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# Planning of smart charging infrastructure for electric vehicles: an Italian case study

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**Abstract.** Nowadays, the large-scale introduction of electric vehicles requires the definition of appropriate infrastructure devices and software solutions. Consequently, the development of those systems should enable them not only to provide the necessary energy amount, but also to participate to the local grid management, improve energy quality, exploit the potential of non-manageable renewables, and support local energy district. The article describes the planning activity of a charging points site located in the area of the central Italy. More specifically, the content includes the analysis of charging procedures and events from the population of users by a local energy provider, identifying vehicle necessities and calculating their expected energy supply based on daytime and local position. The final objective of such clustering is to identify opportunities for energy management, finding and supporting path planning so that it is possible to apply smart charging and vehicle-to-grid energy management strategies. Also, the analysis explains the suitability of the charging location according to the current user charging behavior and hypothesize the implementation of strategies to both maintain user satisfaction and optimize grid impact on the local energy district.

**Keywords:** EV, Charging Point, Energy Demand, V2G, Smart Charging.

## 1 Introduction

In response to the urgent need for sustainable and eco-friendly transportation solutions, the global community is undergoing a paradigm shift from conventional internal combustion engine vehicles to electrically powered alternatives. In this context, electric vehicles (EVs) have been identified as the best promising solution to mitigate climate change, improve air quality and reduce the use of fossil fuels [1]. As the adoption of EVs gains momentum, the pivotal role of charging infrastructure in supporting this transition becomes increasingly evident. In fact, the successful integration of electric vehicles into mainstream transportation necessitates a not only a robust and well-distributed charging point network, but also a robust and resilient interaction with the

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local grid [2]. In this context, smart charging strategies (V1G) and bidirectional power flow charging technologies (V2G) emerges as solutions able to provide stabilization or ancillary services to the grid, and to improve the utilization of renewable energy sources [3]. Beside technical factors, such as the adoption of smart infrastructure and V2Gready EVs, non-technical aspects can determine the feasibility and the scalability of the implementation in the real world. Factors like user perception, nearby renewable energy sources, and the current charging behavior of EV drivers play crucial roles. In this regard, flexible and extended charging sessions, when strategically implemented in V1G and V2G management strategies, can enable a spectrum of opportunities that extend beyond mere energy replenishment. Longer charging session allows to use EV battery for grid stability and couple the energy demand with renewable energy generation [4, 5]. It appears clear that real world charging data needs to be analyzed with the aim not only of characterizing the general everyday usage of charging points but also to identifying possible V1G/V2G implementation for certain charging points (e.g., longer charging time or user flexibility).

In literature, a large number of EV charging data have been investigated, focusing on optimal location for charging points [6], user behavior in relation to policy implications [7], and charging paths affected by different pricing [8]. Other studies have explored the use of cluster algorithms (e.g., k-means) to evaluate charging and user patterns [9, 10], and fewer have addressed the user's flexibility for V1G/V2G application [11]. To date, no study has investigated the possibility of V1G/V2G implementation through the application of clustering techniques for a dataset registered to an Italian scenario. This paper proposes to define a data mining method for charging station dataset, determine a procedure workflow that is applicable and parametrizable to other sources, identify possible opportunities for smart energy management through the application of k-means cluster algorithms for charging point located in the central part of Italy. In conclusion, the data proposed are specific of this context and are up-to-date primary data. It should be noted that in the period 2019-2023 the average amount of energy delivered by charging infrastructure has grown approximately by 600% in few years, so it is necessary to monitor its evolution.

## 2 Research Methodology

### 2.1 Data Description

In this work, we analyzed an EV charging data set supplied by E.S.T.R.A. S.p.A [12], a local energy provider, that refers to charging points (CPs) located in the Italian regions of Tuscany and Marche. In the following points are summarized the structure of the dataset and the main features of the data collection:

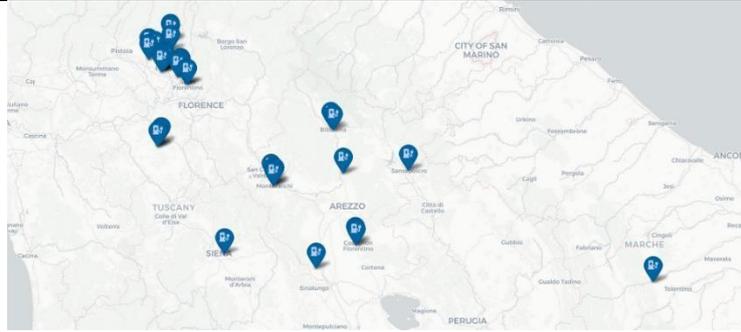
- 34 CPs and 66 Connectors (CON). For 32 CPs 2 connectors were used, and for the other 2 only a single connector was recorded.
- 147 days were analyzed, from November 2022 to May 2023.
- All connectors are alternating current (AC) charger (CCS Type 2 with 22 kW).

- 7498 charging events (CEs), for which total energy delivered and starting/ending dates were registered.

To better represent the results and to anonymize the charging events, a standardized name has been defined for each connector (e.g., from ‘Connector 01’ to ‘Connector 66’). Additionally, the latitude and longitude of CPs were provided, see Figure 1.

**Table 1.** Example of dataset structure, no real data were reported due to confidentiality.

ID CE	ID CPs	N° CON	Country	Start Date	End Date	kWh
89865	Charging Name 1	1	IT	2022-04-03 13:56:29	2022-04-03 19:12:49	5,9



**Fig. 1.** Map of evaluated CPs.

## 2.2 Data Processing Workflow

In this step, we present the method used for preparing and processing the data. Starting with the dataset described above, a preliminary data filtering was performed based on three thresholds through which events were excluded:

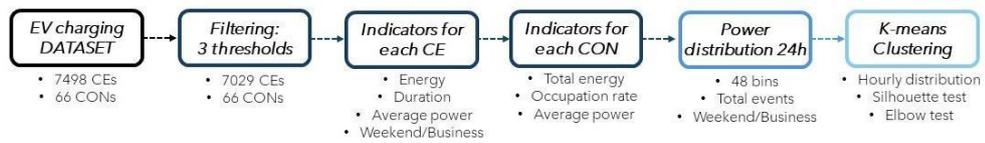
- Energy delivered lower than 0.25 kWh.
- Power exchanged higher than 23 kW, to eliminate any potential incorrect or corrupted charging data, considering that the charging points analyzed operate at a maximum of 22 kW.
- Charging session that lasted less than 10 minutes.
- 6.2 % events were discarded, from 7498 to 7029 CEs.

Furthermore, we extracted the main performance indicators for each event, such as energy delivered, charging duration, average power, and business/weekend days separation. Next, event results were aggregated to their respective connector for which total energy, average power, average charging session duration, occupation rate, and total event for business/working days were calculated. This primary evaluation allowed us to classify the CPs by users’ utilization, pointing out peculiarities that can be useful for charging planning (e.g., V2G services), for potential promotion among consumers (e.g., underexploited by users), and for depicting the distribution of EVs in the surrounding area.

Afterwards, we modelled the power distribution of the charging events aggregated by connectors over the 24 hours; the discretization was done in 30 minutes slice, for a

total of 48 bins in 24 hours. Also, a separation business/weekend day of the power distribution was implemented.

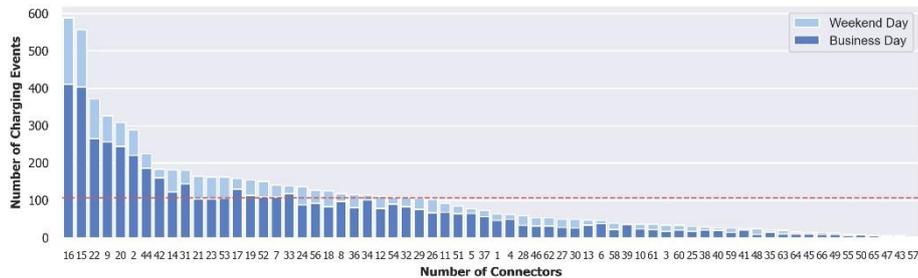
Finally, a k-means clustering algorithm was applied to the power distribution of total event, weekend, and business datasets. Also elbow method and silhouette test were performed to estimate the most suitable number of pre-defined cluster. The test results obtained indicates a set of two pre-defined cluster, to better represent the data clustering. A summary of the workflow is illustrated in the Figure 2.



**Fig. 2.** Data processing workflow.

### 3 Results and Discussion

The results of the data processing method are presented below. The distribution of event among the connectors and the subdivision business/weekend days are illustrated in Figure 3; only five CONs (connector 16, 15, 22, 9 and 20) had registered more than 300 events. As expected, most of the charging sessions have been started in a business day with an average of 73% in respect to total events.

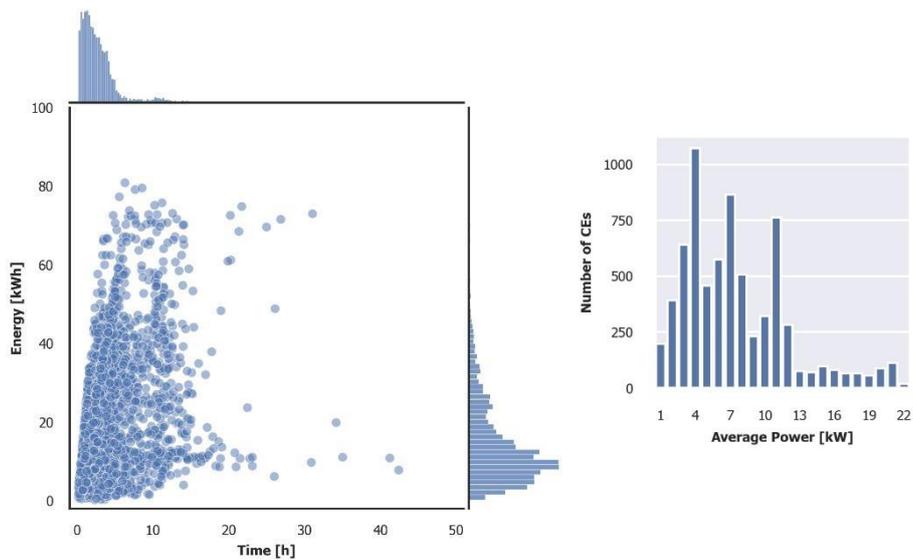


**Fig. 3.** Events for each connector subdivided in weekend and business start day. The red line indicates the average number of events (about 106) considering all the connectors.

In Figure 4, both the correlation energy-duration and the distribution of average power for each CEs are reported. Almost 65% of the charges lasted less than 4 hours and 25% of event lasted between 1 to 2 hours; only 10 charging sessions continued more than 24 hours. On the other hand, maximum energy delivered in a single event was about 81 kWh and 75% of events delivered less energy than 20 kWh. The typology of vehicle connected was not registered, but we can hypnotize that CONs were connected either to small battery size vehicles (e.g., moped, quadricycle, A-segment, B-segment) that

can be fully recharged or to medium-large small battery size vehicle (e.g., C-segment or D-segment) that were disconnected with a partial charge.

Looking at the distribution of averaged power, the peak of the event counting bar plot can be observed in the 3-4 kWh range, see Figure 4 - left chart. The lack of average power values close to the upper limit of AC charger of 22 kW could indicate that most of the charging sessions continued even after the full charge of the vehicle (e.g., in long charging session and low energy delivered) or that the connected vehicles could only be recharged with lower power (e.g., on-board charger with lower output power).



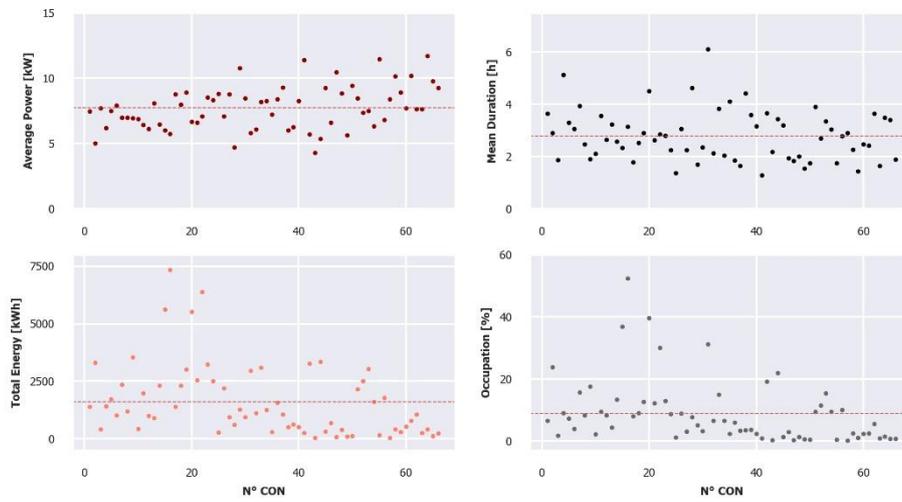
**Fig. 4.** Energy-duration correlation (scatter plot) and event counting (bar plots) on the left; distribution of average power for CEs on the right.

Afterwards, the main indicators (average power, total energy delivered, mean duration and occupation percentage) analyzed for each connector are reported in the Figure 5. Starting from the total energy delivered, we found correlation between number of events and the energy delivered, with connectors 16, 15, 22, 9 and 20 that registered more than 5000 kWh for more than 1500 events. The average power was calculated as the ratio between the energy delivered in the charging session and its duration. The mean for this indicator is 7.7 kW, with a maximum of 11.7 kW for CON 63. As sad before, no connector had reached the maximum available average power of 22 kWh.

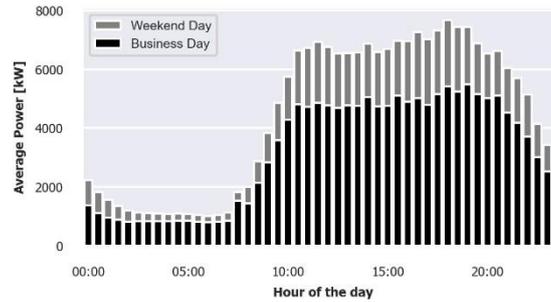
Looking at the average duration and occupation rate (the percentage of usage time respect to total time span evaluated), the mean values are respectively 2,8 hours and 8,8 %. The maximum mean duration is 6,1 hours for CON 30, and the maximum occupation rate is 52.4 % for CON 15. On the other hand, only 9% of all the connector's average durations exceed than 4 hours and 11% of all connectors have an occupation rate above the 20%. Next, the Figure 6 shows the hourly distribution of the sum of all the average powers: most of the power is delivered during the day, with a peak in the late afternoon;

in contrast, the overnight average power is limited. No substantial difference was found between weekend and business days. This preliminary analysis highlighted some of the main challenges for V1G/V2G implementation:

1. Low average duration: limited amount of time in which to use smart energy strategies.
2. Low occupation rate: some of connectors are not used at their full potential due to the scarce usage by EV drivers in the area.
3. Low overnight average power: unfeasible smart management for late-night charges.



**Fig. 5.** Main indicators obtained for the connectors. The red lines in the subplots indicate the average of each indicator.



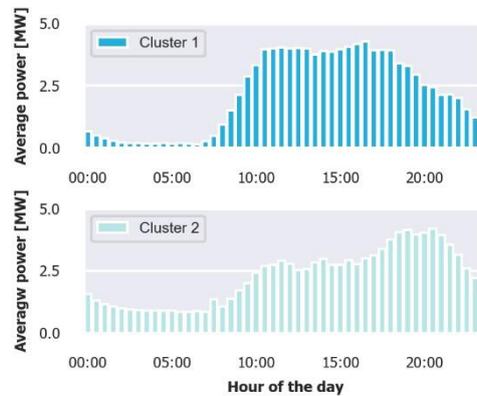
**Fig. 6.** Hourly distribution of the sum of all the average powers.

### 3.1 K-Means clustering

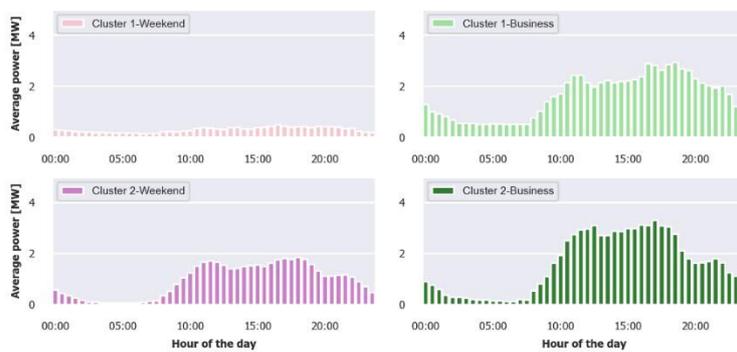
Lastly, a k-means clustering algorithm was applied to total events, weekend, and business datasets to identify correlations between average power and hourly

distribution. To maximize the silhouette coefficient [9], the number of clusters are set to two. The results are reported in the Figure 7 and Figure 8.

For total event analysis, the Cluster 1 (38 connectors) represents charging points near workplaces where users connect their EVs from 8:00 to late afternoon or evening. On the other hand, in Cluster 2 (28 connectors) we find charging points with longer average duration and higher energy delivered; these CPs are probably placed near a residential zone due to the rising average power during daytime (peak at 20:00) and non-zero average power during the night. Similar considerations can be made for business/weekend days clustering: Cluster 2 refers to daytime use near offices or business area, whereas Cluster 1 identifies residential usage with longer charging sessions that last overnight.



**Fig. 7.** Hourly distribution of sum of the all the average power for total events clusters.



**Fig. 8.** Hourly distribution of sum of all the average power for weekend and business day clusters.

Clearly, those results provide a classification on how each connector is used, giving suggestions on which possible smart energy management implementation could be better exploited by the users. Obviously, further evaluations are needed to analyze the

requirements of the single charging infrastructure and to ensure that the services suggested could be actually implemented. The main aspects are listed below:

- Availability in the market of charging infrastructure that support both V1G and V2G and the relatively high costs.
- Vehicle compatibility for V2G technologies for both AC and DC charging systems, which results in limited available users.
- Standardization of communication protocols between charging point, vehicle and grid and the interoperability from one country to another (e.g., ISO 15118).
- Regulatory support for grid integration in energy management strategies.
- Business case development that integrates all the stakeholders (e.g., vehicle owner, charging infrastructure owner, distribution system operator, transmission system operator and energy service companies).
- Consumers' willingness to participate to V2G services and the relative benefits in particular considering economic opportunities.

## 4 Conclusions

In this work, we presented a methodology for charging sessions data analysis with the aim to determine the suitability for the application of V1G and V2G strategies. This approach was applied to an Italian real-world dataset. For events and charging points, total energy delivered, average power, charge duration and hourly distributions were analyzed, highlighting the low charge duration for most events and the almost exclusive use of CPs in the daytime. Then, a k-means cluster algorithm was used, and two clusters characterized by specific usage behavior were identified. Same findings were obtained for weekend and business day. In conclusion, the results showed that this methodology can help energy providers or policymakers not only in the general analysis of a charges dataset, but also to underline strengths and weakness of a possible V1G/V2G implementation for specific charging points' usage in the Italian context. We consider as an outlook:

- The validation this method through geospatial analysis for charging point attractiveness.
- The analysis of the technological requirements for V1G and V2G implementation for each classification, as described above.
- The inclusion of more sophisticated data processing algorithms (e.g., deep learning models).

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