

Towards an Optimal EV Charging Scheduling Scheme with V2G and V2V Energy Transfer

Alexandros-Michail Koufakis*, Emmanouil S. Rigas*, Nick Bassiliades *, Sarvapali D. Ramchurn†

*Department of Informatics, Aristotle University of Thessaloniki, 54124, Thessaloniki, Greece
{koufalex, erigas, nbassili}@csd.auth.gr

†Electronics and Computer Science, University of Southampton, Southampton, SO17 1BJ, UK
sdr1@soton.ac.uk

Abstract—In this paper we propose an optimal Electric Vehicle (EV) charging scheduling scheme with the option of Vehicle-to-Grid (V2G) and Vehicle-to-Vehicle (V2V) energy transfer. In this way, we aim to increase customer satisfaction as well as energy utilization compared to settings where only energy from the grid exists. We assume a single charging station to exist and we present three alternative formulations of the problem of V2G and V2V energy transfer: (a) without additional energy from the grid, (b) with additional energy from the grid, and (c) with additional energy from the grid and battery backup storage. In all cases, we formulate the problems using Mixed Integer Programming (MIP) and solve them off-line and optimally. We evaluate our algorithms in a setting partially using real data regarding energy production from photo-voltaic panels in Belgium and we observe that solution (c) leads to 24% increase in EV satisfaction compared to (a) and to 1.70% increase compared to (b). All algorithms have low execution time and good scalability.

I. INTRODUCTION

At the beginning of the previous decade, the first (hybrid) Electric Vehicles (EVs) were introduced to the market. The main idea behind this move was, and still is, to reduce air pollution caused by CO_2 and other pollutants produced from internal combustion engines, but also to decrease our dependence on fossil fuels. However, later the idea of using the EVs' large batteries as storage devices when they stay unused in parking lots was also introduced [1], [2] (i.e., Vehicle to Grid - V2G energy transfer). Thus, EVs will be able to provide regulation service to the grid and lead to higher utilization of renewable energy.

To-date, a number of different AI-based approaches have been developed to manage V2G problems. For example, some seek to optimize, using mathematical programming, the use of stored energy to cater for low energy production periods from renewables [3], [4], while others have applied coalition formation techniques to coalesce EVs into groupings that can make profitable V2G trades [5], [6] and [7].

Now, based on results of [8], it becomes clear that finding ways to increase energy utilization is an important task. In [9], we have proposed an agent-based negotiation scheme aiming to guide EV owners to change their

charging plan, so that higher energy utilization and EV satisfaction may be achieved. Here, we use V2G-related technologies (i.e., using EVs as temporal energy storage devices, or as providers of energy) to improve energy utilization and EV satisfaction. Moreover, we go a step further and we study the direct transfer of energy between pairs of EVs (i.e., V2V energy transfer). To-date, research on V2V related topics is limited. For example, [10] propose a V2V energy exchange market aiming to reduce the cost of charging for the EVs and the load on the grid, while Sanchez-Martin et al. [11] apply V2V energy transfer for direct load control on battery charging. Finally, You et al. [12] apply techniques that speed up the process of scheduling V2G and V2V energy transfer.

In this paper, we study a centralized offline setting where a number of EVs inform a single charging station about their arrival and departure times, as well as their energy demand (either positive or negative, depending on whether they want to charge or discharge) a day ahead and the system calculates the optimal charging/discharging schedule. In so doing, we assume that (renewable) energy from the grid, as well as a large battery storage at the charging station are also available. We advance the state of the art as follows:

- 1) We propose an offline optimal Mixed Integer Programming (MIP) formulation of the problem of scheduling the energy transfer between EVs aiming to maximize EV satisfaction.
- 2) We propose an offline optimal MIP formulation of the problem of scheduling energy transfer between pairs of EVs, while at the same time energy from the grid is also used.
- 3) We expand the previous formulation by using a battery storage so that any energy excess may be stored there for future use.
- 4) Finally, we evaluate our algorithms in a setting partially using real data on energy production from photo-voltaic panels and we verify the effectiveness of using V2G and V2V energy transfer in increasing energy utilization and customer satisfaction.

II. PROBLEM DEFINITION

In this paper, we study a setting where a number of EVs arrive at a charging station (CS) aiming to either receive or give away a specific amount of energy. In the proposed setting, the CS receives energy from photovoltaic panels where full knowledge of the fluctuations of the energy production is assumed to exist. This is an important assumption, since it guarantees that once an EV is scheduled to charge it will definitely do so. Furthermore, the CS is equipped with an energy storage unit (i.e., a battery), that can be used to store any surplus of energy coming either from the grid, or from the EVs that want to discharge. Thus, the battery is used as an intermediate step for the energy to reach its final destination (i.e., EV \xrightarrow{t} battery $\xrightarrow{t'}$ EV', or CS \xrightarrow{t} battery $\xrightarrow{t'}$ EV). Given a schedule of EV arrivals and departures, as well as the energy demand and energy availability (from EVs and the grid), a number of scheduling algorithms (see Section III) calculate the optimal charging plan, such that the number of the satisfied EVs is maximized, while at the same time the number of energy transactions is minimized (without affecting the number of satisfied EVs). Minimizing energy transactions is important in order to prolong batteries' life.

In more detail, we denote a set of EVs $a_i \in A \subseteq \mathbb{N}$, and the charging station CS which has a number of charging slots $s_j \in S \subseteq \mathbb{N}$ (note that, a charger can do both charging and discharging). Moreover, we assume a set of discrete time points to exist $t \in T \subseteq \mathbb{N}$. At each time point, the charging station has $e_{t,cs} \subseteq \mathbb{N}$ units of energy available for EV charging. On top of this, the charging station is equipped with a battery b responsible for energy storage, which has a maximum e_b^{max} , and a current e_b^t number of energy units. The number of simultaneous transactions between the grid and the EVs, the battery and the EVs, as well as between EVs is bounded by the number of chargers the CS has. However, the transactions between the grid and the battery are not limited.

Now, each EV is defined by a tuple $p_i = \{a_i, t_i^{arr}, t_i^{dep}, e_i^{max}, e_i^{init}, e_i^{req}\}$, where t_i^{arr} is the arrival time at the station, t_i^{dep} is the departure time, e_i^{max} is the maximum amount of energy the vehicle can store in its battery, e_i^{init} is the initial energy, and e_i^{req} is the energy demand. The e_i^{req} can get both negative and positive values. Negative when the EV wants to discharge $|e_i^{req}|$ energy units and positive for the opposite case. An EV can also have $e_i^{req} = 0$, when it just resides in the CS, and in this case it may be used as temporary energy storage.

In the next section, we present a number of charging and/or dis-charging scheduling algorithms.

III. EV CHARGING SCHEDULING ALGORITHMS

In this section, we present a number of centralized, offline MIP formulations of the problem of scheduling EV charging and/or dis-charging, which are solved optimally using IBM ILOG CPLEX 12.6.2. The aim of the following

formulations is to maximize the number of satisfied EVs. Given that these formulations are offline and their solutions are optimal, they can also be used as benchmarks for other online algorithms.

A. Optimal V2V Energy Transfer Scheduling

Initially, we formulate the problem of scheduling the transfer of energy solely between EVs. In this setting, the charging station is providing only the infrastructure (i.e., chargers) for the energy transactions to take place. Thus, neither energy from the grid, nor energy storage exists. In this scenario, at any time point any pair of EVs can participate in an energy transfer between each other, using one charger each. To do so, the EV-provider should have enough energy stored in its battery and the EV-receiver should not exceed its maximum capacity.

In more detail, this formulation contains 3 decision variables: 1) $satisfied_i \in \{0, 1\}$ of binary type denoting if EV a_i is serviced or not, 2) $EVtoEV_{i,i',t} \in \{0, 1\}$, binary variable denoting whether EV a_i charges EV $a_{i'}$ at t , and 3) integer variable $energy_{i,t} \in \{0, e_i^{max}\}$ which denotes the energy level of EV a_i at time point t . The objective function (Eq. 1) to be maximized, consists of the difference between the total number of satisfied EVs and the total number of energy transactions multiplied by a very small number $\mu : |T| \times |S| < 1/\mu$. In this way, the product of μ with the sum of all energy transactions never becomes larger than the maximum possible number of satisfied EVs. Thus, no unnecessary transactions will take place, while the number of satisfied EVs will not be affected. Now, the objective function is maximized under a number of constraints:

Objective Function:

$$\sum_{a_i \in A} satisfied_i - \mu \times \sum_{a_i \in A} \sum_{t \in T} \sum_{a_{i'} \in A} EVtoEV_{i,i',t} \quad (1)$$

Subject to:

$$\forall a_i \in A, \forall t \in T, EVtoEV_{i,i,t} = 0 \quad (2)$$

$$\forall a_i \in A, \forall a_{i'} \in A, \forall t \in T :$$

$$t < t_i^{arr}, t < t_{i'}^{arr}, t > t_i^{dep}, t > t_{i'}^{dep}, EVtoEV_{i,i',t} = 0 \quad (3)$$

$$\forall a_i \in A, \forall t \in T, \sum_{a_{i'} \in A} (EVtoEV_{i,i',t} + EVtoEV_{i',i,t}) \leq 1 \quad (4)$$

$$\forall a_i \in A, energy_{i,t=0} = e_i^{init} \quad (5)$$

$$\forall a_i \in A, \forall t \in T : t > 0, energy_{i,t} = energy_{i,t-1} +$$

$$\sum_{a_{i'} \in A} (EVtoEV_{i',i,t-1} - EVtoEV_{i,i',t-1}) \quad (6)$$

$$\forall a_i \in A, satisfied_i \times e_i^{req} =$$

$$\sum_{a_{i'} \in A} \sum_{t \in T} (EVtoEV_{i',i,t} - EVtoEV_{i,i',t}) \quad (7)$$

$$\forall t \in T, \sum_{a_i \in A} \sum_{i' \in A} (EVtoEV_{i,i',t} + EVtoEV_{i',i,t}) \leq |S| \quad (8)$$

In more detail, one vehicle cannot give energy to itself at any time point (Eq. 2), while for a transaction to take place, both of the participants must be present at

the CS (Eq. 3). Now, Eq. 4 ensures that one EV can be part of, at most one, energy transfer per time point (i.e., simultaneous charging and dis-charging is not allowed). Moreover, the decision variable $energy_{i,t}$ gets initialized with the initial energy of each vehicle (e_i^{init}) (Eq.5), and then for every time point after $t = 0$, its new value is equal to the previous one ($energy_{i,t-1}$) plus the energy received by a_i , minus the energy given during the previous time point (Eq. 6). Now, Eq. 7 ensures that in case a_i is serviced, its $energy_i^{req}$ is covered, otherwise its energy level the time of departure should be equal to the energy level at the time of arrival. Finally, Eq. 8 limits the number of transactions that can take place in one time point by the number of chargers the CS holds. Note that, the maximum and minimum value of $energy_{i,t}$ are enforced internally by CPLEX, thus no constraint is necessary.

In the next section, an extension of this formulation, where EVs can also charge from the grid, is presented.

B. Additional Charging from the Grid

Here, we enhance the previous model by adding one more feature to it, namely the charging of the EVs from the grid. In more detail, at each time point there is an amount of energy available from the grid for the EVs to charge. This energy can potentially be stored in EVs' batteries for later to be transferred to other EVs. This formulation has 4 decision variables. In addition to the three variables presented in Section III-A, binary variable $GtoEV_{i,t} \in \{0, 1\}$ denoting whether a_i is getting charged from the grid at time point t is added to the formulation. The objective function (Eq. 9) is similar to the one in III-A, but the number of energy transactions between the grid and the EVs is also considered in the second part of it.

Objective Function:

$$\sum_{a_i \in A} satisfied_i - \mu \times \sum_{t \in T} \sum_{a_i \in A} (GtoEV_{i,t} + \sum_{a_{i'} \in A} EVtoEV_{i,i',t}) \quad (9)$$

Subject to:

$$\forall a_i \in A, \forall t \in T :$$

$$t < t_i^{arr}, t > t_i^{dep}, GtoEV_{i,t} = 0 \quad (10)$$

$$\forall a_i \in A, \forall t \in T,$$

$$\sum_{a_{i'} \in A} (EVtoEV_{i,i',t} + EVtoEV_{i',i,t}) + GtoEV_{i,t} \leq 1 \quad (11)$$

$$\forall a_i \in A, \forall t \in T, t > 0, energy_{i,t} = energy_{i,t-1} +$$

$$GtoEV_{i,t-1} + \sum_{a_{i'} \in A} (EVtoEV_{i',i,t-1} - EVtoEV_{i,i',t-1}) \quad (12)$$

$$\forall a_i \in A, satisfied_i \times e_i^{req} = \sum_{t \in T} (GtoEV_{i,t} +$$

$$\sum_{a_{i'} \in A} (EVtoEV_{i',i,t} - EVtoEV_{i,i',t})) \quad (13)$$

$$\forall t \in T, \sum_{a_i \in A} (GtoEV_{i,t} + \sum_{i' \in A} (EVtoEV_{i,i',t} + EVtoEV_{i',i,t})) \leq |S| \quad (14)$$

$$\forall t \in T, \sum_{a_i \in A} GtoEV_{i,t} \leq e_{t,cs} \quad (15)$$

Regarding the constraints, Eqs. (2), (3), and (5) from III-A are also used here. On top of these, Eq. 10 makes sure that no transactions between the grid and EVs can happen when an EV isn't at the CS, while Eq. 11 ensures that an EV cannot participate in more than one energy transactions at each time point. Eq. 12, ensures that for every time point and for each EV, value $energy_{i,t}$ is equal to $energy_{i,t-1}$ plus the energy received by a_i , minus the energy provided during the previous time point. Moreover, Eq. 13 ensures that in case a_i is serviced, its $energy_i^{req}$ is fully covered, otherwise it is not serviced at all. Now, Eq. 14 limits the maximum number of energy transactions that can take place a specific time point by the number of chargers. Finally, Eq. 15 limits the number of EVs the CS can charge a particular time point by the amount of available energy.

In the next section, an enhanced formulation of the problem where energy storage also exists is presented.

C. Additional Energy Backup Battery

This formulation of the problem extends the previous one by adding a large battery for energy storage in the charging station. This battery has a maximum energy capacity e_b^{max} , and an initial energy level e_b^{init} . Moreover, energy can be transferred between EVs, between EVs and the grid, and between EVs and the battery (V2G energy transfer). For all cases, a number of chargers $|S|$ is used. However, energy can be transferred from the grid to the battery without the use of a charger and with a rate of one energy unit per time point. This formulation has 8 decision variables: 1) $satisfied_i$, 2) $EVtoEV_{i,i',t}$, 3) $energy_{i,t}$ are the same as in (III-A) and 4) $GtoEV_{i,t}$ is the same as in (III-B). Moreover, 5) integer variable $bEnergy_t \in \{0, e_b^{max}\}$, denotes the energy level in the battery at time point t , and CPLEX enforces internally its value in order to remain within range, without the need for a constraint. On top of this, 6) binary variable $BtoEV_{i,t} \in \{0, 1\}$, denotes if the battery is charging a_i during t , and similarly, 7) binary variable $EVtoB_{i,t} \in \{0, 1\}$, denotes whether the battery receives energy from a_i at t . Finally, 8) binary variable $GtoB_t \in \{0, 1\}$, denotes whether the grid is giving energy to the battery during time t . The objective function (Eq. 16) is similar to the one in III-B, but the number of energy transactions from, or to the battery are also taken into consideration in the second part of it. This objective function is maximized under a number of constraints:

Objective Function:

$$\sum_{a_i \in A} satisfied_i - \mu \times \sum_{a_i \in A} \sum_{t \in T} (BtoEV_{i,t} + EVtoB_{i,t} + GtoB_{i,t} + GtoEV_{i,t} + \sum_{a_{i'} \in A} EVtoEV_{i,i',t}) \quad (16)$$

Subject to:

$$\forall a_i \in A, \forall t \in T : t < t_i^{arr}, t > t_i^{dep} : \\ BtoEV_{i,t} = 0, EVtoB_{i,t} = 0, GtoEV_{i,t} = 0 \quad (17)$$

$$\forall a_i \in A, \forall t \in T, GtoEV_{i,t} + BtoEV_{i,t} + EVtoB_{i,t} + \\ + \sum_{a_{i'} \in A} (EVtoEV_{i,i',t} + EVtoEV_{i',i,t}) \leq 1 \quad (18)$$

$$\forall a_i \in A, \forall t \in T, t > 0, energy_{i,t} = energy_{i,t-1} + \\ \sum_{a_{i'} \in A} (EVtoEV_{i',i,t-1} - EVtoEV_{i,i',t-1}) + \\ GtoEV_{i,t-1} + BtoEV_{i,t-1} - EVtoB_{i,t-1} \quad (19)$$

$$\forall a_i \in A, satisfied_i \times e_i^{demand} = \\ \sum_{t \in T} (GtoEV_{i,t} + BtoEV_{i,t} - EVtoB_{i,t} + \\ \sum_{a_{i'} \in A} (EVtoEV_{i',i,t} - EVtoEV_{i,i',t})) \quad (20)$$

$$bEnergy_{t=0} = e_b^{init} \quad (21)$$

$$\forall t \in T, t > 0, \\ bEnergy_t = bEnergy_{t-1} + GtoB_{t-1} + \\ \sum_{a_i \in A} (EVtoB_{i,t-1} - BtoEV_{i,t-1}) \quad (22)$$

$$\forall t \in T, \sum_{a_i \in A} (GtoEV_{i,t} + BtoEV_{i,t} + EVtoB_{i,t} + \\ \sum_{i' \in A} (EVtoEV_{i,i',t} + EVtoEV_{i',i,t})) \leq |S| \quad (23)$$

$$\forall t \in T, GtoB_t + \sum_{a_i \in A} GtoEV_{i,t} \leq e_{t,cs} \quad (24)$$

Eq. 17 ensures that no transactions take place when an EV isn't in the CS. Moreover, when an EV is in the station, it can take part at, at most, one transaction at any time point t (Eq. 18). Now, Eq. 19 keeps track of EVs' energy level ensuring that at every time point after $t = 0$, its energy is equal to the energy in the previous time point plus the energy received by any source, minus the energy the EV discharged. Similarly, Eq. 20 takes into consideration the new kind of transactions (i.e., EV to battery and battery to EV), along with the previous ones, (V2V and G2V) in order to determine if an EV's e_i^{req} can be achieved, and accordingly the decision variable $satisfied_i$ is set to either 1 or 0. Moreover, decision variable $bEnergy_t$ is initialized (Eq. 21), and for every time point after $t = 0$, the $bEnergy_t$, that keeps track of battery's energy level, is equal to the value at the previous time point plus the amount of energy received by the battery from the EVs and the grid, and minus the energy given to the EVs by the battery (Eq. 22). On top of this, the maximum number of energy transactions is limited by the number of chargers (Eq. 23). Note that, the number of chargers required for a transaction is equal to the number

of EVs taking part in the transaction (i.e., V2V needs two chargers, G2V needs one, and grid to battery doesn't need any). Finally, Eq. 24 sets an upper limit to the energy the grid can provide either to EVs or the battery, based on the amount of available energy at this particular time point. Note that, constraints (2), (3), and (5) from III-A are also used in this formulation. In the next section, the three formulations are evaluated in a realistic setting and for a number of scenarios.

IV. EVALUATION

In this section, a number of experiments are conducted so as the pre-defined formulations to be evaluated. In so doing, the time frame in which the experiments take place is one full day, which is divided into 96 15-minute intervals ($T = 96$). The time frame begins at 5:00 am so as photovoltaics to be producing energy the first half of the day and the CS potentially store the excess energy for the rest. For each time point, the CS has an amount of available energy units (derived from photovoltaic panels) with a maximum value of 6 units. Data related to energy production from photovoltaics are taken from nationwide measurements in Belgium¹, which are later scaled down to be within the range $[0, 6]$ in order to better match the size of the CS. The energy data is fixed for all our experiments and the total available energy for one day is 196 units (we assume each unit of energy to be equal to 1kWh). The battery is assumed to have no initial energy stored ($e_b^{init} = 0$), and a max capacity of 48 energy units ($e_b^{max} = 48$ - i.e., the capacity of an average EV), while the CS has 8 chargers ($|S| = 8$). Note that, every V2V energy transfer needs 2 chargers, one for the EV-provider and one for the EV-receiver (i.e., EVs are connected to each other through the charging station's infrastructure). Also, for all energy transactions the rate of transfer is set to one energy unit per time point. The EVs have an energy capacity of 24 units ($e_i^{max} = 24$), and their initial energy is drawn from a uniform distribution and can take any value within range $[0, 24]$. Their arrival time (t_i^{arr}) is also drawn from a uniform distribution and can be any time point up until the 85th, as we assume that on the last 10 time points no EVs enter the CS. The departure time is calculated based on a Gaussian distribution with $mean = 24 + t_a$, and $\sigma = 8$ and the energy demand (e_i^{req}) is drawn from a uniform distribution. Note, that the duration of each EV's stay in the station is calculated in this way so as its energy demand to be able to be covered in terms of time. Note that, for all experiments a PC equipped with an i7-4790k and 16 GB of ram was used. In what follows [EVs] stands for the formulation where only the EVs participate in the transactions (Section III-A), [Grid] stands for the formulation where there is also energy from the grid available (Section III-B), and [Grid-B] stands for the formulation where the supportive battery also exists

¹Data from <http://bit.ly/1ADOxAL>

in the station (Section III-C). Finally, after we confirm the advantages of V2G service (Section IV-A), we evaluate the algorithms according to execution times (Section IV-B), customer satisfaction (Section IV-C), and the number of energy transactions (Section IV-D).

A. Significance of V2G and V2V Service

Initially, we evaluate the [Grid] and the [Grid-B] algorithms against a setting, where simple EV charging exists (i.e., neither V2G nor V2V service). Thus, we are using the offline EV charging scheduling algorithm as this is described in [9] (we refer to it as [simple]). In so doing, and in order the comparison to be fair, for both [Grid] and [Grid-B] we assume that all EVs need to charge and no EV is providing energy. Note, that V2V transactions still exist but only with energy previously received from the grid. Thus, the total amount of available energy is the same for all settings. Now, as can be seen in Figure 1, the use of V2G and V2V service leads on average to 27.81% higher EV satisfaction for the [Grid] and to 32.41% higher satisfaction for the [Grid-B]. Moreover, as can be seen in Figure 2, the use of V2G and V2V service leads on average to 7.53% higher energy utilization for the [Grid] and to 15.61% for the [Grid-B]. Thus, the significance of the existence of storage devices (i.e., battery storage at the station as well as V2V and V2G service) in order to achieve higher customer satisfaction and better energy utilization is confirmed. Therefore, in the next sections [EVs], [Grid] and [Grid-B] algorithms are evaluated against each other for a number of metrics and their performance is thoroughly discussed.

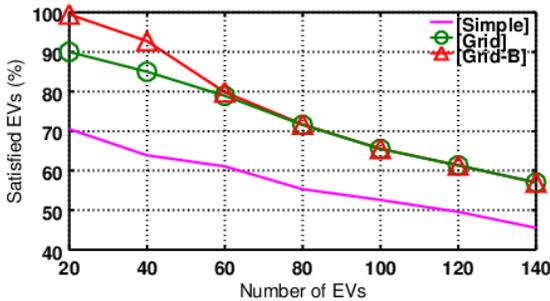


Fig. 1. Customer Satisfaction (%) with and without V2G

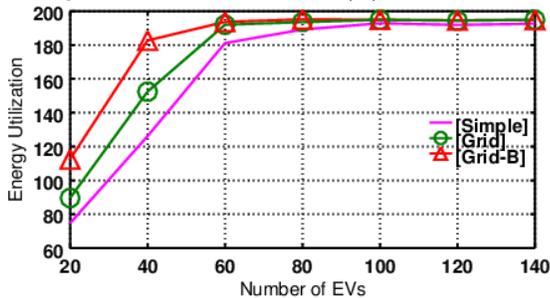


Fig. 2. Energy Utilization with and without V2G

B. Execution Time

Highly combinatorial problems, similar to the ones studied here, are known to suffer from high execution times. Thus, here the execution times, and therefore the

scalability, of the proposed algorithms is evaluated. In more detail, for all algorithms we observe a similar trend, as the execution times increase quadratically. However, as seen in Figure 3, [EVs] has a much lower rate of growth than the other two formulations. [Grid] and [Grid-B] have almost indistinguishable execution times, despite [Grid-B] constantly satisfying greater numbers of EVs (see Section IV-C). For [Grid] and [Grid-b], the higher execution times compared to [EVs] were expected due to the more complex problems they represent. However, interestingly [Grid-B] although it uses the battery storage and contains a larger number of decision variables has similar execution times with [Grid]. A possible explanation is that the battery is actually providing more options for charging scheduling, which simplifies the solution.

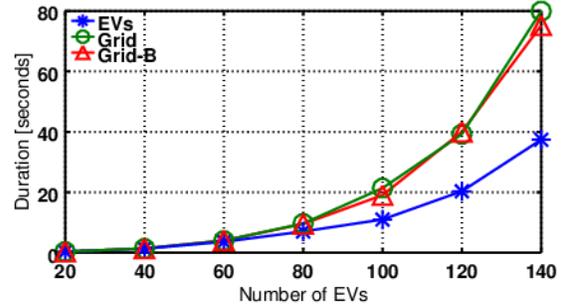


Fig. 3. Execution times

C. Customer Satisfaction

Apart from execution times, the maximization of the number of satisfied EVs is also crucial. Figure 4 shows that [EVs] performs worse compared to the other two formulations. This was expected, as in this formulation the energy is received only from the EV-providers which are on average 30% of the total. Especially for small numbers of EVs, the gap is larger as, due to the fact that EVs' arrival times are distributed over time, the stay of many EVs in the station does not overlap in terms of time (we can call it *time proximity problem*). Thus, energy transfer is impossible. Later, the number of satisfied EVs increases until the number of 60, but then slightly decreases again. This could be explained due to the fact that as the number of chargers is limited, the station cannot support all the desired transactions. Now, comparing [Grid] to [Grid-B] we can observe that the first has lower effectiveness compared to the second for small numbers of EVs. This is due to a combination of two facts: 1) similarly to [EVs] energy storage in EVs is not always possible and 2) energy production from photovoltaics has an uneven distribution across the day. However, when the number of EVs increases, more EVs are used for temporary energy storage, and the energy is better utilized, thus leading to more EVs being serviced. In contrast, [Grid-B] satisfies nearly 100% of EVs for small numbers of EVs, as the battery negates the time proximity problem the other two formulations face. For large numbers of EVs, a small decrease in EV satisfaction is observed for both [Grid] and [Grid-B], as the total energy demand is raising

to levels close, and later above, the total energy the grid can provide. Overall, and considering the costs associated with it, we observe that on any number of EVs the usage of the battery storage increases the number of satisfied EVs, but this increase is greater for low numbers of EVs (i.e., around 5% improvement). Finally, regarding EV-receivers, (i.e., EVs that need to charge), their satisfaction is, in the worst case, at around 90% for [Grid-B]. It has been observed (see Figure 5) that [EVs] is quite sensitive to the EV-providers - EV-receivers ratio, while both [Grid] and [Grid-B] are more robust. Note that, the difference in EV satisfaction in Figures 1 and 4 is due to the fact that in Figure 4 EV-providers also exist, increasing the total amount of the available energy.

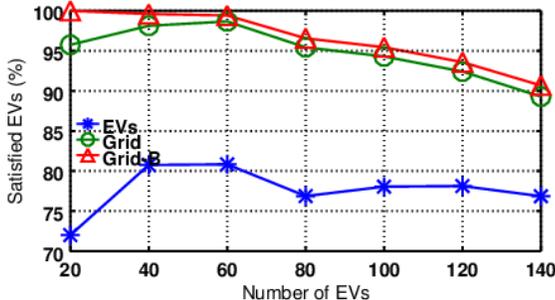


Fig. 4. Customer satisfaction (%)

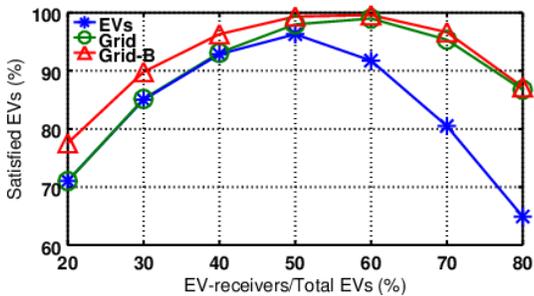


Fig. 5. Customer satisfaction (%) - 100 EVs

D. Energy Transactions

Energy transactions reduce batteries' life time and cause energy losses and therefore, they should be minimized. Figure 6 shows that for [EVs] the growth of the number of transactions is linear, and lower compared to the other two formulations. Formulations [Grid] and [Grid-B] show a rapid increase on the number of transactions until the number of EVs reaches 80 when the rate of growth slows down, as the energy from the grid starts to be inadequate. Overall, the number of transactions vary similarly to the number of satisfied EVs but with lower gradient, especially for [Grid] and [Grid-B]. This is due to the fact that as the number of EVs increases, solutions where fewer energy transactions are required can be found.

V. CONCLUSION AND FUTURE WORK

In this paper we have presented three offline optimal solutions of the problem of EV charging scheduling, where energy transfer between EVs is supported. Through a number of experiments we have proven the efficiency of energy storage devices (i.e., EV batteries, or batteries at

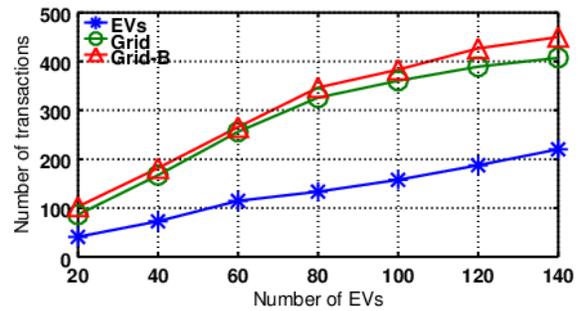


Fig. 6. Number of energy transactions

the CS) towards the higher utilization of the available energy and higher EV satisfaction. Moreover, we have shown that all algorithms have relatively low execution times and good scalability. For future work we target to study mechanism design techniques to further enhance the V2V energy transfer and provide incentives to EV owners to participate as sellers in such markets. Moreover, we aim to develop online algorithms which will add higher realism and better usability for real-world deployments.

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