A Renewable Source Aware Model for the Charging of Plug-in Electrical Vehicles

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Abstract: The number of Electric Vehicles is estimated to continuously rise over the next years. While this trend is expected to lead to a reduction in CO_2 emission, existing electrical grids have not been planned to support a large number of electrical vehicle's batteries charging simultaneously. The integration of distributed production using renewable energy sources is seen as a solution to meet the requirements of battery charging. Renewable sources are however affected by variation and lack of predictability, due to the environmental factors they depend on, which are the cause of inefficiencies and mismatches in the required demand-response equilibrium. In these conditions, the model and the associated scheduling algorithms to use in medium to large charging parks play an important role, due to the implications it has in their operational costs and in the maximization of the return of investments made in renewable sources. In this paper we propose and evaluate a charging model that engages users to participate in demand response measures, by giving them the ability of selecting two energy components for the charging of their electrical vehicles, one of which varies according with the variable nature of renewable sources. Based in this model we propose one scheduling algorithm and compare it with several other solutions, demonstrating that the proposed solution is able of achieving a significant cost reduction with significant low computational complexity and processing times, while achieving a high ratio of renewable energy usage.

1 INTRODUCTION

As the number of Plug-in Electrical Vehicles (EVs) is expected to rise over the next years, electrical grids have to prepare to accommodate a potential large number of such vehicles (Wansart and Schnieder, 2010). Legacy distribution grids however, are far from reaching that capability. In fact, several studies held in several countries show that current electrical grids do not tolerate EV penetration rates above 5-15% (Lopes et al., 2011). In order to adapt these grids to this trend, several measures should be considered, including an increase in production and implementing the scheduling of battery charging to avoid simultaneity.

In terms of production, the introduction of Distributed Energy Resources (DER) in the distribution grid, especially those that use renewable energy sources, is seen as an opportunity to reduce CO_2 emissions. These power sources however are sometimes characterized as Intermittent Resources (IRs), because they depend on environmental factors which make them vary significantly over time and difficult to predict with accuracy.

In order to reduce the mismatches between production and consumption several solutions can be considered, including Demand-Response (DR) and energy storage. The introduction of these solutions can, not only reduce the investments needed in renewable sources, but also accelerate its return, by maximizing its utilization.

The usage of batteries to support energy storage enables a higher flexibility in the control of loads, but comes with the drawback of introducing efficiency losses, higher investment costs and maintenance expenses due to battery lifecycles. In terms of EV batteries, the costs associated with the reduction of battery lifecycles show that feeding electricity back into the grid is only justified in very limited time frames and scenarios (Link et al., 2010). However, EV batteries can still play an important role if they adapt their charging rates according with the production obtained from renewable sources. Thus, if correctly managed, electric vehicles can be

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used to increase electrical grid stability.

In this paper we address the problem of scheduling the charging of a large number of plug-in electrical vehicles in public parking facilities. As input, a centralized EV aggregator obtains, from each vehicle driver, the information about the amount of energy that needs to be allocated to its individual EV and the expected deadline for charging completion. Given these targets the aim of the charging operator is to run a scheduling mechanism that reduces the cost of the electricity bought to a Distribution System Operators (DSO), taking into consideration different tariff rates and the local production obtained from renewable sources.

Some papers have already addressed some of the problems faced by EV charging. Among them, in (Link et al., 2010; Schmutzler et al., 2011), algorithms are presented that adjust the charging of EVs taking into consideration tariff rates, together with local and grid level power limitations. For instance, in (Schmutzler et al., 2011) the power that is used for charging of electric vehicles is made to vary inversely with a cost indicator, which in turn reflects the tariff rates and/or the power obtained from renewable sources. The proposed model considers that the power availability from distributed generation and renewable sources is reflected in price variations. This model however does not consider that local generation from renewable sources is available at the charging premises.

In (Sundström and Binding, 2010) the authors present and evaluate an optimization algorithm for the charging schedule of EVs managed by a fleet operator. The algorithm considers constrained grid conditions and uses driver historical trip data to forecast energy requirements for EV usage.

In (Chen et al., 2012) the authors address an algorithm that formulates the charging problem using a threshold test for admission control and a greedy algorithm for scheduling. While the proposed algorithm already considers local production from renewable sources it deals with renewable sources variability considering the option of non-completion penalties when a reservation is not assured.

In this paper we present and evaluate a charging model and associated scheduling algorithm to apply to battery charging of electrical vehicles that is able of optimizing the scenarios where local generation is available and also those where it isn't. Different from (Chen et al., 2012) we consider that any EV entering the charging premises communicates the deadline for charging completion and two amounts of charging energy levels, one guaranteed and another non-guaranteed. The guaranteed part needs to be authorized by an admission control procedure when an EV enters the charging premises. The non-Guaranteed part builds an eco-friendly solution which assures that the EV will be charged using only renewable sources.

The rest of the paper has the following structure. Section 2 introduces the factors involved in EV charging with renewable sources. Section 3 presents the proposed optimization model. Section 4 describes the implemented simulation platform and the obtained results in different scenarios. Finally section 5 concludes the paper.

2 CONTEXT

A model for the charging of plug-in electric vehicles needs to consider several factors including power variability, electricity tariffs, electric circuit constraints, while reflecting user requirements and its assessment.

The variability associated with renewable power sources makes the dynamic adjustment of demand difficult to implement, especially when non-elastic loads are being used. Also, these variations are difficult to predict with accuracy, affecting the efficiency of the scheduling algorithms that decide when loads should work. In other to assure a continuous supply, the power generated from these sources is normally combined and complemented with the power obtained from distribution operators and paid according with their tariff rates.

In terms of tariffs, the forecasted supply and demand data is already being mapped to electricity prices paid by Distribution System Operators, as for instance happens in (OMI-Polo Español S.A., 2010). In some countries dynamic tariffs are also being introduced at the client level (Utility-Scale Smart Meter Deployments, 2011), because constant tariff rates have shown not correlate with the marginal costs of production (Joskow and Wolfram, 2012).

While load scheduling has been until now made non-automatically, the introduction of automatic management systems could cause demand hikes at low price periods, causing a disruption of supply, due to overloading. Thus, the definition of a charge schedule management system should also take into consideration local (Electrical installation guide, 2013) and grid level (Rolink and Rehtanz, 2011) electrical circuit constraints. These constraints are normally presented in the form of simultaneity factors (*fs*) (Electrical installation guide, 2013; Rolink and Rehtanz, 2011).

Finally, a model that implements charge

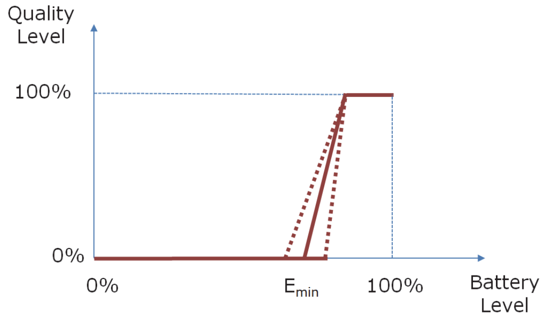

Figure 1: Assumed user's quality assessment function in response to the battery level of their Electric Vehicle.

scheduling should consider human requirements and its final assessment. In terms of requirements, some studies like (Mobilität in Deutschland, 2010), enable the modelling of EVs charging behaviours using mobility information of cars.

The assessment of the EV supply equipment derives partially from the charge level of the EV battery when compared with the energy required for the next trip. As far as we know, there are no studies that translate the subjective assessment of EV users. Basically we can assume that above a certain battery charging limit (E_{min}) users can tolerate different battery charging levels, as they have little impact in their mobility. On the contrary, if, after a charging period, the battery level of an EV is lower than E_{min}, the subjective evaluation of the scheduling mechanism will show dissatisfaction. Such subjective evaluation curve is shown in Figure 1.

In order to reflect these factors in the following we define a model that considers two charging levels.

3 PROPOSED CHARGING MODEL

Given the above mentioned constraints, we now define a model for the charging of Electric Vehicles that comprises two thresholds. These energy components are:

- Guaranteed Energy part (E_G)– comprises the minimum guaranteed amount of energy that the user requests to be supplied to a specific EV until the end of the charging period;
- Non-guaranteed Energy part (E_N)– an amount of energy allocated to the EV that will only rely on renewable sources and thus depends on the power generated locally and its availability.

The first level assures the minimum energy level that a user expects to find in battery, after a given charging period. It corresponds to the E_{min} of figure 1. Above that limit, the EV supply equipment will only rely on renewable energy power to charge the EV battery, up to its maximum capacity. Thus the total energy requested by an EV v (E_{Tv}) is given by:

$$E_{Tv} = E_{Gv} + E_{Nv} \tag{1}$$

The Non-guaranteed Energy part introduces flexibility into the charging process, since the resulting charge energy can vary according with the intermittent power generated by renewable sources. When the power produced by renewable sources surpasses the forecasted power, EV batteries are used to store excess production, reducing the need for non-vehicle batteries at premises.

Users can select the amount of energy they request for each of the components, taking into consideration that the Non-guaranteed Energy part uses a 100% eco-friendly power. The Non-guaranteed Energy part is also expected to be paid with a lower tariff motivating them to use it as much as possible.

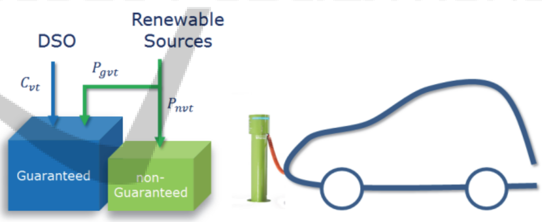

Figure 2: Power distribution between the Renewable Energy Sources and Guaranteed and non-Guaranteed Energy requests.

3.1 Mathematical Formulation

As represented in Figure 2, the Guaranteed Energy part is assured through two power components: an electrical grid component (C_{vt}) plus a renewable source component (P_{gvt}). As for the non-Guaranteed Energy part, it only makes use of renewable power (P_{nvt}).

For each electric vehicle v, a minimization of the objective function (2) should be met, by selecting the charging level C_{vt} within [t_{vpi},t_{vpf}] of EVs, in order to minimize the sum of all costs paid to the DSO, according with the set of tariff rates T_p.

$$min \left[\sum_{v=1}^{n} \sum_{p=1}^{m} T_p \int_{t_{vpi}}^{t_{vpf}} C_{vt}\, dt \right] \tag{2}$$

The minimization of equation (2) is subject to several conditions:

i) Each charging request from a newly arriving EV needs to pass through an Admission Control procedure that verifies if the Guaranteed part of the requested energy can be assured. Thus, at any given time instance *t*, the sum of all guaranteed charging powers may not exceed the maximum power of the whole parking facility:

$$\sum_{v=1}^{n}(C_{vt}+P_{gvt}) \leq P_{max} \tag{3}$$

Equation (3) assures that the Guaranteed Energy part will never fail in case an unexpected reduction of the renewable source power is verified.

ii) Also, at each time instance *t*, the sum of power allocated to each electrical vehicle *v,* from both electrical grid and renewable sources cannot exceed the EV maximum charging power (P_{vt}):

$$C_{vt}+P_{gvt}+P_{nvt} \leq P_{vt} \tag{4}$$

iii) Equation (5) assures that for each electrical vehicle v, the Guaranteed Energy part is fulfilled:

$$\int_{t_i}^{t_f} C_{vt}+P_{gvt}\,dt = E_{Gv} \tag{5}$$

iv) A maximization of the non-Guaranteed charging energy should be met, constrained by the maximum power requested by the vehicle driver:

$$max\left[\int_{t_i}^{t_f} P_{nvt}\,dt\right] \leq E_{Nv} \tag{6}$$

In order to assure the maximization of the utilization of renewable energy, as expressed in equation (6) a negative cost is applied to renewable energy utilization, and thus a virtual cost reduction in terms of optimization algorithm is verified when using that energy.

```
scr= sort charging requests starting
by      soonest leaving hour

for each non allocated scr
     allocate renewable energy for
     the guaranteed part (EG)
       until exhaustion
for each non allocated scr
     allocate DSO energy for the
     guaranteed part (EG) starting
       by the lowest tariff that
     still has available energy
for each non allocated scr
     allocate renewable energy for
     the non-guaranteed part (EN)
     until exhaustion
```

Algorithm 1: Adapted EDF algorithm according with the proposed model.

Finally, when all the above criteria are met, the scheduling algorithm should try to assure the charging of the Guaranteed Energy component as quickly as possible, as a variable number of new vehicles will arrive later to the park.

3.2 Scheduling Algorithms

Given the restrictions presented in last subsection, we will now test four main methods of charge scheduling, including two benchmark algorithms such as First-Come/First-Serve (FCFS) and Earliest Departure First (EDF) plus a Linear Programming (LP) optimization solution and a Gradual model.

As a first solution we have considered a First-Come/First-Serve (FCFS) algorithm, where, at each time interval *t*, the available power (including the one obtained from renewable sources) is allocated to EVs until its exhaustion. In this case, EVs are charged by the order of arrival, considering that, at all time instants the maximum power obtained from the DSO is constant and cannot surpass a pre-defined power limit (P_{max}).

The EDF algorithm was adapted to the model considered in this paper, being summarized in Algorithm 1. In the following we will refer to this algorithm as Adapted EDF (AEDF).

As in the FCFS solution, in the Gradual algorithm we have considered that EV battery charging occurs by their arriving order but, in a process similar with the one described in (Schmutzler, Wietfeld, Jundel, Voit, 2011), the charging power ($P_{max/TARIFF(t)}$) varies inversely with the tariff cost. In this case, we have considered that the maximum charging power of all EVs in the charging facilities is given by:

$$P_{max/TARIFF}(t) = P_{max} \cdot \left[1 - \frac{Cost(t) - DayCost_{min}}{DayCost_{max}}\right] \tag{7}$$

where P_{max} refers to the maximum power that can be obtained from the higher level operator/circuit, *Cost(t)* refers to the tariff cost for the time instant *t*, and $DayCost_{min}$ and $DayCost_{max}$ correspond respectively to the minimum and maximum intra-day tariff prices.

Finally, the Linear Programming optimization model takes into consideration several parameters shown in Figure 3. The objective function of the model aims at minimizing costs, subject to the constraints presented section 2.2.

Given the aforementioned algorithms, next section will outline the implemented simulation platform and the tests performed.

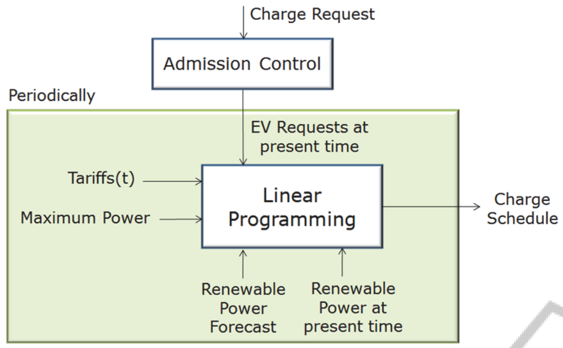

Figure 3: Diagram of the Linear Programming optimization module.

4 SIMULATION PLATFORM AND RESULTS

In the following we describe a set of simulations considering a parking facility with a maximum of 50 charging stations. The maximum charging power of each EV (i.e. P_{vt}) was set to 3 kW.

Figure 4 presents the considered tariff rates, obtained from (OMI-Polo Español S.A., 2010) for the 1st of August 2013 and the generated power (in kW) obtained from renewable energy sources (for the same day, measured in the south of Portugal) considering a peak production of 83 kW. The grid is simulated using a discrete-event simulation with time slots of 15 minutes.

We considered that EVs arrive to the parking station according to a Poisson distribution with mean 9 (i.e., 9 a.m.) and the duration of the charging was made to vary according with a normal distribution with mean 6 (hours) and standard deviation of 4

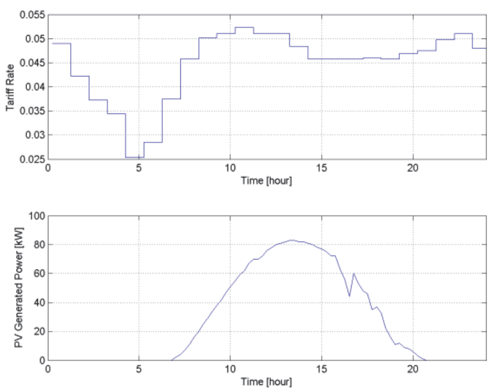

Figure 4: Tariff prices (upper part) and power generated using photovoltaic panels (bottom) in August, 1st, 2013.

hours. To model the total energy requested by each EV we have also considered a normal distribution with mean 10 (kWh) and standard deviation of 4 (kWh).

4.1 Scenario 1

In the first scenario we considered that no renewable energy sources were available at the charging premises and that all charging requests were guaranteed.

As the maximum power received from a DSO is an important parameter that is expected to be minimized, we have evaluated how different values of P_{max}, ranging from 60 kW (f_s=*0.4*) to 165 kW (f_s=*1.1*) in steps of 15 kW contribute to the efficiency of each algorithm.

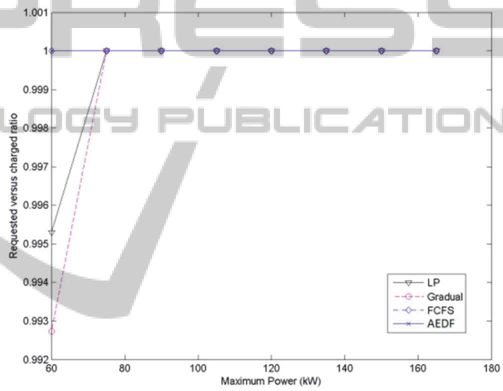

Figure 5: Ratio of EV requests that were fulfilled when not using renewable energy sources.

Figure 5 presents the obtained results in terms of the ratio of EV requests that were fulfilled (as P_{max} varies). As can be verified, when P_{max} was equal to, or higher than, 75 kW all the algorithms were able of fully assuring the requested energy quantities. However under 75 kW only the FCFS and AEDF algorithms were able of fully charging all vehicles. These results reflect an important issue. A higher degree of freedom should be given to the algorithms that perform load shifting, as they will likely request higher power levels when tariffs are lower. If loads are postponed and more EVs later arrive to the charging station, there is a risk of not being able of serving all requests. That risk increases as P_{max} decreases.

Using the same conditions, Figure 6 shows how different values of P_{max} contribute to the cost efficiency of each algorithm. As can be verified, as of P_{max} increases the cost of both FCFS and Gradual

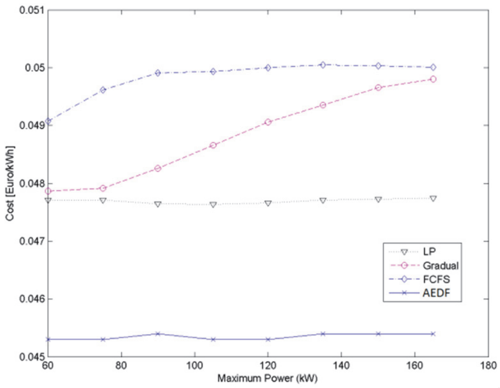

Figure 6: Cost comparison of the three algorithms when production from renewable energy sources is not included.

algorithms increases. These results come from the fact that in the performed tests most EVs arrive to the park when the tariff rates are higher. Thus increasing P_{max} has a direct impact in the cost of these two algorithms as more power can be allocated to EVs. On the contrary, the cost of the other two algorithms, the LP and AEDF, has shown not to vary significantly with P_{max}. The lowest cost was assured by the LP algorithm.

4.2 Scenario 2

In the following scenario we considered that a renewable energy source (shown in Figure 4) was available at the charging premises and that all charging requests were guaranteed. Given the results obtained in previous tests, we have considered P_{max} to be equal to 90 kW.

Using these conditions we have performed systematic tests with 30 runs to evaluate the performance of the charging algorithms in terms of costs and renewable energy usage. In each execution we introduced a random variation between what was the forecasted renewable power and the power that was actually available, for both, in each time instant and for a day period. This method approximates our tests with what really happens when dealing with forecasting the power of renewable sources.

Table 1 reflects the results of the algorithms in this scenario. This table reflects the cost that the charging operator would have to pay (and not the cost paid by the EV driver). As can be verified in Table 1, both, the LP and AEDF algorithms are both able to use the highest amount of the available renewable energy, and thus receive the lowest amount of energy from distribution operators. Both solutions are able of significantly reducing electrical costs when compared with the FCFS and Gradual algorithms.

Table 1: Results of the Simulation tests in Scenario 2.

Parameter	Scheduling Solution			
	FCFS	Gradual	LP	AEDF
Cost (€)	6.40	6.30	0.030	0.035
Non-Renewable Energy Used (kWh)	129.01	127.03	0.95	0.75
Renewable Energy Used (kWh)	360.24	362.23	488.30	488.50
Total Energy (kWh)	489.25	489.25	489.25	489.25
Number of EVs Charged	50	50	50	50

4.3 Scenario 3

As in the previous scenario, in this case we considered that the renewable energy source was available at the charging premises. However, we have now defined that users were requesting part of the energy as Guaranteed and the other part as Non-guaranteed. Specifically, we have considered that 85% of the energy requested in scenario 2 was now demanded as Guaranteed and another 25% was requested as non-Guaranteed. In this sense we assume that in this scenario users are predisposed to let the EV Supply Equipment (EVSE) charge 10% more energy than in the last scenarios for three reasons: (1) the non-Guaranteed part is expected to be cheaper; (2) users are aware that this energy is 100% renewable; and (3) it isn´t guaranteed that they will get the requested amount.

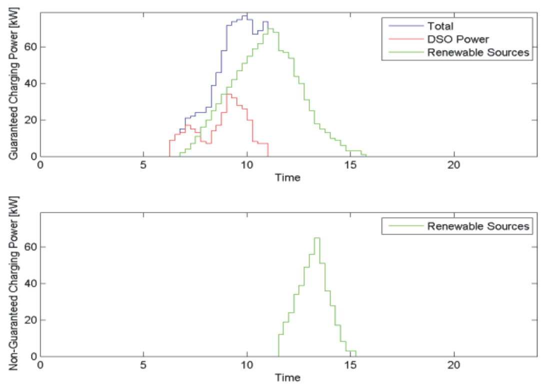

Figure 7: Aggregated Power consumption of all EVSEs for the Gradual algorithm, in terms of Guaranteed (upper part) and non-Guaranteed charging (bottom part) components.

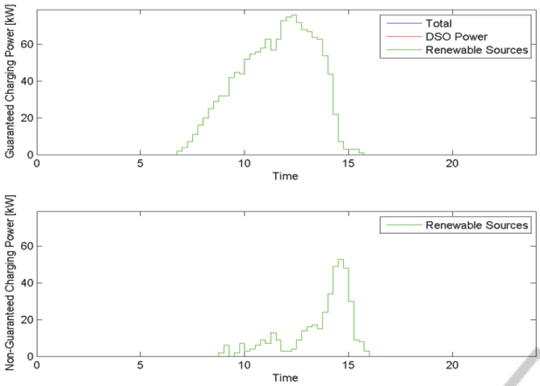

Figure 8: Aggregated Power consumption of all EVSEs for the LP algorithm including the Guaranteed (upper part) and non-Guaranteed charging (bottom part) components.

As in the previous scenario, we have considered P_{max} to be equal to 90 kW. As in the previous scenario we have performed systematic tests with 30 runs to evaluate the performance of the charging algorithms in terms of costs and renewable energy usage. In each execution we introduced a random variation between what was the forecasted renewable power and the power that was actually available, both at each time instant and during a day period.

For the same set of EV's arriving times and requested energy, Figures 7 and 8 present the results of a one day simulation, respectively for the Gradual and LP algorithms concerning the power consumed by all EVSEs. As can be verified in these plots, the LP algorithm is able of relying only on renewable energy to charge both the Guaranteed and non-Guaranteed components.

Table 2 reflect the results of the algorithms in this scenario. When comparing the results of Table 2 with the ones of Table 1 (scenario 2), it can be verified that on average there is a cost reduction in all algorithms, even with an increase of nearly 10% of energy allocated to EVs. Also, when comparing both scenarios, a higher consumption of renewable energy is verified, with a correspondent decrease in the total amount of energy obtained from the upper level distribution operators.

The reason behind the fact that all algorithms are able of charging more energy using less power from the DSO (when compared with previous scenario) comes from the flexibility introduced by the model regarding the partitioning into Guaranteed and Non-guaranteed energy components. What happens is that in those days when more renewable power is available, the proposed model is able of using it, and for those days when it is not, it is able to adapt better by recurring less to the distribution operator.

Table 2: Results of the Simulation tests in Scenario 3.

Parameter	Scheduling Solution			
	FCFS	Gradual	LP	AEDF
Cost (€)	5.12	5.11	0.023	0.022
Non-Renewable Energy Used (kWh)	105.08	104.85	0.72	0.47
Renewable Energy Used (kWh)	434.78	435.00	532.23	539.38
Total Energy (kWh)	539.85	539.85	532.95	539.85
Number of EVs Charged	50	50	50	50

As can be verified in Table 2, both the LP and AEDF algorithms are able of using the highest amount of the available renewable energy, and thus achieve the lowest cost. The main difference between the two algorithms stands in their computational requirements. In fact, when using an Intel(R) Core(TM) i7-4770 microprocessor the AEDF algorithm took on average 216 milliseconds to schedule 50 charging requests, which compares with the 14.1 seconds required by the LP algorithm. As each driver would have to wait for the end of the scheduling algorithm to know if the requested energy could be granted, the time that the algorithm takes to obtain a solution is an important factor that needs to be considered in its evaluation.

Figure 9 compares both the LP and the AEDF algorithms in terms of computation time, when scheduling a varying number of EVs. It shows that the LP solution suffers from severe scalability problems, which can prevent it from being implemented in a real scenario with several dozen vehicles. On the contrary the execution times of the AEDF algorithm are not only much lower than the LP ones, but also they increase linearly with the number of EVs being scheduled.

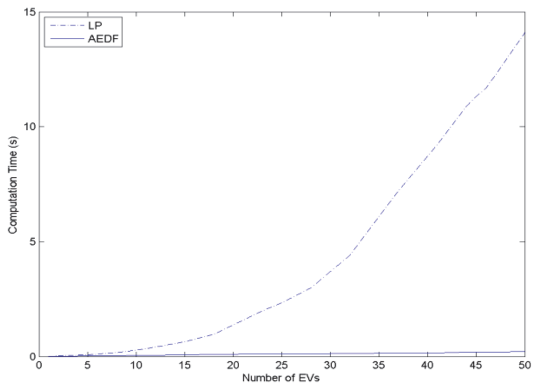

Figure 9: Computation times of the LP versus AEDF algorithms for the scheduling of different numbers of EVs.

5 CONCLUSIONS

This paper proposes and evaluates a novel model for the charging of plug-in electric vehicles that includes the local production of energy resulting from renewable sources. The model is designed to motivate users to participate in demand response measures, making their EVs serve as energy storage units when surplus energy is generated, by being aware of the variability that such sources impose.

The tests and results obtained show that the proposed model is able of achieving a cost reduction in all the tested algorithms while assuring a higher consumption of renewable energy. Among the tested scheduling algorithms, the proposed AEDF solution has shown to be able of achieving a significant cost reduction with a significant lower computational complexity and processing times, when compared with the LP algorithm. The obtained results have demonstrated that the AEDF algorithm can be used in charging facilities with 50 or more vehicles.

Finally, the flexibility introduced by the model regarding the partitioning into Guaranteed and Non-guaranteed energy components has shown to support a better adaptation to the variable nature of renewable sources.

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