applied to three cases, by highlighting the aspects that can affect the results, whereas Section IV reports the concluding remarks.

II. Proposed Methodology

The present work proposes a methodology to correctly design a smart storage management for EV batteries in a residential electrical plant is shown in Fig. 1.

It includes a PV generator, residential loads, and an electric vehicle. The EV battery is charged by a charging station, and it can work both as controllable load (i.e., it can be charged from PV or the grid), or as controllable generator, (i.e., it can discharge to supply local loads). The PV generator is connected to the local AC bus through a DC/AC converter. No other storage systems exist, and thus, if the PV production is higher than the load and the car is not at home, the surplus is injected into the grid. The proposed methodology is shown in Fig. 2.

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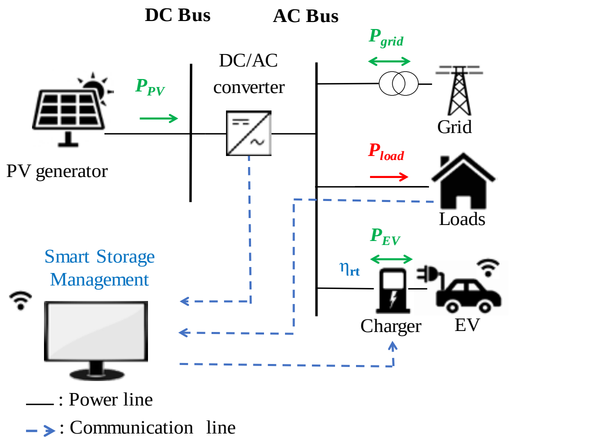

Fig. 1. Scheme of the residential building with a PV plant and EV charger

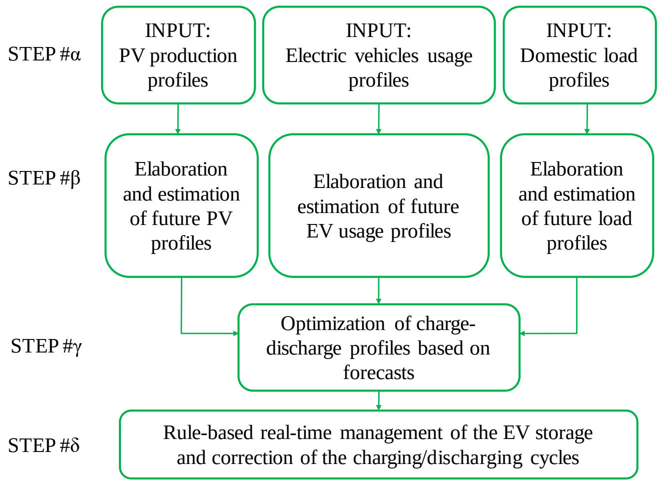

Fig. 2. Flowchart of the proposed procedure

In the STEP #α, the system imports in a database all the available historical data related to EV usage, PV generation and residential load profiles. In STEP #*β*, each data set is elaborated to estimate the future profiles (provided as weekly profiles with a 15-min time step). This step is explained in Sections II-A, II-B and II-C. In particular, for the EV usage profile forecasts algorithm in II-B, a data driven approach which combines statistical operations and clustering methodology (*kmedoids)* is used. For load and PV forecasts in II-C, an Autoregressive Moving Average Algorithms (ARMA) is used. The authors are aware about the possibility to use other machine learning methodologies (such as Artificial Neural Networks, ANNs) for forecasting Load, PV and EV usage profiles. However, ANNs return highly accurate results in an hourly and sub-hourly scale, while diverging for daily scale [29,30]. Therefore ANNs result inaccurate for the time windows considered in our work. In STEP #*γ*, an Energy Management Algorithm (EMA) uses the estimated energy flows to calculate the optimal charging/discharging patterns (Section II-D) Finally, STEP #*δ* consists of the real-time management of the storage based on real time data by taking into account the optimized results. In particular, the Battery Management System compares real energy flows and checks if they differ from the forecasted values. If necessary, charge-discharge profiles are changed, in order to follow the optimization criteria and always guarantee the safe and correct operation of the battery (Section II-E). Finally, in terms of hardware implementation, the methodology requires that the EV owns an on-board hardware able to collect the EV usage data and forecast the day-ahead behaviors referring to the car, and bidirectional converter. At the house side, a smart charger capable to collect on site production and consumption data is required, to forecast the day-ahead behaviors of load and generation, and to finally perform STEP #γ and STEP #δ.

A. Elaboration of intial EV usage profiles through clustering

In order to improve the battery management, some works propose the forecast of EV usage profiles [31–35]. The forecasts addressed in those works are based on the *aggregation* of a consistent number of EV cars, but they do not analyze in detail the prediction of a *single vehicle*.

On the other hand, the present work focuses on the behavior of an individual EV obtained from a clusterization applied to 215 EV usage pattern available in [28] covering three years (2013-2015). In particular, the database includes the departure and the arrival time, the distance and the energy consumed for every travel, but it does not include the destination. Thus, the information related to the presence of the car at home is missing, even if it is important for the clustering procedure. Therefore, an assumption is made: each EV is considered parked at home mainly during night. Moreover, it is assumed that if more than two trips are done between the first and the last trip of the day, at least one has as destination the user's home.

The EV presence at home is checked for each time step (1-min) and is stored in a boolean variable $x_{pres,t}$ indicating the presence of the EV. At time step t, the parameter $x_{pres,t}$ = 1, if the car is present at home, or $x_{pres,t}$=0 if the car is away. All x_{pres} status, among the period of observation of the EV, define the Boolean vector $\mathbf{x}_{pres}$. The average $\bar{x}_{pres}$, calculated on all the values included in $\mathbf{x}_{pres}$ represents the fraction of time in which the car is parked at home (i.e. the fraction of time in which EV storage exist). The $\bar{x}_{pres}$ values are the input of clusterization process, which aim to define of the most representative vehicles to perform simulations and generalize the results.

Clustering is performed with the k-medoid technique, which derives from the k-means algorithm [36]. These algorithms create groups of similar EV profiles by performing an iterative procedure. For each group, the algorithm defines a *centroid*, which is the (fictitious) profile that better represents the profiles in each group. The assignment of one profile to the correct group is performed comparing it with the current centroids, and thus each EV profile is included in the group with the most similar centroid. After each assignment, the centroid inside each group is updated to take into account the characteristics of the new added profile. The procedure is repeated until the distance between each group and respective centroid is minimized [37].

The main issue of these algorithms consists of the definition of the number of clusters k, that needs to be assumed a priori. A Silhouette Clustering Algorithm (SCA) can be useful to solve this issue [38]. In fact, the SCA defines if a profile is well represented by its group, or it should be part of another existing group, helping in the definition of the total number of clusters. In particular, the SCA calculates a dimensionless index S_{clust} that can range from -1 to 1. A high positive value indicates that the object is well represented by its cluster and it is poorly represented by the other clusters. Thanks to the combination of k-medoids and SCA, the optimal number of clusters that well represents the whole database is defined. The best silhouette average value (S_{clust} = 0.60) is obtained by dividing the whole database in three clusters. Therefore, the three respective centroids are chosen as representative EV's. In order to compare the different EV usages, this work considers four weeks: the fourth week of January, the first week of May, the third week of July, and the second week of October. These weeks are chosen among the dataset in order to have representative seasonal weeks especially with respect to the PV production and the load consumption profiles. Fig. 3 shows the comparison between the three chosen EV profiles EV#1, EV#2 and EV#3, during the fourth week of January. The x-axis shows the time-distribution of the trips during the entire week for the three EV profiles. The energy consumptions (in kWh) for each trip are shown on the y-axis. In addition, the shaded areas are used to indicate the periods of time in which the car is parked at home, i.e. the time in which EV storage could be used.

It can be noticed that EV#2 presents the most systematic behavior during the week compared to the other profiles. In fact, the car is not available during the working hours, while it is present during the night and often also during the weekend. Regarding the energy requirements, trips on weekends have higher consumption than the ones related to the weekdays. This profile is assumed to be related to a *typical worker profile*, working not far from home. In this case, the total presence at home is $\bar{x}_{pres,EV\#2}$ = 0.80.

Conversely, EV#1 presents higher energy consumption for working day trips. In this case the presence at home is the lowest ($\bar{x}_{pres,EV\#1}$= 0.70).

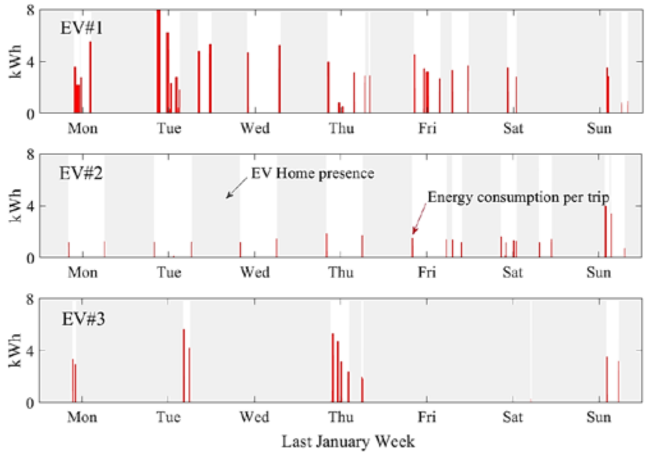

Fig. 3. Comparison between EV#1, EV#2 and EV#3 profiles during the last week of January

Finally, the EV#3 profile is characterized by the highest presence of the car at home (with $\bar{x}_{pres,EV\#3}$= 0.90), and also a less regular use. According to the analysis conducted in [27], the case of EV#3 can be considered as a freelance user. Table I reports more details about the three EV profiles in the four considered weeks. The energy consumption during the week is defined by the parameter E_{cons}, while $\bar{X}_{PV}$ represents the percentage of time in which PV is producing *and* EV is at home.

As above described the consumption of EV#1 is the highest among the four considered weeks. However, the match of the PV is poor. On the other hand, EV#3 present a lower consumption and a better match with PV with respect to EV#1. Finally, EV#2 represents an intermediate situation.

TABLE I. COMPARISON OF EV USAGE PROFILES.

		Jan	May	Jul	Oct
EV#1	E_{cons} **[kWh]**	110	65	80	76
	$\bar{X}_{PV}$ **[%]**	14	17	35	12
EV#2	E_{cons} **[kWh]**	36	35	30	32
	$\bar{X}_{PV}$ **[%]**	6	20	33	8
EV#3	E_{cons} **[kWh]**	45	20	38	50
	$\bar{X}_{PV}$ **[%]**	30	48	50	29

B. *Forecast of Electric Vehicle Usage Profiles*

Fig. 4 shows a flowchart containing the subroutine used to estimate the future use of the EV starting from historical data. In STEP#A, the historical data are imported for each day of the week, i.e., all Mondays are selected and analyzed, followed by the other days. In STEP#B, all the Mondays included in the database are extracted and the number of trips per each Monday is calculated. For example, considering a 1-year database the total number of Mondays is 52, and therefore 52 numbers of trips are stored in a vector $\mathbf{n}_{global}$. Then, in STEP#C it is defined the estimated value of trips that will occur in future Mondays n_{estim}, calculated as the statistical mode of the vector $\mathbf{n}_{global}$. In STEP#D, a subgroup $\mathbf{N}_{mode}$ is defined: it is a matrix containing the information only related to the Mondays with number of the trips corresponding *exactly* to the statistical mode n_{estim}.

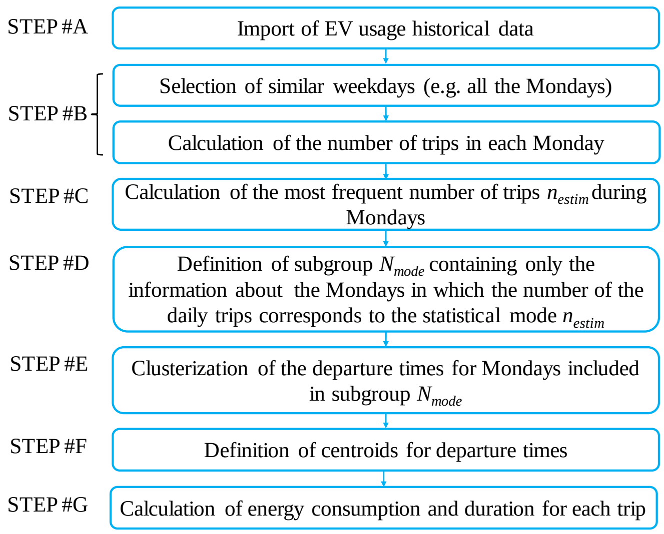

Fig. 4. Scheme of the subroutine for the esimation of EV usage profiles

After the definition of the expected number of trips per day, it is necessary to estimate also the departure time, the duration, and the energy consumption for each future trip. With this purpose, STEP#E performs the clusterization of the departure

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times occurred during the previous Mondays. In particular, the clusterization is carried out through k-medoids technique; only the information of the matrix N_{mode} is used for this operation. The centroids of the cluster are the first outputs of the procedure: they are calculated in STEP#F and provide information about the most probable departure times for the next Mondays. Finally, in STEP#G, trip duration and energy consumption of each trip are calculated as the average values considering all the trips occurring in a defined time-frame centered on the centroids. The same procedure is repeated for all the days of the week.

Fig. 5 shows an example of comparison between a measured EV usage profile (EV#2) and the related EV forecast, based on historical data. The forecast is performed according to the above described subroutine and refers to the winter week.

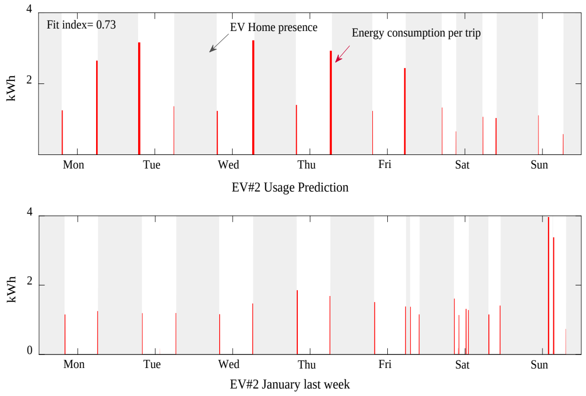

Fig. 5. Estimated and real EV usage profiles: EV#2 during january week

As in case of Fig. 3, Fig. 5 shows the distribution of the trips during the entire week. In addition, the shaded areas indicate the periods of time in which the car is expected to be parked at home. These areas are estimated on the base of the Boolean vector $\hat{\mathbf{x}}_{pres}$ defined similarly to $\mathbf{x}_{pres}$ in Section II-A.

In the specific case, the forecast of departure times is accurate (there is a good correspondence between the real and the forecasted trip times). However, in order to quantify these results, it is necessary to calculate the error between the expected consumption and the measured EV usage profiles. For every reference time window of two hours, the error Err_{EV} is calculated as the difference between measured consumed energy $E_{EV,meas}$ and the related prediction $E_{EV,pred}$, normalized by the average energy consumption $\bar{E}_{EV,meas}$ among the different time windows. The Forecast Quality Index (*FQI*) is then defined as the difference between the unitary value and the average of the errors Err_{EV}. The index assumes its maximum value 1 in the theoretical case of exact prediction, while it could assume negative values in case of poor estimation.

$$FQI_{EV} = 1 - \overline{Err}_{EV} \tag{1}$$

with

$$Err_{EV} = 1 - \frac{|E_{EVmeas} - E_{EVpred}|}{\bar{E}_{EV,meas}} \tag{2}$$

Table II shows the above described quality indexes for the three considered case studies (EV#1, EV#2, and EV#3). The index values are obtained for the three vehicles during the four seasons.

TABLE II. COMPARISON OF EV USAGE PROFILES.

	$FQI_{EV\#1}$	$FQI_{EV\#2}$	$FQI_{EV\#3}$
Jan	0.65	0.73	0.82
May	0.77	0.76	0.79
Jul	0.62	0.75	0.83
Oct	0.74	0.81	0.81

The indexes lie between 0.6 and 0.8. In particular, the highest values are obtained for the third case (EV#3) because, as described in Section II-A, this EV is generally parked at home, i.e., its use variability is low and easily predictable. Nevertheless, the prediction of EV#2 is well matched with the related real data: EV#2 is much more used than EV#3, but its usage profile is systematic, and it well represents the use of a daily worker.

C. Forecast of load and PV Production profiles

In order to optimize the management of the EV battery, it is necessary an estimation of future residential load and PV generation profiles. For this purpose, another subroutine, based on an Auto Regressive Moving Average (ARMA) algorithm [39], is introduced. In order to predict a week profile, it is performed the ARMA using the days before and after the week that has to be forecasted (or target week). For example, Fig. 6 shows the data used for the forecast of load consumption. The inputs are the 45 days before the target week and the 45 days after, respectively.

The values referring to the 45 days after are obtained from the previous year. The same procedure is used for PV production, with a different time frame, i.e. 30 days before and after the target week[1].

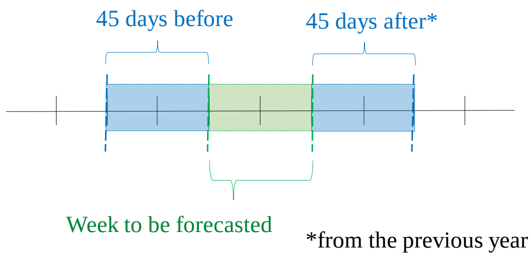

Fig. 6. Time frame used for the residential load forecasts

Fig. 7 shows the comparison between the measurements of PV production and residential loads (Fig. 7a), and estimated profiles (Fig. 7b) during a winter week. The residential load and the PV production profiles are derived from a measurement campaign carried out during the years 2016-2017 in a household located in Northern Italy. The PV generator is a roof-mounted 6 kWp plant (inclination 15°, azimuth 90° W, latitude 45◦ 04’, longitude 7◦ 41’). The data have been scaled to obtain an equivalent 9 kWp power plant. Residential loads refer to a family of two people, which uses the most common appliances and an electric boiler for hot water. The description of the load and PV profiles is presented in [40]; the

[1] These time frames have been obtained by an iterative procedure: different time frame been checked and chosen on the basis of the defined quality estimation indexes values

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measurement uncertainties and the other main specifications of the data acquisition systems are reported in [41].

Both data-sets have a resolution of 1-min. In the case of PV generation, the estimated profile well matches the average real production, with the highest deviation in case of a rainy day (Wednesday).

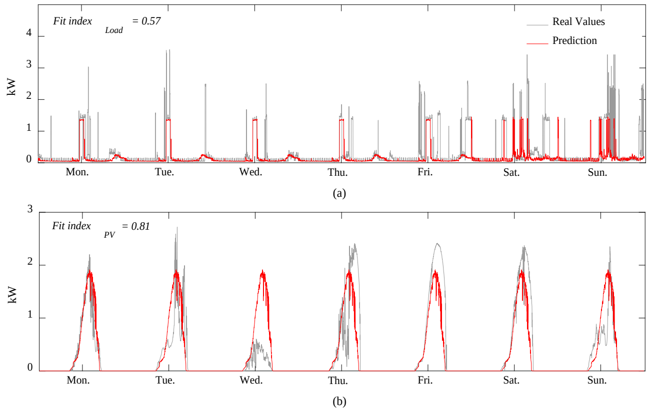

Fig. 7. Comparison between predictions and actual values for household loads (a) and PV generation (b) in the last week of January

Regarding loads, the variability is much higher, due to not regular behavior of the people in the family.

In order to quantify the quality of the forecasts, two quality indexes are introduced. In case of loads, for every reference time window, an error Err_{load} is calculated as the difference between measured absorbed energy $E_{load,meas}$ and the related prediction $E_{load,pred}$ normalized by the average energy consumption $\bar{E}_{load,meas}$ among the different time windows. The forecast quality index FQI_{load} is the difference between the unitary value and the average of the error Err_{Load}.

$$Err_{load} = \frac{|E_{load,meas} - E_{load,pred}|}{\bar{E}_{load,meas}} \tag{3}$$

$$FQI_{load} = 1 - \overline{Err}_{load} \tag{4}$$

The same criterion is used to calculate the forecast quality index for PV production

$$Err_{PV} = \frac{|E_{PV,meas} - E_{PV,pred}|}{\bar{E}_{PV,Pred}} \tag{5}$$

$$FQI_{PV} = 1 - \overline{Err}_{PV} \tag{6}$$

where $E_{PV,meas}$ is the measured PV production, $E_{PV,pred}$ is the predicted energy, and $\bar{E}_{PV,Pred}$ is the average PV energy produced in the reference period.

Table III shows the indexes calculated for the four weeks,. In all of them, the PV production is better estimated than load profiles. This is due to a lower variability in terms of energy of the PV in the time window considered. The only exception is October, in which the high variability in solar radiation (due to a long succession of sunny and cloudy days) leads to a worse forecast.

D. Optimization of charge-discharge profiles based on forecasts

In the proposed procedure, the future optimal charge-discharge profiles of the EV battery are obtained by minimizing the electricity exchange with the grid.

TABLE III. Comparison of EV Usage Profiles.

Week	FQI_{Load}	FQI_{PV}
29-05/Jan	0.57	0.81
01-7/May	0.54	0.65
17-23/Jul	0.68	0.86
09-15/Oct	0.63	0.35

This optimization is performed *before* the real time management, and it is based only on the forecasted power profiles. As defined in Section II-B, the expected presence at home of the EV is defined by the Boolean variable $\hat{\mathbf{x}}_{pres}$. Due to the presence of this variable, the following problem statement is formulated as a Mixed Integer Linear Programming (MILP). As above mentioned, the optimization consists of objective function defined in (7a), which is the minimization of the sum of grid exchanges ($P_{grid,t}$) in the N time steps composing the analyzed period (e.g., a week). The constraints of the optimization problem are defined as follows:

- The first constraint shown in (7b) imposes a null value for EV battery power ($P_{batt,t}$), if the car will not be at home i.e., if the Boolean $\hat{\mathbf{x}}_{pres}$ is equal to 0 in the time-step t.
- The constraint in (7c) consists of a charging power adjustment that limits the charge and discharge of the battery in order to do not exceed the Point of Delivery (POD) contractual power P_{contr}. The charging power adjustment is a control logic truly performed by most of the commercial EV chargers, as shown in [42]–[43].
- The constraint in (7d) is the power balance based on forecasted profiles.
- The constraint in (7e) ensures that the charged/discharged energy lies in the State of Charge (SOC) lower and upper boundaries, i.e., SOC_{min} and SOC_{max}, respectively

Finally, the SOC is defined by Equations (7f) and (7h), where E_{EVpred} is the EV absorbed energy per trip predicted, R_{batt} is the battery charged/discharged energy ratio, and $E_{tot,batt}$ is the capacity of the battery. From Equations (7f) and (7h) it can be seen that the only difference between charging and discharging consists in the round trip efficiency η_{rt}.

$$\min_{P_{batt,t}} \sum_{t=1}^{N} |P_{Pgrid,t}| \tag{7a}$$

s.t.

$$|P_{batt,t}| = 0 \qquad \forall t | \hat{x}_t = 0 \tag{7b}$$

$$P_{batt,t} \leq P_{contr} - P_{load,pred,t} \qquad \forall t \tag{7c}$$

$$P_{grid,t} = P_{PV,pred,t} - P_{load,pred,t} - P_{batt,t} \qquad \forall t \tag{7d}$$

$$SOC_{min} \leq SOC_t \leq SOC_{tmax} \qquad \forall t \tag{7e}$$

where

$$SOC_{t+1} \coloneqq SOC_t - \frac{E_{EVpred}}{Etot,batt} + R_{batt,t} \tag{7f}$$

$$R_{batt,t} \coloneqq \begin{cases} \frac{P_{batt,t} \cdot t}{E_{tot,batt}} \; if \;\; P_{batt,t} \geq 0 \\ \eta_{r,t} \cdot \frac{P_{batt,t} \cdot t}{E_{tot,batt}} \; if \;\; P_{batt,t} \leq 0 \end{cases} \tag{7g}$$

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The two SOC limits SOC_{min} and SOC_{max}, have been chosen according to battery degradation criterion. In particular, battery degradation can result from *over discharge* and *over charge* [45]. Therefore, the minimum and maximum SOC have been set to 30% and 95% respectively, similar to [46]–[51]. The round-trip efficiency η_{rt} is not easily estimable since it depends on many factors, such as technology of the battery, topology of the charge/discharge regulator, distance from the EV plug-in point to the PV source and the load connection points. However, the main producers of residential systems for the PV energy storage declare for their systems a round-trip efficiency around 80% [42]–[44].

In addition to the minimum level for the battery (SOC_{min}=30%), necessary to preserve battery life, another quota of energy is kept in the storage as an energy reserve. This reserve (expressed as a quota of the storage capacity E_{batt} in kWh) is added to the EV's SOC_{min} obtaining a new minimum threshold $SOC_{min,tot}$. It is calculated considering two factors: the predictability of the considered EV (or its Forecast Quality Index) and the predicted PV availability. In particular, three different cases are considered:

- Case #1: FQI >70 and a predicted PV availability > 50% of the total EV need

$$SOC_{min,tot} = SOC_{min} + 0.8 \cdot E_{for,travel}/E_{batt} \tag{8}$$

- Case #2: for FQI >70 and a predicted PV availability < 50% of the total EV need

$$SOC_{min,tot} = SOC_{min} + 1.5 \cdot E_{for,travel}/E_{batt} \tag{9}$$

- Case #3: for FQI <70 and a predicted PV availability < 50% of the total EV need

$$SOC_{min,tot} = SOC_{min} + 1.5 \cdot E_{for,travel}/E_{batt} \tag{10}$$

where $E_{for,travel}$ is the forecasted energy during the next period of time when the car is not at home in kWh.

The optimization provides the expected power (charged or discharged) from the storage $P_{batt,t}$. For the sake of clarity, in order to distinguish between expected powers and real time values, it is introduced a command vector for the rule-based logic. Thus, the $P_{batt,t}$ is discretized as reported in (11). This command vector $\mathbf{z}_{EV}$ is able to suggest an optimized power pattern, leaving the choice of the exact power values to the real-time logic:

$$z_{EV,t} \coloneqq \begin{cases} 1 & if\ \ P_{batt,t} > 0 \\ 0 & if\ \ P_{batt,t} = 0 \\ -1 & if\ \ P_{batt,t} < 0 \end{cases} \tag{11}$$

E. Rule-based Real-Time Management

The Rule-based real-time logic finally applies the effective charging/discharging EV battery power in each *t*. The real-time management working principle is shown in Fig.8, where the actual applied battery variables are distinguished with a star. First, the logic checks if the car is available at home. If the car is not at home, nothing happens, and the battery power is zero. Otherwise, three different cases are possible according to the states of the command $z_{EV,t}$.

The case $z_{EV,t}$ = 1 means that the command is requiring a charge. The logic, checks if there is PV production, and a positive answer will result in a charging fed by the PV when its production is greater than the load. If the answer is negative (e.g., during the dark hours), the charging power for the battery charging is taken from the grid and dynamically set for not exceeding P_{contr}.

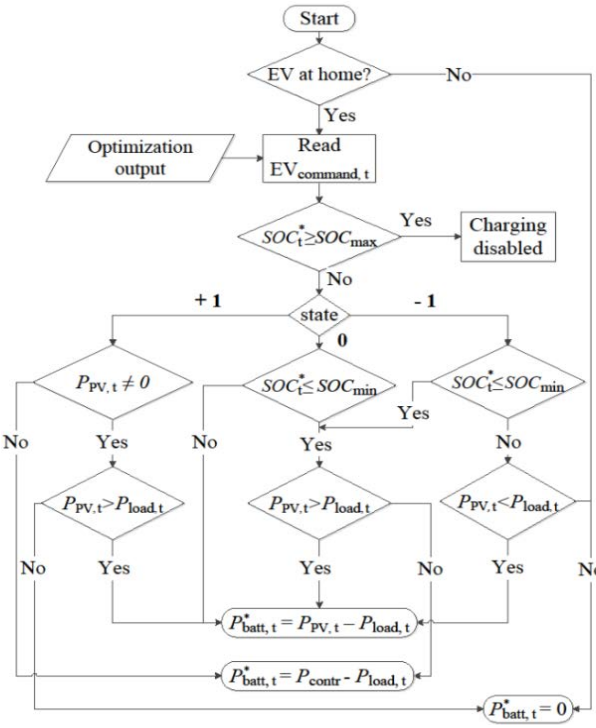

Fig. 8. Flowchart of the real-time management logic

The case $z_{EV,t} = -1$, means that the command is requiring a discharge. The logic checks if SOC^* is less than the lower limit. If the answer is positive, the command vector is changed in the zero state. Otherwise, if the answer is negative, the EV battery will supply the fraction of the load that is not supplied by the PV generator.

The case $z_{EV,t}$= 0 means that the command vector is not requiring any specific battery state or was disabled from precedent steps. In this case, if SOC^*_t is greater than the minimum, $P^*_{batt;t}$ will follow the instantaneous positive or negative difference between PV and load, addressing real-time balancing and maintaining $P_{grid,t}$ equal to zero. On the contrary, only charging will be enabled from the PV or directly adjusted from the grid.

Finally, in order to avoid overcharge, in case of $SOC^*_t \geq 95\%$, the control will only permit discharge.

III. Simulation Results

The case studies refer to the scheme shown in Fig. 1. The total capacity of the battery is chosen 40 kWh, according to the analysis conducted in [27]. Finally, the simulations have been run with an initial SOC value of 25% charged from an external source.

A. Energy Indicators

Two indicators are used in this work to measure the effectiveness of the proposed methodology: Self-consumption (S_{cons}) and Self-sufficiency (S_{suff}).

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The self-consumption index S_{cons} is defined as the ratio between the amount of energy produced by the PV which is directly consumed by the house and the car and the total amount of PV energy produced in a defined time interval [52]:

$$S_{Cons} = E_{match} / E_{PVtotal} \tag{12}$$

where $E_{PVtotal}$ represents the total amount of PV energy produced. and E_{match} represents the portion of energy directly produced and consumed.

Unlike, the self-sufficiency index S_{suff} is the ratio between the amount of energy produced and consumed and the sum of the energy requirements of the house and the car [53][54]:

$$S_{Suff} = E_{match} / E_{Ltotal} \tag{13}$$

where E_{Ltotal} represents the local energy demand, thus house and car energy needs.

It is possible to express E_{match} through the following sum

$$E_{match} = E_{lgc} + E_{batt,wheel} + E_{dis,PV} \tag{14}$$

where:

- E_{lgc} is the energy locally produced by PV generators and immediately consumed by residential loads.
- $E_{batt,wheel}$ is the energy locally produced by PV generators and stored in the EV battery that will be used by the EV.
- $E_{dis,PV}$ is the portion of the energy discharged by EV battery to feed local loads, originally produced by PV.

Fig. 9 aims to clarify the introduced energy quantities and provides an example of daily power profiles for an EV-PV home system. For sake of simplicity, in Fig. 9 the EV is considered at home all day.

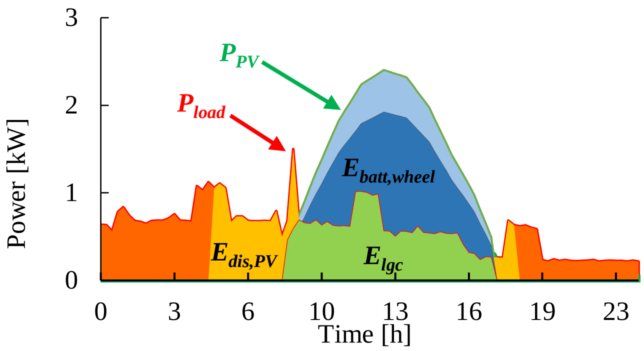

Fig. 9. Daily power profiles and energy balance for an EV-PV-home system

B. Energy balance results

The proposed methodology is applied to three case studies. For each case study, the residential load and PV generation profiles are identical. On the contrary, the EV Usage profiles are different. As described in Section II-A, the selected EV profiles are the centroids of a database composed of 215 EVs. As a result, EV#1, EV#2 and EV#3 are different and well represent three typical electric vehicle usage profiles. Regarding the simulate time frame, four weeks are considered to represent the four seasons.

The results are compared with respect to the ordinary rule-based logic without forecasts described in [27]; which is, thus, chosen as reference logic. Table IV and Table V report the proposed and the reference logic results in terms of self-consumption and self-sufficiency respectively. As expected, due to the highest presence at home, EV#3 reports the best results overcoming the complete self-sufficiency in the weeks of May and July thanks to the energy stored into the EV battery. The worst case is instead represented by EV#1 which is characterized by high EV consumption at the wheel and low presence at home.

Table VI highlights the percentage deviation achieved from the proposed logic with respect to the reference one. From the comparison it results evident that the proposed logic creates some slight improvements in the warm seasons. On the contrary, no tangible differences are observed in the cold seasons.

More in detail, the proposed logic guarantees performance effects if the obtainable PV energy in charge (EV_{PV}) is similar or higher compared to the EV consumption at the wheels ($EV_{PV}/EV_{Wheel} \geq 1$). The obtainable PV energy in charge is here defined as the PV availability when the car is at home; thus, it represents the maximum theoretical battery capacity that can be possibly charged from the PV .

This behavior is easy to explain with the fact that if the PV availability is very low with respect to the car needs, the grid charging time positioning does not have any impact in energetic terms. To make more visible this dependence, Table VII reports the obtainable PV energy in charge with respect the EV consumption, confirming that the logic performance for both indexes is strongly dependent on this rate. However, in terms of self-sufficiency, little improvement becomes visible even with lower PV availability thanks to a wiser exploitation of the battery capacity.

Moreover, in one case (EV3 January week), a slight under-performance with respect to the reference logic is obtained. This is due to the imprecise forecasting that have left to a not optimal battery management. This aspect will be fully investigated in the next section.

TABLE IV. SELF CONSUMPTION: PROPOSED AND REFERENCE LOGIC.

	Proposed Logic			Reference Logic		
	EV#1 %	EV#2 %	EV#3 %	EV#1 %	EV#2 %	EV#3 %
Jan	54	41	88	54	41	89
May	35	43	43	35	40	42
Jul	58	38	43	57	35	40
Oct	45	22	69	45	22	69

TABLE V. SELF SUFFICIENCY: PROPOSED AND REFERENCE LOGIC.

	Proposed Logic			Reference Logic		
	EV#1 %	EV#2 %	EV#3 %	EV#1 %	EV#2 %	EV#3 %
Jan	24	36	70	24	35	69
May	54	95	119	53	87	113
Jul	104	119	121	100	109	111
Oct	22	18	46	22	18	44

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TABLE VI. PROPOSED LOGIC PERCENTAGE DEVIATION.

	S_{cons}			SS_{uff}		
	EV#1 %	EV#2 %	EV#3 %	EV#1 %	EV#2 %	EV#3 %
Jan	-	-	-1	-	-	-3
May	-	+7,5	+2	+2	+7,5	+5
Jul	+3,5	+9	+7,5	+4	+9	+9
Oct	-	-	-	-	-	+5

TABLE VII. OBTAINABLE PV ENERGY IN CHARGE WITH RESPECT TO THE EV CONSUMPTION.

	EV_{pv} / EV_{Wheel}		
	EV#1 %	EV#2 %	EV#3 %
Jan	26	44	146
May	64	191	723
Jul	155	745	470
Oct	28	20	83

For matter of comparison, Table VIII shows the energy indicators calculated for the four weeks without any EV. It can be noticed S_{Cons} is lower than when EV#1, EV#2 or EV#3 are considered. On the other hand, in some cases, especially in the seasons with lower solar radiation, S_{Suff} can result higher in the case without EV, because the absence of the EV brings to a reduced total electric load that is satisfied by the PV generator.

TABLE VIII. ENERGY INDEXES FOR THE BASE CASE WITHOUT EV.

	S_{cons} %	SS_{uff} %
Jan	26	44
May	15	63
Jul	8	52
Oct	14	23

C. Further discussions

From the above results it follows that the performance of the proposed logic depends on two factors: quality of the forecasting and PV availability. Regarding the forecast uncertainty, with the aim to investigate the full potential of the methodology, the logic was tested with real data as input (exact predictions). Table IX shows the percentage deviation of the results obtained with exact prediction with respect to the reference logic. The results, in this latest case, are clearly higher respect the proposed logic with forecasting. In particular, improvements in self-consumption and self-sufficiency of 17% and 19% respectively have been recorded for EV#3 in the week of May, when the theoretical PV energy in charge is seven times higher than the car energy need. Moreover, exact prediction leads to a visible improvement in self consumption even for the week of May of EV#1 characterized by a relatively low theoretical PV energy in charge (64% of the car energy need). Furthermore, no underperformance has been obtained in the specific case of EV#3 January week.

Regarding the PV availability, with the aim to investigate its effect, the logic was tested for different the PV plant sizes. Fig. 10 and Fig 11 show the behavior of the proposed logic both with forecasts and exact predictions for the worst case of EV#3 January week. In particular, Fig. 10 reports the self-consumption indexes while Fig. 11 provides the self-sufficiency indexes.

TABLE IX. EXACT PREDICTION PERCENTAGE DEVIATION.

	S_{cons}			SS_{uff}		
	EV#1 %	EV#2 %	EV#3 %	EV#1 %	EV#2 %	EV#3 %
Jan	-	-	-	-	+3	+1
May	+3	+8	+17	+ 2	+9	+19
Jul	+9	+14	+10	+10	+15	+9
Oct	-	-	-	-	-	+5

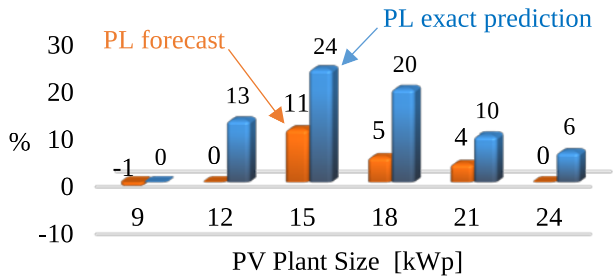

Fig. 10. Self-consumption of the proposed logic with forecasts and exact predictions for the EV#3 January week for different PV plant sizes

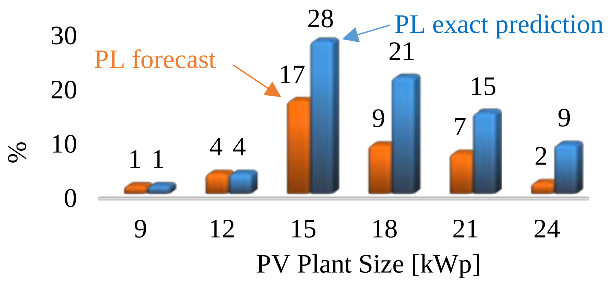

Fig. 11. Self-sufficiency of the proposed logic with forecasts and exact predictions for the EV#3 January week for different PV plant sizes

The results show that already with 12 kWp plant the proposed logic does not anymore underperform the reference, while a potential 15% increment in self-consumption is obtainable with exact predictions. For the specific case and the EV battery capacity considered (40 kWh), the best result is achieved with the 15 kWp plant. In this case, the improvements of the proposed logic reach 10% and 20% for self-consumption and self-sufficiency, respectively. The potential improvements of exact predictions are in the order of 25% and 30% respectively. Higher PV plant sizes lead to an earlier battery capacity filling, by reducing the possibility of the logic to operate, thus reducing the benefits.

IV. CONCLUSIONS

This work proposed a new methodology to manage the charge/discharge of an EV battery connected to a household with a PV plant. The methodology uses historical data and complete forecasting for all the variables of the system (EV consumption, PV generation, load), in order to optimize the real time battery management. The aim of the optimization is the reduction of the grid exchange, improving self-consumption and self-sufficiency.

The three case studies represent three EV usages derived from the application of a clustering technique to the usage

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patterns of 215 vehicles. The proposed logic has been compared to the reference rule-based logic without forecasting. The results have shown that tangible improvements are achieved (up to 9%) if the PV availability is not too low with respect to the EV energy needs. In order to investigate the full potential of the methodology, also the exact prediction case has been considered, by showing an improvement up to 15%, even with a lower PV generation.

An additional analysis has been made, by considering the worst-case scenario: if PV availability increases, the benefits of the proposed logic will increase as well. In case of 15 kWp, the improvement with respect to the reference logic is around 25%.

Future work will aim to apply the proposed forecast logics to a higher number of vehicles in order to increase the reliability of the bidirectional power transfer operations to and from the vehicles considering a wider kinds of loads (office, commercial centers, and so on). In this framework, emerging players (as aggregators) will play a fundamental role which needs to be properly addressed by considering the technical specifications of the used devices.

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