EVS30 Symposium
Stuttgart, Germany, October 9 - 11, 2017

Smart Charging Impact on Consumer and Environment

Maricica Nistor, André Dias
CEiiA // Centre of Engineering and Product Development,
Av. D. Afonso Henriques, 1825, 4450-017 Matosinhos, Portugal
{*maricica.nistor, andre.dias*}@*ceiia.com* *

Abstract

Awareness of smart charging technologies for the electric vehicle (EV) is fundamental to achieve energy-efficient charges. We propose an integrated methodology using Markovian processes and real-time strategies for private environments that, based on consumer needs, dynamic tariffs, grid conditions, renewables production, local storage, and EV constraints, provide the most economical way to charge the EV. A cloud-based mobility platform or a local management system are proposed to perform the advanced optimization algorithms. The results show that the electricity cost and the CO_2 emissions can be significantly reduced, while the consumer requirements are maximized.

Keywords: multi-objective algorithms, charging profile, smart charging, modular architecture

1 Introduction

Smart charging of EV is a widely used term nowadays and encompasses several factors. In terms of power grid capacity, smart charging can indicate that the consumer is able to charge his EV taking into account the grid limitation. Regarding the energy market, the solution related to smart charging can imply the charging according to the existing dynamic prices. Further, once with the proliferation of technology, the user participates even more in demand response programs and becomes a decision maker of his EV charging control, hence smart can signify the interaction of consumer in the EV charging. In addition, smart charging can be used when the EV charging load is supplied by the local storage and micro-generation resources in a cost-effective way. An indeed smart charging solution considers simultaneously all these factors, thus, reflecting the power grid connectivity, the energy market prices, the user's needs, and other available energy resources.
The literature already contains a large number of publications that address this topic. For example, [1] finds a match between the charging rate of EV and the available capacity of the network, while [2] introduces wind power generation and shows that the controlled charging reduces in half the cost of integrating plug-in hybrid EV. Furthermore, the authors in [3] propose deterministic algorithms with the goal to minimize the charging costs, study the EV battery charging and discharging impact, and balance the power grid levels, while [4] uses deterministic and non-deterministic algorithms to find features from the user and the charge point historical data in order to minimize the charging cost. Moreover, the introduction of the new standard protocols facilitates the implementation of smart charging techniques, as explained in [5]. For the residential environments and small business sectors, smart charging is applied for various purposes. For example, the reduction of the voltage deviation and overloading equipment are presented in [6], while the study of the State of Charge (SoC) distribution for the battery capacity optimization and the impact of EV charging are analyzed in [7]. The more recent works by [8] and [9] provide insights about modeling and control the EV charging rates by capturing the characteristics of the battery and the real-time pricing (RTP) tariffs. Furthermore, local and centralised charging strategies are

*This work has been supported by Fundo de Apoio à Inovação - ADENE Agência para a Energia, under the project Personal Energy Device (http://ped.ceiia.com).

compared in [10] and the work concludes that: (1) local control charging requires minimal communication infrastructure and is sufficient for lower EV penetration levels, but it has no communication links to the rest of the network and requires larger safety margin to maintain the operating limits, (2) centralised control charging provides real time insight into operating conditions at all points in the network, better utilization of network capacity, but it requires significant communication infrastructure across network and third parties to control charging rates. Centralised charging technologies are also mentioned in [11] with the aim to collect and compute data and control the EV charging, while the authors in [12] present a smart EV charging system with the goal to schedule the charging in order to maximize the available grid resources.
The literature that addresses smart charging techniques focuses on: (1) limiting the grid impact, (2) minimizing the electricity cost for the user, (3) introducing the renewables impact, and (4) adding insights on communication and infrastructure needs. Research work still requires the study of several aspects, including the definition of integrated system able to perform both offline and real-time mobility and energy services (e.g., integration of other EVs), the integration of various energy resources, e.g., renewables and non-renewables, showing the environmental impact provided by the EV charging, the implementation of smart charging algorithms that considers simultaneously the user's needs, the tariff fluctuation, the energy resources availability, and the grid impact.
Our approach focuses on small business sectors and residential buildings and aims to optimize the EV charging from the user's perspective with the goal of minimizing the electricity costs and the environmental impact, while maximizing the user's needs. The approach integrates demand prediction solutions using online applications and considers (1) the user as a decision maker that is able to manage the charging of his EV, (2) the existence of the dynamic tariffs, (3) the integration of various energy resources, including renewables, (4) the integration of other loads that limit the power grid capacity, and (5) EV characteristics. Our main contributions are:

- *Modular architecture*: providing a flexible system for local and centralized smart charging models integration.
- *Multi-objective optimization models*: using a mathematical model for day-ahead tariffs and strategies for Real-Time-Pricing (RTP) tariffs.
- *Charging profile:* including information on when, from where, and how much to charge the EV.

The rest of the paper is organized as follows. Section 2 provides the model description, while Section 3 the numerical results. The work concludes with Section 4.

2 Model Description

The high level architecture of the entire system is modular in order to ensure easy integration of all necessary components. The interconnection between the modules is presented in Figure 1, where each module has a defined role which is briefly presented in the following:

- *Energy Provider Module*: This module is responsible for the energy distribution. The energy tariffs may also be supported by this module.
- *Platform Module*: This is a cloud-based mobility platform that has a central role and (1) provides real-time services to the user/operators/administrators and (2) integrates new systems and services. The main features are shown in the following: (I) collect the data from: a) the energy provider (e.g., information about the available energy, tariffs), b) the third parties, c) the charge point (e.g., technical limitations, charging process), d) the user (e.g., historic information, preferences), e) the HEMS/BEMS (Home Energy Management System/Building Energy Management System) (e.g., renewable energy availability, battery status), f) EV (e.g., battery capacity, EV SoC), (II) monitor and control: a) the charge point (e.g., charging process, remote control, firmware update, real-time availability, reservation, authorization), b) EV (e.g., charging), (III) perform analysis regarding: a) the charging profile (when, from where, and how much to charge), b) the charge point (e.g., load management, CO_2 emissions), c) the user (e.g., analysis about the user consumption, future charging profiles), d) the billing and payment.
- *Third Parties Module*: Other parts may interact with the platform, e.g., different energy markets, telecommunication operators, car manufactures.
- *Micro-generation Module*: This module is responsible for renewable energy production which is then stored using local storage, used to supply the load, or sold to the power grid.
- *Battery Module*: The storage module collects energy from renewables or from energy provider and provides energy to supply the load. The micro-generation and local storage module form the local resources.

- *HEMS/BEMS Module*: This module is a local residential controller that has the following features: (1) collect and monitor: a) data from the Battery Management System (BMS), b) charging and discharging the local battery, (c) data from the EV (e.g., SoC), (d) data from the user, (2) control energy consumption and production: a) store the renewable energy from the utility grid using the local battery pack, b) supply the load, c) sell to the grid the renewable resources, (d) control voltage when the energy is supplied to the grid, (3) perform local analysis (e.g., charging strategies).

- *User Interface Module*: Using RFID or mobile application, the user is able to access to the charge point. With the mobile or web application, he is able to access the historical data and control his chargings (e.g., start/stop), see analysis reports and savings. He can also introduce manually his driving preferences using the HEMS/BEMS or the mobile/website application and access the EV using the mobile app.

- *Charge Point Module*: This module has the following features: (1) control the charging meaning a) load balancing, b) perform commands received from the platform, c) report charging events, (2) identify/authorize the user locally using the authorization list or centrally via the platform, (3) make available information relevant for the user (e.g., tariff, charged power).

- *EV Module*: This module refers to the EV that needs to interact with the user, the charge point, and the platform (exchange information about distance traveled, energy consumed) in order to be charged in an efficient way. EV is able to communicate with the user and the platform through a mobile device controller installed inside.

The interconnection between the modules is presented in Figure 1. We assume a local wireless/power line communication/cable connection between the local resources, HEMS/BEMS and the charge point. The connection between the EV and the charge point is only made through the charging cable. The charge point uses GSM/GPRS/UMTS technologies to communicate with the cloud-based platform, EV is communicating with the platform through GSM/GPRS/UMTS technologies, and the user interaction with the platform, EV, HEMS/BEMS is only possible through website and mobile app or manually with the HEMS/BEMS. The proposed optimization models can be implemented either (1) on the platform level or (2) on the HEMS/BEMS level.

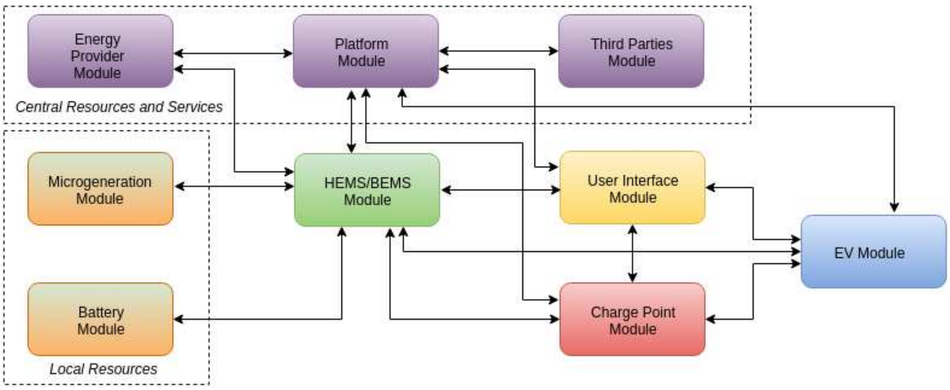


Figure 1: Modular architecture

2.1 Demand Prediction

The demand for EV charging is predicted at the platform or Home/Building Energy Management System (HEMS/BEMS) level. One way is using historical data about the user's chargings. In this case, machine learning/data mining models are performed, where the accuracy of the models depends on the quantity and the quality of the historical data used. Another prediction option is based on data introduced or shared by the user about his needs. For example, the user can explicitly specify the trip details for the next period of interest. The platform performs the trip distance and the required power to be charged. The trip distance can be calculated using the application from Google called Google Maps Distance Matrix API. This application measures the distance and the duration between the start and the end point. Another possible example of prediction is when the user shares his calendar. The steps considered for the implementation are shown in Figure 2. The input data represents the user calendar, the start and end location, the time interval, and the EV average consumption. In this case, the user needs to introduce the period of interest to calculate the demand (e.g., a day, or a time interval), the start location, i.e., the location where he starts the trip, and the end location, i.e., the location where he finishes the trip. Two applications from Google can be applied. One application is Google Calendar API that tracks the events from the Google calendar for a user. The calendar events need to have an address written in the field "where". We only count for the events that have valid addresses and create a list with the events

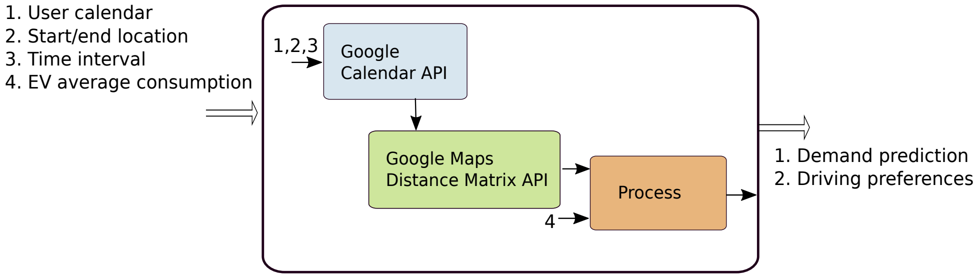


Figure 2: Demand prediction using user's calendar.

founded in the period of interest. The second application is Google Maps Distance Matrix API. For each two chronological events from the previous created list, the application provides the distance and the duration traveled by car. This will easily help to identify the time intervals when the user needs to drive, i.e. the driving preferences. The "process" block means the calculation of the metrics of interest, namely the demand prediction and the user's preferences for driving the EV.

2.2 Charging Profile

The charging profile contains information about the charging session for a period of interest, i.e., when, from where, and how much to charge the EV. We propose two algorithms for the calculation of the charging profile. One algorithm is offline considering the day-ahead tariffs and the other is online based on RTP tariffs. The offline algorithm is a multi-objective optimization method valid for day-ahead tariffs and uses a Markov Decision Process (MDP) together with the well-known value iteration algorithm [13] to solve the appropriate policies [14]. The online algorithm considers RTP tariffs, strategies regarding the utilization of power grid utility, and the allocation of other resources is performed using the results from the offline algorithm. More details about the online algorithm is given in the following subsection. The algorithms can be used together as explained in Figure 3. The input parameters for both algorithms are: the demand, the resource powers, the time interval, the battery/EV constraints, the driving preferences, the grid constraints. The only difference between the online and offline algorithms in terms of input data is the power grid tariff (RTP). Both algorithms consider data for weather and tariff from the external sources. The demand prediction, i.e., the power to be charged, for the next period of interest and the driving preferences are assumed to be known from the previous calculations from the demand prediction.

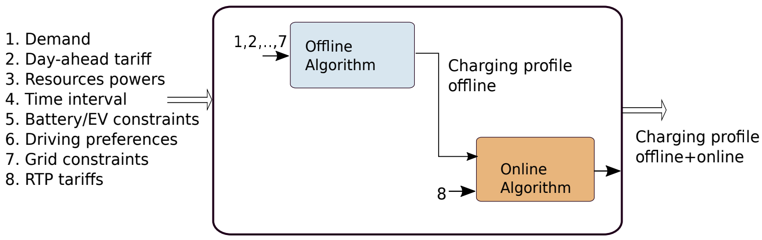


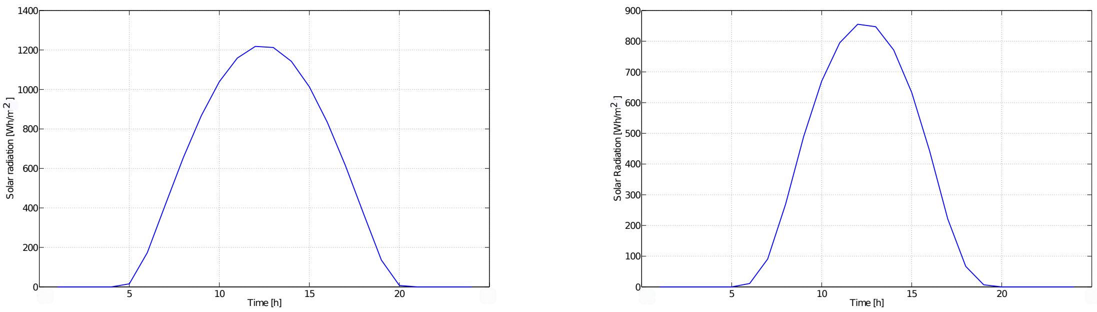
Figure 3: Charging profiles using online and offline algorithms

2.2.1 Online Algorithm

Online algorithm considers strategies for RTP tariffs regarding the power grid utility with the description in Algorithm 1. The significance of *other resources (MDP)* is that the other resources except the power grid are used in the same manner as they are planned using MDP algorithm. The strategies used to charge the EV and the local battery follow the criteria and the order below. The EV SoC updates each time slot. The *threshold* value represents a tariff used to decide the utilization of other resources and it is previously defined.
Given the charging profile, we simply calculate the total cost and CO_2 emissions for the EV charging. The cost in each time slot is given by the powers allocated multiplied by the tariffs of the resources used in that time slot. The total cost is then computed by aggregating the costs obtained in each time slot. The other metric, the CO_2 emissions obtained from the EV charging, is calculated using the powers used to charge the EV from each resource, which are then converted into energy and multiplied by the average CO_2 emissions corresponded to the energy provided from each resource.

Algorithm 1 Online algorithm: strategies to charge the EV and the local battery using RTP tariffs

Data: demand, day-ahead tariff, resources powers, time interval, battery/EV constraints, driving preferences, grid constraints, RTP tariff, results from MDP (usage of other resources except power grid)
Result: charging profile
define *threshold*
for each time slot from the planning period **do**
    if *RTP tariff* $<$ *threshold* **then**
        charge EV from other resources (MDP), if not enough
        charge EV from grid
    else if *EV SoC critical* **then**
        charge EV from other resources (MDP), if not enough
        charge EV from battery, if not enough
        charge EV from grid
    else if *EV driving and tariff other resources* $<$ *threshold* **then**
        charge battery from other resources
    else if *EV driving and RTP* $<$ *threshold* **then**
        charge battery from grid
    else
        charge EV from other resources (MDP), if not enough
        charge EV from battery
    end if
end for



(a) Summer season

(b) Winter season

Figure 4: Solar radiation.

3 Numerical Results

In the following we perform numerical results to show the benefits of our work. The solar energy is produced by a 2.4 kW photo-voltaic array, 96% DC-AC conversion efficiency. The historical data during one year for the weather (source: [15]) and RTP (source: [16]) are also provided. For the weather data, a distribution fitting tool is used to perform data for summer and winter periods and the solar radiation obtained is provided in Figure 4. The tariff for renewable energy is assumed constant and equal to 0. The solar energy produced is calculated by multiplying solar radiation by the solar size and by the conversion efficiency. For the MDP approach, the discount factor is $\eta = 1$ and the value iteration is $\zeta = 0.01$. The numerical results are performed during one day.

3.1 One EV

The settings applied for the utilization of one EV are given in Table 1. For the CO_2 emissitions, we assume that one EV consumes 0.2 kWh/km and given the power charged during a specific period, we get the consumption of one EV in kWh/km. Then, to obtained the saved CO_2 emissions we multiply the consumption of one EV by the average CO_2 emissions provided by each resource, i.e., for the energy mix from the grid, we assume 223 gCO_2/kWh, while for the renewable resources, we consider 0 gCO_2/kWh. First, the offline algorithm is performed for a flat tariff (0.041 \$), without considering local batteries and renewables. The results are provided in Figure 5(a). The users preferences for the utiliza-

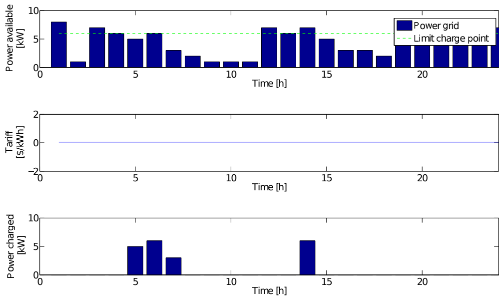
Table 1: Settings for one EV

Parameter	Value
Time period	1440 minutes (1 day)
Number of time slots	24
Dimension of a time slot	60 minutes
Charge point power limit and number of sockets	6 kW, 1 socket
Driving preferences	time slots:$\{1, 3, 11, 19\}$
Demand prediction	10 kW until time slot 7, 20 kW until time slot 18
Average CO_2 emissions for a conventional vehicle	120 gCO_2/km
Average CO_2 emissions for the mix of energy	223 gCO_2/kWh
CO_2 emisssions for renewables	0 gCO_2/kWh
EV consumption	20 kWh/100 km
EV battery	min_{EV}=0.1 kWh, max_{EV}= 22 kWh, initial value is min_{EV}
Local batteries	min_B=0.1 kWh, max_B= 22 kWh, initial value is min_{EV}

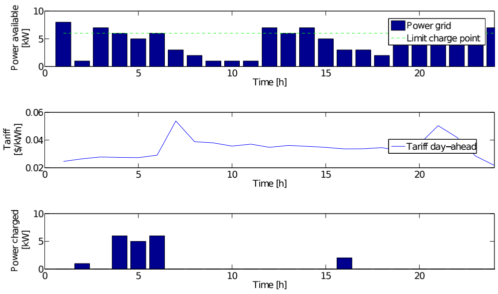
Table 2: Cost and CO_2 emissions comparison between one EV and one conventional car.

Case/Metrics		EV		Conventional car
		Summer	Winter	
Offline alg., flat tariff	Cost [\$]	0.82	0.82	4
(w/o solar, w/o battery)	CO_2 [gCO_2/km]	44	44	120
Offline alg., day-ahead tariff	Cost [\$]	0.57	0.57	4
(w/o solar, w/o battery)	CO_2 [gCO_2/km]	44	44	120
Offline alg., day-ahead tariff	Cost [\$]	0.168 ± 0.003	0.33 ± 0.002	4
(w/ solar, w/o battery)	CO_2 [gCO_2/km]	≈ 6.6	≈ 28.6	120
Online alg., RTP tariff	Cost [\$]	0.061 ± 0.01	0.09 ± 0.01	4
(w/ solar, w/ battery)	CO_2 [gCO_2/km]	≈ 28.6	≈ 41.8	120

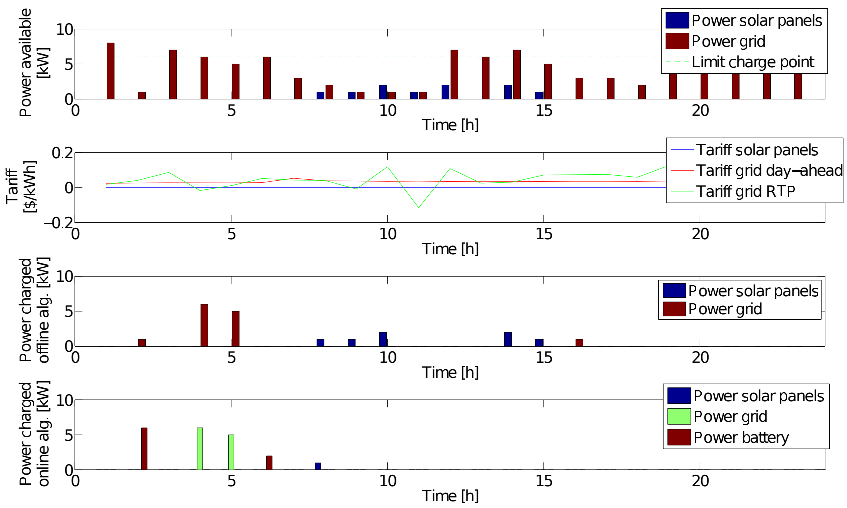
tion of the EV are fulfilled, the total cost is 0.82 \$, and the CO_2 emissions are reduced to 44 gCO_2/km from 120 gCO_2/km. The charging profile, $\{\text{when, from where, how much}\}$, in this case is represented by $\{\{5h, grid, 5kW\}, \{6h, grid, 6kW\}, ...\}$. Second, the results are provided for a day-ahead tariff (varying between 0.021 \$ and 0.053 \$) and using the offline algorithm without considering local batteries and renewables, as shown in Figure 5(b). The cost in this case decreases to 0.57 \$ and the CO_2 emissions are the same as in the previous case.
Third, two cases are considered. A day-ahead tariff with renewables and without local batteries and a RTP tariff with renewables and local batteries. We consider an ideal local battery, where the charging and discharging are lossless and nearly instantaneously. The threshold value compared with the RTP is given by the average of the day-ahead tariff. The results are provided in Figure 5(c) and Figure 5(d). The costs related to each algorithm for the winter season are 0.33 \$ and 0.09 \$, respectively, and for the summer season are 0.16 \$ and 0.06 \$, respectively. The user's preferences are satisfied for both cases. For winter season, the CO_2 emissions are reduced to 28.6 gCO_2/km for offline algorithm and to 41.8 gCO_2/km for online algorithm. In case of the summer season, the CO_2 emissions are reduced to 6.6 gCO_2/km for offline algorithm and to 28.6 gCO_2/km for online algorithm. The online algorithm uses more the grid resources given the condition imposed about the tariff and hence, the CO_2 emissions are higher than in the case of offline algorithm. The charging profile can be simply read from the figures. For example, for the summer season, the charging profile is represented for the offline algorithm by $\{\{6h, \textit{solar panels}, 1kW\}, \{7h, \textit{solar panels}, 1kW\}...\}$ and for the online algorithm by $\{\{2h, battery, 6kW\}, \{4h, battery, 2kW\}, \{6h, \textit{(solar panels, grid)}, (1kW, 5kW)\}...\}$.
The summary of the results and a comparison with the conventional car are provided in Table 2. For one EV, the costs and the CO_2 emissions are significantly reduced depending on the tariff type, the user's



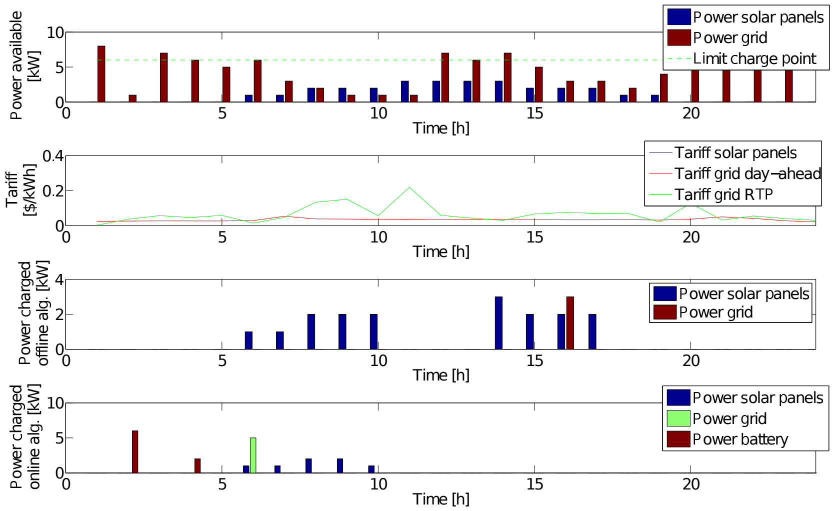
(a) Offline algorithm and flat tariff



(b) Offline algorithm and day-ahead tariff



(c) Offline/online algorithms and day-ahead/RTP tariff, winter season



(d) Offline/online algorithms and day-ahead/RTP tariff, summer season

Figure 5: Results for one EV.

preferences, and the availability of resources.

Table 3: Settings for a fleet of 5 EVs

Parameter		Value
Time period		1440 minutes
Number of time slots		24
Dimension of a time slot		60 minutes
Charge point power limit and number of sockets		6 kW, 3 sockets
Driving preferences	EV 1	time slot $\{2, 3, 4\}$
	EV 2	time slot $\{11, 12, 13, 14\}$
	EV 3	time slot $\{7, 8, 14, 15\}$
	EV 4	time slot $\{1, 2, 3, 4\}$
	EV 5	time slot $\{21, 22, 23, 24\}$
Demand prediction	EV 1	15 kW until time slot 24
	EV 2	5 kW until time slot 10 and 12 kW until time slot 22
	EV 3	3 kW until time slot 6 and 10 kW until time slot 21
	EV 4	7 kW until time slot 13
	EV 5	17 kW until time slot 20
CO_2 emissions for the mix of energy		223 gCO_2/kWh
CO_2 emissions for renewables		0 gCO_2/kWh
EV consumption (same for all)		20 kWh/100 km
EV battery (same for all)		min_{EV}=0.1 kWh, max_{EV}= 22 kWh, initial value is min_{EV}

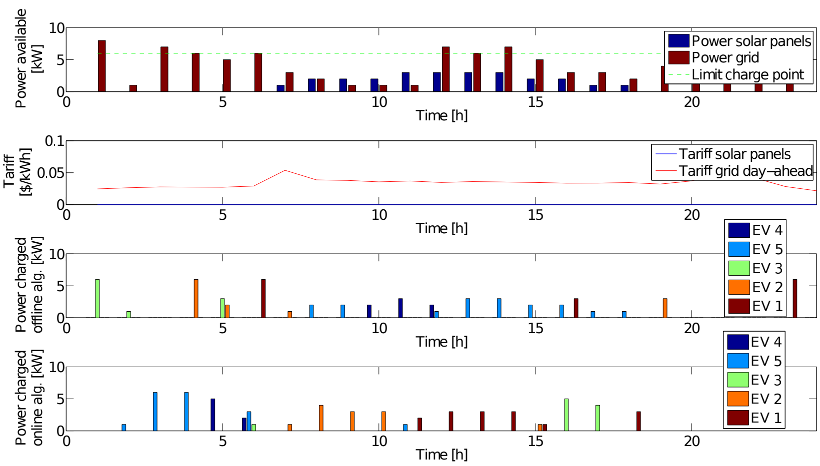


Figure 6: Results for the EV fleet, summer season.

3.2 Fleet of EVs

The algorithms can be further applied to a fleet of EVs. This can be the case of a shared charge point in a neighborhood community. First, we analyze a fleet of 5 EVs with the settings given in Table 3. Here, the optimization needs to consider a scheduling mechanism for the allocation of the EV chargings, since a limited number of EVs can be charged at once. The charge point has a limited number of sockets, which can be used simultaneously as long as the charge point power is not exceeded. We consider that the EVs can be scheduled according to some criteria, for instance the user type, the order of request, the time to charge, the time to finish the charge. We assume that the vehicles are scheduled according to the time to finish the charge, i.e., the order is EV 4, EV 5, EV 3, EV 2, EV 1. We also assume the same tariff and the same resources for both algorithms in order to compare the charging prices. The power available to be charged from renewables and grid is the same as in the previous case for one EV. We apply both algorithms during summer season and show in Figure 6 the results in terms of scheduling the EVs and the

Table 4: Costs and CO_2 emissions for 5 EVs

Case/Metric		EV 1	EV 2	EV 3	EV 4	EV 5
Offline	Cost [$]	0.45±0.001	0.31±0.004	0.27±0.003	0	0.001±0.001
alg.	CO_2 [gCO_2/km]	33.45±0.001	24.53±0.004	22.3±0.003	0	0±0.001
Online	Cost [$]	0.05±0.001	0.2±0.001	0.22±0.001	0.2±0.001	0.45±0.001
alg.	CO_2 [gCO_2/km]	4.46±0.001	8.92±0.001	15.61±0.001	15.61±0.001	35.68±0.001

Table 5: Charging types for a fleet of 20 EVs

Type	Driving preferences [h]	Time preferences [h]	Demand [kW]	EVs
Urgent	-	7	15	1
Normal	no pref.	24	15	2,3,...,18
Promotion	-	-	15	19, 20

power charged and in Table 4 the costs and CO_2 emission results. The power charged for each vehicle is an aggregation of the power used from the available resources. The results show that valid solutions are found using both algorithms.
Further, we propose to show a case for a fleet of 20 EVs when the users can choose the charging type as follows: $urgent$ meaning that the user is able to pay an extra cost, but his EV is charged using the available power and with high priority, $promotion$ meaning the user has no preference for charging and accepts promotional chargings proposed by the system, and $normal$ meaning that the system considers the charging preferences, but the EVs are not charged with high priority. For the first two situations, the optimization algorithms are not applied, but the results from these charging types are used when performing the optimization algorithms for the normal chargings. A comparison with a dumb charging is provided, where dumb means charging as soon as the EV is connected to the charge point. In this case, the EVs are assumed to be connected to the charge point at the beginning of the planning period. The settings consider the solar energy produced during the summer season the same as in Figure 6, the number of sockets is 3, $P = 20$ kW, and the power available from the grid is enough to charge all the EVs in a specific time slot, min_{EV}=0.1 kWh, max_{EV}= 22 kWh. The preferences are given in Table 5, the same settings are applied for all the EVs with the same charging type. In terms of results, we show the costs for each vehicle considering the charging order from the left to the right side in Figure 7. The findings demonstrate that the dumb charging gives the highest costs, while the costs for the offline and online algorithms depend on the usage of renewable energy, i.e., the RTP algorithm uses the renewable energy for the first scheduled EVs, while the MDP algorithm allocates the EV 8, 9, 10, 14, and 15 to charge from renewables.

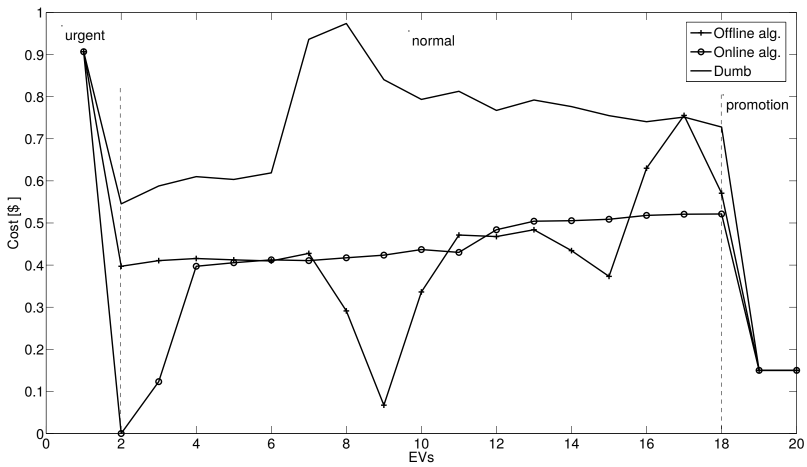


Figure 7: Costs for 20 EVs, charging order from the left to the right side

4 Conclusion

The work represents a step-forward in the implementation of smart charging algorithms for EV fleets considering integration with external data sources. We developed a model for day-ahead and RTP tariff that based on renewables, user's requirements, EV and local battery constraints, power grid limitations, schedules in the most economical way the time to charge the EV. We showed the modular architecture required for the integration of both models. The results are valid for specific seasons, any time resolutions, tariffs and number of resources. The choice of the resources to charge the EV influences both the costs and the CO_2 emissions, the consumer can trade-off between the metrics that are more relevant to him. The integration of the models with the cloud-based platform can be further extended to more charge stations considering the distribution of power grid limitations.

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Authors

Maricica Nistor received the PhD degree in telecommunication engineering from University Porto, Portugal, in 2014. She is a Project Manager at CEiiA, part of Mobility and Intelligent Systems unit. Her interests lie in the general areas of smart grids, smart cities, and mobility.

André Dias is Head of Intelligent Systems at CEiiA where he coordinates the development of ICT-based products focusing on advanced smart mobility concepts. He holds Master of Science degrees in Aerospace Engineering both from IST Instituto Superior Técnico, in Lisbon, Portugal, and SUPAERO Institut Supérieur de lAéronautique et de lEspace, in Toulouse, France.