Towards an Agent-based Negotiation Scheme for Scheduling Electric Vehicles Charging

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Abstract. We consider the problem of scheduling Electric Vehicle (EV) charging within a single charging station aiming to maximize the number of charged EVs, as well as the amount of charged energy. In so doing, we propose one offline optimal solution using Mixed Integer Programming (MIP) techniques, and two online solutions which incrementally execute the MIP algorithm each time an EV arrives at the charging station. Moreover, we apply agent based negotiation techniques between the station and the EVs in order to service EVs when the MIP problem is initially unsolvable due to insufficient resources (i.e., requested energy, charging time window). We evaluate our solutions in a setting partially using real data, and we show that when applying negotiation techniques, the number of EVs charged increases on average by 7%, energy utilization by 6.5%, while there is only a small deficit (about 10%) on average agent utility which is unavoidable due to the fact that the initial incremental demand-response problem is unsolvable.

1 Introduction

Electric vehicles (EVs) are an efficient alternative to internal combustion engined ones when it comes to running costs, environmental impact and quality of driving. However, these advantages come with a certain cost, as EVs suffer from short range and long charging times. In order such problems to be reduced, a large number of charging stations with state of the art facilities (i.e., fast chargers, or battery swappers) should exist. However, here there is a quandary problem, as drivers will not buy EVs if charging stations are not available, and companies, organizations, or even countries will not invest in charging facilities unless many EV-customers exist.

In this paper, we claim that multi-agent systems can be proved useful in partially solving such problems and making EVs popular. In particular, we study a setting where EVs arrive at a single charging station and need to charge. The EVs are self-interested agents that need to maximize their profit (i.e., maximize energy charged and minimize waiting time), while the charging station aims to maximize the number of serviced EVs and the utilization of the available energy.

To date, a number of papers trying to solve similar problems exist in the literature [9]. For example, Bayram et al. [1] assumes a large number of charging points, each of them having pre-ordered a certain amount of energy. They use a centralized mathematical programming algorithm to optimally allocate the energy to EVs, so as to service the maximum number of EVs. The authors evaluate the mechanism in a setting where both selfish (want to charge at the nearest charging point), and cooperative EVs exist, and verify the performance of their algorithms. In turn, [6] propose dynamic programming algorithms that schedule the charging of EVs according to the availability of energy while guaranteeing the intended journeys can be completed. They also show that their solutions can adapt to fluctuations in energy generation from renewable sources thus increasing EV penetration to the grid. Instead, in [4], agents state time windows within which they will be available to charge, and bid for units of electricity in a periodic multi-unit auction (one auction per time step). In order to ensure truthfulness, the authors developed a mechanism that occasionally leaves units of electricity unallocated (burned), even if there is demand for them. In addition, using more traditional agent-based negotiation techniques, Gan et al. [3], implement an iterative procedure to allow EVs to negotiate the charging rate (at different time points) with a utility company (that broadcasts a price signal to control charging). Crucially, they show that, should the charging characteristics of all EVs be known, an optimal solution is reached in a decentralized fashion. Finally, the authors in [5] and [2] propose methodologies for coping with the important problem of placing the charging stations in such places so that the number of EVs they service can be maximized.

The common characteristic of the majority of the work in this field is that the preferences of the EVs, once communicated to the charging station(s) are taken for granted (e.g., to [1], [6], and [4]). In other words, the preferences of the EVs do not change. The main difference of our approach is that here, we propose an agent-based scheme where in case an EV's preferences cannot be fulfilled, the station can negotiate with it and suggest a different charging plan. In contrast to [3], charging characteristics of all EVs are not assumed to be known. Note that, negotiation techniques [7] have already been considered as an efficient method to increase the participation of various actors within the smart grid [8].

We advance the state of the art as follows:

1. We propose an offline optimal solution to schedule the charging of EVs in a single charging station aiming to maximize energy utilization and EV satisfaction (i.e., number of serviced EVs).
2. We propose an online algorithm, which incrementally uses the aforementioned optimal formulation, for EV charging scheduling.
3. We extend the aforementioned algorithm with the ability to start a negotiation procedure with the EVs (by making counter offers to them) in case a charging plan based on their initial preferences cannot be calculated. In this vein, we propose three algorithms for calculating the offers that are made to the EVs during the negotiation procedure.

4. Finally, we empirically evaluate our proposed algorithms in a setting partially using real data (renewable energy generation) and we prove the efficiency of the negotiation technique in increasing EVs satisfaction and energy utilization

2 Problem Definition

In this paper, we study a setting where a number of EVs arrive at a single charging station over time and need to charge. We assume that each EV has his own agent which communicates to the charging station the EV's needs and constraints and tries to satisfy them in the best possible way. In a real scenario, such an agent could reside on the navigation system of the car. At the same time, the charging station aims to serve as many clients as possible in order to maximize its profit, as well as the total welfare of the agents. In so doing, it takes into consideration its available resources (i.e., charging slots, available energy (both renewable and non-renewable energy is assumed to be available to the charging station)), as well as the EVs' constraints.

In more detail, we denote the set of EV-agents $a_i \in A$, and the charging station c which has a number of charging slots $s_j \in S$. Moreover, we assume a set of discrete time points $t \in T$ to exist. At each time point, the charging station has $e_t \in E$ energy units available for EV charging (note that, energy storage is not supported). The number of charging slots, as well as the amount of energy set an upper limit to the number of EVs that can charge simultaneously. Now, for each EV we define a tuple $p_i = \left\langle a_i, t_i^{sys}, t_i^{arr}, t_i^{dep}, e_i^{max}, e_i^{min} \right\rangle$. In more detail, upon its arrival to the system at time point t_i^{sys}, each EV i informs the charging station about its arrival time at the station $t_i^{arr} \geq t_i^{sys}$ (i.e., the EV can inform the charging point about its preferences the time it arrives to it, or earlier), the preferred departure time t_i^{dep}, as well as the maximum e_i^{max} and minimum e_i^{min} energy that it prefers to charge.

Now, once an EV has informed the charging station about its preferences, the station applies a scheduling algorithm to decide on its charging schedule. In case, given the EV's and station's constraints, such a schedule is impossible to be computed, the station begins a negotiation procedure with the EV, during which a number of counter offers / suggestions are communicated to it. During this procedure, the EV can either accept or reject the offers. This procedure is presented in detail in Section 3.3.

3 EV Scheduling Algorithms

To solve the problem of EV charging scheduling, three approaches are considered. In more detail, the charging station's parameters (i.e., number of chargers, and available energy) are assumed to be known in advance, while the EVs' preferences can either be known in advance (offline approach - see Section 3.1) or can be made known dynamically (online approaches - see Sections 3.2, 3.3).

3.1 Offline Optimal Solution

In this section we present a centralized, static, optimal Mixed Integer Programming (MIP) formulation of the problem (developed using IBM ILOG CPLEX 12.5) which is used for benchmarking purposes, but it also acts as an important building block for the online algorithms presented in the following sections. The aim of this formulation is to find the optimal charging plan such that both the number of EVs serviced, and the amount of energy charged are maximized. Thus, the objective function to be maximized (Equation 1) is a weighted sum of these two values. The weights show the priority that the station gives to the two values. The formulation contains two binary decision variables: 1) decision variable $a_{i,t} \in \{0, 1\}$ denoting whether an EV i is charging at time point t, and 2) $b_i \in \{0, 1\}$ denoting whether an EV is serviced or not. The objective function is maximized under a number of constraints:

Objective Function:

$$w_1 \times \sum_{a_i \in A} \sum_{t \in T} a_{i,t} + w_2 \times \sum_{a_i \in A} b_i \tag{1}$$

$$\text{where } w_1 + w_2 = 1$$

Constraints:

$$\forall a_i \in A, \sum_{t=t_i^{arr}}^{t_i^{dep}} a_{i,t} \times b_i \leq e_i^{max} \tag{2}$$

$$\forall a_i \in A, \sum_{t=t_v^{arr}}^{t_v^{dep}} a_{i,t} \times b_i \geq e_i^{min} \tag{3}$$

$$\forall t, \sum_{a_i \in A} a_{i,t} \leq |S| \tag{4}$$

$$\forall t, \sum_{a_i \in A} a_{i,t} \leq e_t \tag{5}$$

In more detail, every vehicle i must charge a number of energy units between its minimum and maximum preferred values (Equations 2 and 3), while the number of the vehicles that charge simultaneously must not exceed the total number of charging slots (Equation 4). Finally, the total number of energy units charged at one time point, should not exceed the total number of the available energy units (Equation 5). From now on, we will refer to the MIP formulation of the problem as *Optimal* which takes as input parameters all tuples $p_i, \forall a_i$.

3.2 On-Line Scheduling Algorithm without Suggestions

To this point, the number and the preferences of the EVs were assumed to be known in advance. However, here, the EVs inform the charging station about their preferences dynamically, the time they arrive at the system (see Algorithm 1). Once the station receives a new charging request, it calls the optimal scheduling algorithm giving as input the preferences of the new EV as well as the charging plan of the EVs that have already arrived at the past, while constraints 6 and 7 are added to the MIP formulation. In more detail, the EVs $a_i \in charged \subseteq A$ that have already been scheduled to charge are constrained to receive the number of energy units (i.e., e_i^{total}) that was decided the first time (Equation 6), within the predefined departure time (Equation 7). What can change is the time points that the EV will actually charge. Regarding the new EV, the charging station is free to decide whether or not it will be charged, as well as the time points the charging will take place. Note that, the case where an EV can book a slot for charging and then cancel it, or leave the charging station earlier than its predefined time is not studied.

$$\forall a_i \in charged, b_i = 1 \tag{6}$$

$$\forall a_i \in charged, e_i^{total} = \sum_{t \in T} a_{i,t} \tag{7}$$

Algorithm 1 Dynamic EVs Scheduling Algorithm Using MIP

```
for ∀t ∈ T do
    for ∀a_i ∈ A : t_i^arr = t do
        {All EVs arriving at t are assigned to set current.}
        current ← current + p_i
    end for
    Call Algorithm 2(current)
end for
Return: ∀a_i ∈ A, a_{i,t}, e_i^total and charged
```

3.3 On-Line Approach with Suggestions

Similarly to the previous algorithm, here EVs' preferences become available dynamically, the moment the EV arrives at the system. However, in addition to what has been studied so far, here the charging station has the ability to make counter offers / suggestions to the EVs in case it is impossible to cover their needs as they are communicated to it at first. In more detail, once an EV arrives at the system and communicates its needs to the station, it applies the optimal scheduling algorithm as this has been described in Algorithm 1. In case a feasible solution does not exist and a schedule cannot be calculated, then the station

Algorithm 2 EVs Scheduling Algorithm

Require: *current*

Call $Optimal(current)$

{Each EV that has charged and is not in set *charged*}

for $\forall a_i \in A$ **do**

  if $(b_i = 1)$ AND $(a_i \notin charged)$ **then**

    $charged \leftarrow charged + a_i$

    $e_i^{total} = \sum_{t \in T} a_{i,t}$

  end if

end for

Return: $(\forall a_i, t\ a_{i,t},\ e_i^{total},\ b_i)$ and *charged*

starts a negotiation procedure and makes a number of counter offers to the EV, which can either be accepted or rejected (see Algorithm 3 and Figure 1). In order to capture the EV's reply, variable $r_i \in \{0, 1\}$ is defined which is actually drawn from a probabilities distribution. In the next section, the algorithms that are used in order to calculate the station's suggestions to the EVs are presented.

Algorithm 3 EVs Scheduling Algorithm with Suggestions.

for $\forall t \in T$ **do**

  for $\forall a_i \in A : t_i^{arr} = t$ **do**

    $current \leftarrow current + p_i$

  end for

  Call Algorithm 2(*current*)

  {For the EVs that couldn't be scheduled for charging}

  for $(\forall a_i \in current : b_i = 0)$ **do**

    $count = 4$

    while $(accepted! = 1)$ AND $(count \leq 6)$ **do**

      {We call Algorithms 4, 5, 6 consecutively (see Figure 1).}

      Call Algorithm count

      $accepted = r_i$

      $count = count + 1$

    end while

  end for

end for

Return: $\forall a_i \in A,\ a_{i,t},\ e_i^{total}$ and *charged*

3.3.1 Suggestions Calculation Algorithms Here, we describe how the charging station calculates the offers made to the EVs during the negotiation procedure. As one can see in Figure 1, this negotiation phase has up to three steps. In each one, the station is making an offer to the EV, which can either be accepted or rejected. This negotiation starts from the stations' most preferred solution, where the proposed amount of energy is identical to the original, thus its utilization is maximized, but the charging time window is widened, then, at the second step the time window remains the same but the amount of proposed

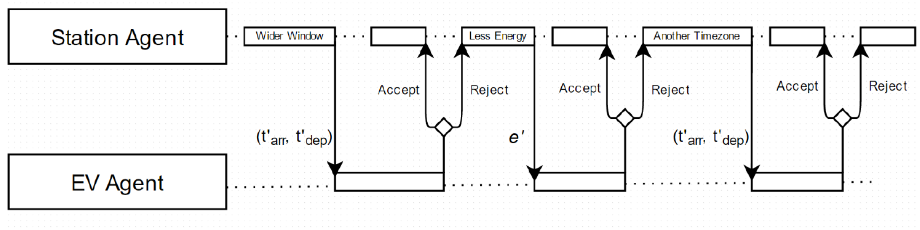

Fig. 1. EV- Station Negotiation Procedure

energy is reduced (the maximum available energy should be at least equal to the minimum amount asked by the EV), and finally a totally different time window but with the initially desired amount of energy is proposed to the EV.

1. Step 1: Here the station calculates a **wider time window** (see Algorithm 4) in order to provide to the EV at least the minimum energy it has asked for. In so doing, the station aims to widen the predefined time window until the necessary energy becomes available. Firstly, the window is widen to the right (i.e., future time points) and if enough energy is still not available, it is also widen to the left, given that the EV's arrival time at the system is different (smaller) compared to the arrival time at the station. For every time point that an available energy unit is found, variable $energy \in N$ is increased by one. If such a time window is not found, or the new time window has a not $acceptable_\tau \in \{0, 1\}$ size ($acceptable_\tau$ is defined by the user), or the EV rejects the offer, the station goes to the next step.
2. Step 2: In case enough energy is not available within the time window defined by the EV, the station calculates whether a **smaller amount of energy** (see Algorithm 5) can be provided within these time limits. In so doing, the station has already decided a percentage $acceptable_e \in [0, 1]$ of the initial energy within which an offer can be made to the EV. In other words, the station searches within the time window if $e_i^{min} \times acceptable_e$ energy units are available. In case enough energy is not found, or the EV rejects the offer, the station goes to the next step.
3. Step 3: Finally, the station can calculate a **different time zone** (see Algorithm 6) for an EV to charge. In so doing, the time window within which the EV will charge is shifted across the set of time points (constrained so as the arrival time of the EV is not violated), while the tightness of the window is also taken into consideration (i.e., the first and the last time points at which an EV will charge should not be too far from each other). Note that, the main difference with Algorithm 4 is that here the time window can be completely different compared to the initial one, while in 4 the initial window acts as a pivot, and is always part of the offer.

Algorithm 4 Wider Window Calculation Algorithm.

Require: $\forall i, p_i$, *acceptable*

{First widen window to the right. If desired energy not found, widen window to the left. If acceptable window is found suggest to EV. Initial window acts as a pivot}

$t_i'^{arr} = t_i^{arr}$; $t_i'^{dep} = t_i^{dep}$; $found = 0$; $energy = 0$

{The available energy in the initial time window is calculated.}

for $(\forall t \in T : (t \geq t_i^{arr})$ AND $(t \leq t_i^{dep}))$ **do**

  if $(e_t > 0)$ AND $(\sum_{a_i \in A} a_{i,t} < |S|)$ {If enough energy and chargers exist} **then**

    $energy = energy + 1$

  end if

end for

{$t_i'^{dep}$ is increased by 1 until necessary energy found, or final time point is reached.}

while $energy < e_i^{min}$ **do**

  $t_i'^{dep} := t_i'^{dep} + 1$;

  if $(e_{t_i'^{end}} > 0)$ AND $(\sum_{a_i \in A} a_{i,t_i'^{end}} < |S|)$ **then**

    $energy = energy + 1$;

  end if

end while

{$t_i'^{arr}$ is decreased by 1 until necessary energy is found, or t_i^{sys} is violated.}

while $energy < e_i^{min}$ **do**

  $t_i'^{arr} := t_i'^{arr}$ - 1;

  if $(e_{t_i'^{end}} > 0)$ AND $(\sum_{a_i \in A} a_{i,t_i'^{end}} < |S|)$ **then**

    $energy = energy + 1$

  end if

end while

{If energy is found and time window not too large.}

if $(energy \geq e_i^{min})$ AND $((t_i'^{dep} - t_i'^{arr}) \div (t_i'^{dep} - t_i'^{arr}) > acceptable)$ **then**

  found = 1;

end if

Return: $t_i'^{arr}$, $t_i'^{dep}$, $energy$, $found$

Algorithm 5 Less Energy Calculation Algorithm.

Require: $\forall i, p_i$, *acceptable*

{Searches in given window how much energy is available. If more than acceptable percentage, then suggest to EV.}

$energy = 0$

for $(\forall t \in T : (t \geq t_i^{arr})$ AND $(t \leq t_i^{dep}))$ **do**

  {If enough energy and chargers exist.}

  if $(e_t > 0)$ and $(\sum_{a_i \in A} a_{i,t} < |S|)$ **then**

    $energy = energy + 1$

  end if

end for

$percentage = energy \div e_i^{min}$

if $percentage \geq acceptable$ **then**

  $found = 1$

end if

Return: $energy$, $found$

Algorithm 6 Another Time Zone Calculation Algorithm.

Require: $\forall i, p_i$, *acceptable*

$t_i^{\prime arr} = t_i^{sys}, t_i^{\prime dep} = t_i^{sys} - 1$

{If the longest time window based on $t_i^{\prime arr}$ is large enough for the station to provide the minimum required energy.}

$energy = 0, penalty = 0$

while $(|T| - t_i^{\prime arr}) \geq (e_i^{min})$ **do**

  while $((energy < e_i^{min})$ and $(t_i^{\prime dep} < (|T| - 1)))$ **do**

    $t_i^{\prime dep} = t_i^{\prime dep} + 1$ {Increase new window to the left}

    if $(e_t > 0)$ and $(\sum_{a_i \in A} a_{i,t} < |S|)$ **then** {If enough energy, chargers exist}

      $energy = energy + 1$

    else

      $penalty = penalty + 1$

    end if

  end while

  {If $t_i^{\prime dep}$ has reached the final time point, no window can be found}

  if $(t_i^{\prime dep} = |T|)$ **then**

    Break

  else

    {If a window containing the desired energy is found check if it sparse}

    if $(penalty \div (t_i^{dep} - t_i^{start} + 1) \leq acceptable)$ **then**

      found = 1; break

    end if

  end if

  {If a legitimate window was not found, increase start time by one and continue}

  if $(e_{t_i^{\prime arr}} > 0)$ and $(\sum_{a_i \in A} a_{i,t} < |S|)$ **then**

    $energy = energy - 1$

  else

    $penalty = penalty - 1$

  end if

  $t_i^{\prime arr} = t_i^{\prime arr} + 1$

end while

Return $t_i^{\prime arr}$, $t_i^{\prime dep}$, $found$

4 Evaluation

We evaluate our algorithms according to execution times (see Section 4.1), performance (i.e., EVs charged, EVs' utility, and energy utilization) (see Section 4.2), and sensitivity (i.e., dependence of the performance on the number of charging slots) (see Section 4.3).

Throughout the evaluation, we assume the charging station to operate 24hours a day (we want to show how the system operates in a full day) and 288 time points to exist (i.e., 1 time point = 5 minutes - as our energy data was measured every 5 minutes). The day is divided into 4 zones, each one with 72 time points where the zones are equivalent to: 1) morning to noon, 2) afternoon, 3) evening to night, 4) early morning of the next day. Also, the charging station has 5 chargers (this is a number that fits our EVs data so as the scenario to be realistic). On top of this, we assume that all EVs have the same charging rate, which is one unit of energy at each time point. Moreover, EVs arrival times are generated by Gaussian distributions, where the probability for an EV to arrive during the first and third time zones is higher compared to the rest, and energy demand is generated by a uniform distribution. Also, the weights in our objective function are 50-50, which means that the station tries to maximize the serviced EVs and its profit with the same priority. Finally, we use real data regarding energy production from renewable energy sources (photovoltaic), generated by the International Hellenic University's solar panel park (energy, measured in kilowatts per hour, generated by a single solar panel with a five-minute interval). We assume that in every five minutes (i.e., 1 time point) an EV uses 0.6kW/h (1 energy unit) for charging. Finally, the collected data is transformed from kW/h to energy units, and it is multiplied by 5, as we also assume that the station contains five solar panels (energy that fits the EVs data).

4.1 Execution Times

Execution time and scalability is a major factor in the usability of a given scheduling algorithm. For this reason, here, keeping all parameters but the number of EVs fixed, we measure the execution time of both the online and the offline algorithms. For a setting with $30 - 300$ EVs (see Figure 2), we could argue that for the optimal algorithm the execution time increases near linearly, while for the online without suggestions increases super-linearly with a rather low rate of growth, while for the online with suggestions the execution time increases super-linearly with a rather high rate of growth. However, in the worst case, the average execution time does not exceed the 100 secs, thus making even the online with suggestions usable for large settings. Remember, that the online algorithms call the optimal one incrementally when an EV arrives at the system, and therefore their larger execution times were expected. Also note, that the online algorithm with suggestions has an even larger execution time as it includes also the execution of the algorithms for calculating the suggestions. Finally, we should mention that the execution time of the online algorithm with suggestions depends on the number of EVs that accept an offer and the negotiation round that this happens, as the calculation of the offers is time consuming (i.e., calculation of fewer offers leads to lower execution time).

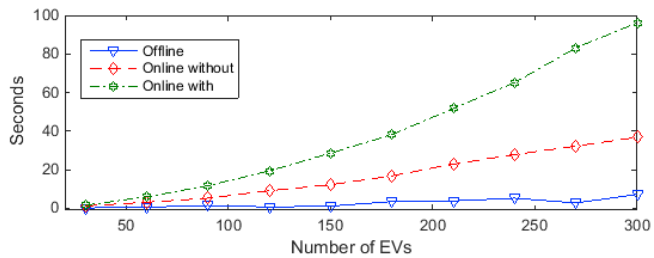

Fig. 2. Algorithms' Execution Time

4.2 EV Satisfaction and Energy Utilization

Here, we evaluate the performance of our proposed algorithms in terms of EV satisfaction (i.e., number of serviced EVs and average utility), as well as energy utilization (see Figures 3, 4, 5 and Table 1). In terms of EV satisfaction, the offline algorithm is better than the online one without suggestions. This was expected given the fact that in the offline approach full knowledge of EV demand is assumed to be known in advance. Now, in terms of energy utilization, the gap between the two approaches is smaller, as even though the online algorithm charges less EVs, it uses about the same amount of energy. This happens because the online algorithm decides to charge more vehicles with high needs for energy compared to the offline one. Thus, the station still has a good profit, but many agents are unsatisfied. When it comes to the online algorithm with suggestions, in settings with 30 - 100 EVs, is clearly ahead of the online without suggestions and close to the optimal solution, while from 100 until 150 EVs remains ahead of the online without suggestions but with a smaller gap. Here, we can point out the fact that the online algorithm shows the bigger improvement in settings with small to medium number of EVs. For larger number of EVs, the station starts becoming too congested and therefore the negotiation procedure becomes less effective. If you see this in correlation with the high execution times when the number of EVs increases, we could argue that the online with suggestions may not worth being used for large number of EVs. Regarding energy utilization, the online with suggestions has a clear advantage for small and medium number of EVs where more available charging slots exist, while later it starts leveling off.

In terms of agent utility, the offline and the online algorithm without suggestions achieve 100% utility of the EVs that have been serviced, as their needs, and constraints are fully covered. Now, the online algorithm with suggestions achieves an average utility of about $88 - 90\%$ as despite the fact that more EVs are charged, some of their initial constraints are relaxed. This small deficit on average agent utility is unavoidable due to the fact that the initial incremental demand-response problem is unsolvable. In order to measure the utility, for every agent that will finally charge, we compute the Euclidean distance between its initial preferences and what it finally gets. Later, this value is normalized to $[0, 1]$. We notice that, at 30 to 60 EVs the utility is high, at 60 EVs it drops and then it continuously increases. This can be attributed to the fact that at 30 EVs not many suggestions have to be made as initial EV preferences can be fulfilled, thus the utility is high. At 60 to 120 EVs the utility drops, as in this window, the station is neither too empty, nor too congested, and therefore many EVs accept offers during the negotiation procedure. From 120 to 150 EVs, the station is already too congested with EVs charging within their initial preferences and therefore, less offers are being made to EVs.

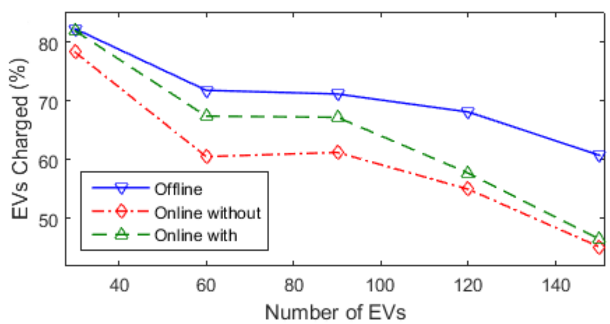

Fig. 3. EVs Charged

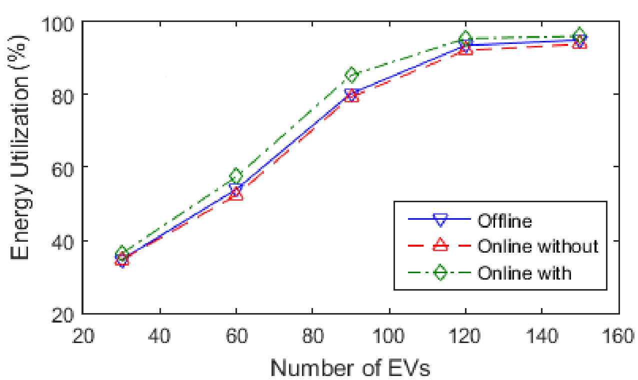

Fig. 4. Energy Used

Now, regarding the online algorithm with suggestions, its performance is directly related to the attitude of the agents during the negotiation procedure. In other words, the more cooperative the agents are, the more successful, the negotiation is. Therefore, we conducted a set of experiments where different levels of agent cooperation is assumed to exist. A cooperative agent is defined as an agent which has a high probability of accepting an offer (80% to 90%), while a non-cooperative agent is an agent with low probability of accepting offers (25%

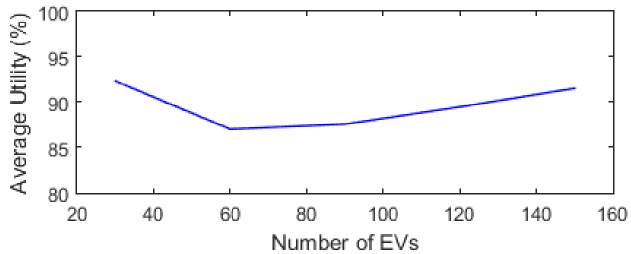

Fig. 5. Average Utility

Table 1. Algorithms Comparison - 5 Chargers

		Number of Evs		
		60	90	150
EVs Charged	On-Line vs Off-Line	-15.48%	-14.63%	-25.79%
	Strategy vs On-Line	11.43%	9.80%	2.88%
Energy Utilization	On-Line vs Off-Line	-2.95%	-1.19%	-1.18%
	Strategy vs On-Line	9.59%	7.54%	2.29%
Agents' Utility	On-Line vs Off-Line	0.0%	0.0%	0.0%
	Strategy vs On-Line	-12.95%	-12.4%	-8.45%

to 30%). As can be seen from Figures 6, 7, 8, when the majority of the agents are cooperative higher number of them are serviced and energy is better utilized, however the performance is worse in a setting where the majority of the agents are non-cooperative. Also, as expected, the utility of the cooperative agents is lower, as they accept more changes to their initial preferences.

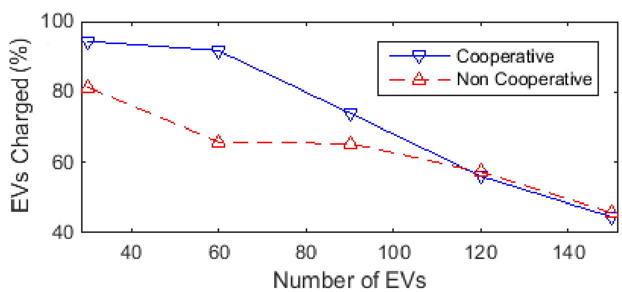

Fig. 6. Number of serviced EVs

4.3 Sensitivity Analysis

Here we further evaluate our algorithms, in a setting where the number of chargers varies but infinite amount of energy exists. We can observe (see Figure 9) that for settings with up to 90 EVs the online algorithm with suggestions performs better compared to the offline one especially for small numbers of chargers. This can be explained due to the fact that when chargers are few, the initial preferences of many EVs may not be able to be covered, and thus the negotiation procedure is more efficient. In contrast, for larger numbers of EVs, full knowledge of future demand gives a big advantage to the offline one, and therefore it is

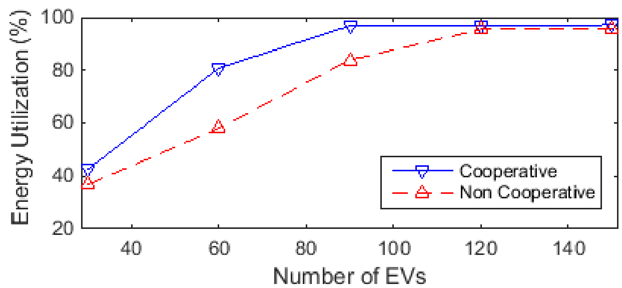

Fig. 7. Energy Utilization

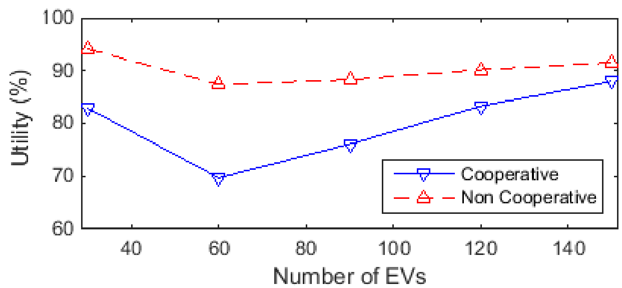

Fig. 8. Average Utility

better than the online one. Moreover, when the station becomes too congested, minimal space for feasible suggestions exists. Thus, we can conclude that overall, the offline algorithm is less sensitive to the change of the number of chargers.

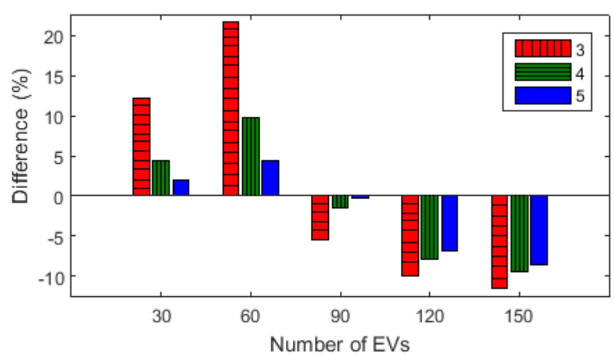

Fig. 9. Offline VS Online with Suggestions with Different Number of Chargers

5 Conclusions and Future Work

In this paper, we propose a number of algorithms for the problem of scheduling EV charging at a single station. In more detail, we present an offline optimal algorithm, and two online ones which incrementally call the optimal one when an EV arrives at the station. Moreover, we use agent-based negotiation techniques between the charging station and the EV-agents. Through an in depth empirical evaluation, we show that the performance of our solutions depends on the number of EVs, the energy they need to charge, the time of the day they need to charge, and the number of chargers that exist at the charging station. Moreover, we show that such negotiation techniques can prove to be efficient in increasing the number of serviced EVs and the utilization of the available energy, with only a small decrease in the average utility of the EVs. In this way, EVs that otherwise would not charge, now the can be charged either a smaller amount of energy or in a different time window.

Future work will look at applying learning techniques so as EVs' profiles to be modeled [10]. In this way, personalized suggestions can be made from the station to the EVs during the negotiation procedure in order to increase the probability of an EV accepting an offer. Moreover, mechanism design techniques will be applied so as to force EVs to always report their preferences truthfully (currently, truthfulness is assumed). Finally, sophisticated load balancing techniques will be investigated so as the integration of the charging station and the EVs to the smart grid to take place in the most smooth and efficient manner.

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