Offline and Online Electric Vehicle Charging Scheduling with V2V Energy Transfer

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We propose offline and online scheduling algorithms for the charging of Electric Vehicles (EVs) in a single Charging Station (CS). The station has available cheaper, but limited, energy from Renewable Energy Sources (RES). Moreover, the EVs are capable of and willing to participate in Vehicle-to-Vehicle (V2V) energy transfers, that are used for reducing the charging cost and increase RES utilization. The algorithms are centralized and aim to minimize the total charging cost for the EVs. Initially, we formulate the problem as a Mixed Integer Programming (MIP) one and we solve it optimally assuming full knowledge of EV demand and energy generation. Later, we propose an online algorithm that iteratively calls the offline one and copes with unknown future interruptions by arriving EVs and with the inability to predict accurately RES production. Additionally, a novel technique called Virtual Demand is developed that increases the demand of already existing EVs, in order to store renewable energy and later transfer it via V2V to EVs that will arrive at the CS in the future. This technique is used for mitigating the inefficiency due to the uncertainty about future actions that real-time scheduling entails. In a setting with up to 150 EVs and using real data regarding RES production, our algorithms are shown to have low execution times, while the use of Virtual Demand increases RES utilization by 12% and reduces cost by 3.3%.

***Index Terms*—Electric Vehicles, charging scheduling, Vehicle-to-Vehicle (V2V), Renewable Energy Source (RES), Mixed Integer Programming (MIP).**

I. Introduction

CLIMATE change induced by the greenhouse effect, is an overwhelming problem that threatens to disrupt human societies worldwide. For that reason, recent international agreements determine that the CO_2 emissions, caused by the consumption of fossil fuels, must be reduced within the next decades. The transportation sector is accountable for a substantial portion of fossil fuel consumption. Thus, the introduction of Electric Vehicles (EVs) is one of the main pathways to reduce the greenhouse effect.

EVs are more efficient than conventional vehicles in converting the available energy into motion, which means that even if the electricity they use is produced from fossil fuels, they result in smaller pollution [1]. However, in order to realise their intended benefits, the majority of their energy should be produced by renewable energy sources (RESs). At the same time, it is a fact that the present electric grid and the power generating facilities are not sufficiently advanced to sustain the uncoordinated charging of large numbers of EVs. Thus, it is crucial to upgrade the related infrastructure to the so called *smart grid*. In spite of the difficulties imposed by EV introduction, they can offer great opportunities to the grid and the overall power regulation. For example, coordinated EV charging can render RES very efficient, despite their fluctuating production patterns [2].

Electric vehicles have the ability to discharge while connected to the grid, resulting in returning some of the energy surplus back to it. This is called Vehicle to Grid (V2G) energy transfer and lets the EVs act as electricity storage devices for the grid (virtual power plants) [3]. V2G is largely studied as a way to reduce the discrepancies between the power production and consumption [4]–[6]. That way, the intermittent production from RES can be utilized more efficiently [7], [8], rendering RESs more economically viable [9]. Moreover, V2G capabilities could be used as means for the EV owners to interact with a flexible electricity market, both at individual level [10] as well as a part of EV-coalitions [5], [11].

Extending the idea of V2G, the direct transfer of energy between EVs (Vehicle to Vehicle energy transfer [6] - V2V) is also possible (i.e., energy transfer can take place using a charging station's infrastructure). V2V can further increase the flexibility of EVs as grid regulators and strengthen their position in the electricity market. V2V is expected to be useful mostly in a context of a group of EVs that work towards a common goal, be it maximizing the RES usage [12], reducing their collective charging cost [13], [14], or even providing stabilization services to the grid [15]. Companies have been found to use the 9% of EVs sold in the UK the years 1999-2008 [16] and on 2013 the majority of EVs were bought by governments and companies [17], thus, a centralized approach at an organization level is valid.

In order for the V2G and V2V capabilities to be beneficial, they must be used in an intelligent way. Previous work has proposed studying the EVs as agents that act on their own accord [18], [19], while others propose the use of a centralized aggregator that collects information about the relevant components and calculates the optimal actions [14], [20]. However, a range of parameters needed to calculate an optimal charging/discharging plan is not always available. For example, EV owners might be reluctant to share their mobility plans, or even unable to do so, while the power availability depends on solar irradiation and end-user consumption, that are hard to predict accurately. Techniques such as the introduction of fuzziness [21] aim to simulate more accurately the real world deployment of such EV-managing, by introducing uncertainty. Real time charging scheduling is important and can be applied widely as it depends only on present information, does not require EVs to predefine their activity, or having precise

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knowlegde on future power availability.

In this paper, we study a centralized algorithm that manages the charging of EVs, in a single Charging Station (CS), that also acts as an aggregator. The charging cost for all the EVs is paid by a single organization, that owns the EVs, or has an agreement with them, and the CS aims to reduce the overall cost. The setting has available RES, which produces power of lower cost than the grid's, but its production is not consistent. While EVs arrive at, and depart from the CS randomly, the optimal charging/discharging schedule is produced, taking advantage of V2V capabilities. We initially study the EV-charging scheduling in an offline scenario, where the necessary information is available a priori, to set a benchmark. Consecutively, we extend it to be applicable in an online scenario where the CS is informed about the EVs as they arrive, while coping with the uncertainty of the RES production.

We advance the state of art in the following ways: 1) We propose an online algorithm that iteratively uses Mixed Integer Programming (MIP) in order to optimize the EV-charging within a single CS, in respect to overall charging cost, using differently priced sources of electric power. Moreover, V2V capabilities are incorporated within the online MIP formulation. 2) We propose introducing one virtual EV that causes the real EVs that are currently in the CS to store more RES energy than their actual demand, in order to complement energy demand of future EVs. 3) Using real data regarding energy production from solar panels in Belgium we show that the use of virtual demand increases RES utilization by 12% and reduces cost by 3.3%, while in all cases our algorithms have low execution times and good scalability.

The work in this paper draws inspiration from [12], but implements two major advancements: 1) A number of additions were made to the core functionality that necessitated a large redesign of the optimization model. 2) A new algorithm for real time charging scheduling that uses the optimization model was implemented. Additions to the core functionality include introducing charging efficiency, different energy sources and more flexible charging rate. Real time (Online) scheduling introduces an algorithm that wraps the optimization model and additionally a novel technique is developed that aims to mitigate the lack of information about future EV activity.

The rest of the paper is organized as follows: in Section II the related work is presented. In Section III the problem is defined and Section IV presents the offline formulation, in order to proceed to the online solution in Section V, which also includes the virtual demand algorithm. Finally, Section VI presents the evaluation of our algorithms and Section VII concludes and gives ideas for future work.

II. Related work

EVs' large batteries can, if well managed, become a valuable asset to a smart electricity grid [4]. As discussed earlier, the stored energy can be used to smooth out the fluctuating production of electricity from renewable sources. Moreover, the provision of V2G services can potentially be very profitable for EV owners. V2G services can be provided either in an one-to-one basis (each EV will sell its own spare energy to the grid), or in the form of collectives of EVs which act as one entity and trade electricity. Indeed, unless operating through an aggregator, it is impossible for individual EVs to sell V2G services in electricity markets where buyers typically buy energy in Megawatt-hours rather than kilowatt-hours [22].

As it is outlined in a previous work of ours [2], the majority of the related work is focused on managing the charging and discharging of EVs, in association with the grid. For example, in [13], [14], [20] the studies use optimization techniques to schedule the charging of EVs, while utilizing V2V capabilities. The optimal schedule is determined by hourly-changing electricity prices. In addition, Galus and Andersson [23] propose algorithms for an aggregator to trade energy in the energy market by both managing the charging and discharging of the EVs. Based on the current SOC (State Of Charge) of the vehicles, the desired SOC and the time of departure, it is able to optimise the amount charged in the batteries in order to make a profit by reselling a quantity that leaves the EVs with enough to go onto their onward journeys. The researchers in [24] instead, use particle swarm optimization (PSO) [25] to optimize charging and discharging of EVs. PSO is used to schedule the charging and/or discharging activities of the vehicles so as cost and emissions to be minimized. The authors show (using data from [26]) that their mechanism can trade-off emission reduction for cost reduction (i.e., when charging cost is low, EVs prefer to charge and therefore emissions are high, whereas, when charging cost is high, emissions are low as EVs prefer to discharge). However, in these works, a single centralized aggregator calculates the schedule offline, assuming full knowledge of EVs' demand and constraints.

Online scheduling is studied to a lesser extent. He et al. [27] produce an optimal charging schedule based on prices derived from forecasts about grid load, in order to minimize charging cost. The optimization formulation includes V2G capabilities but no V2V. In addition, Mohamed et al. [21] study the cost minimization of EV charging. The scenario that is studied is similar to ours, meaning that there is a single CS equipped with RES (solar energy) and it utilizes V2V. However, the solution is based on a fuzzy controller that sets the (dis)charging rates, according to a set of handcrafted rules that classify the EVs to various charging levels. Those levels limit the minimum and maximum rates that the fuzzy controller can set to the EVs. Moreover, the study covers a limited time period, that is the standard working hours of a day. Our work instead, uses mathematical programming to optimize EV charging and it can handle any level of energy input and output and can easily be adapted to different problem settings. Also, our work studies the charging process using RES production in a 24-hour base. Thus, we cope with the problem of using RES (in particular Solar energy), during nighttime via V2V.

III. Problem Definition

In this paper, we study a setting where a single Charging Station (CS) manages the charging of incoming EVs. The vehicles announce to the CS their arrival and departure time and the requested amount of energy to charge. The CS acts as an aggregator that collects the EVs' charging requests and constraints and calculates the (dis)charging schedule aiming to minimize the charging cost. The CS can be aware of the EV requests either in advance (offline scenario), or in real time (online scenario). It is assumed that the fleet of EVs belongs to a single company which covers their collective charging cost, thus, the EVs are willing to employ their V2G and V2V abilities. The same strategy could be applied even if the EVs acted within one EV-coalition. Furthermore, the CS has a number of parking spots, each one equipped with a bidirectional charger, that can direct power to (EV charging), and from (EV discharging) the EVs [28] (such chargers have already been deployed in the UK and Finland amongst others). As discussed earlier, the discharging of EVs is often studied as a mean to regulate grid load, but in our case, such energy is used to directly charge other EVs. Thus, no energy is returned to the grid, but the utilization of RES increases. Cost from battery wear due to charging cycles is omitted, as it is expected to be insignificant, based on an analysis on similar setting [29]. Moreover, it is reported that the most important factor on battery degradation are temperature and depth of discharge (DOD) [30]. In our setting, temperature is assumed to be regulated internally and the DOD is partial.

The setting is studied within a discrete time horizon, that is divided into a number of equal length intervals that we call Time Points (TPs), $t \in T \subset \mathbb{N}$. A set of EVs $i \in A \subset \mathbb{N}$ arrive and depart from the CS throughout the time horizon. The set of vehicles that are present in the CS on a particular time point t is denoted by $A'_t \subseteq A$. The EVs are defined by a tuple $p_i = \{t_i^{arr}, t_i^{dep}, SoC_i^{max}, SoC_i^{req}, SoC_i^{init}\}$, where $t_i^{arr} \in T$ and $t_i^{dep} \in T$ are the arrival and departure times of the EV. $SoC_i^{max} \in \mathbb{R}^+$ denotes the maximum charge the battery can hold, measured in kWh, $SoC_i^{req} \in [0, SoC_i^{max}]$ is the desired energy level or state of charge, $SoC_i^{init} \in [0, SoC_i^{max}]$ is the initial energy level at t_i^{arr}. Note that the vehicles request to reach the specific energy level SoC_i^{req}, which isn't necessarily their maximum state of charge. However, it is greater than the original energy level, meaning all vehicles want to charge.

EV charging takes place either by directing energy through the grid (G2V) or by directing energy from another EV (V2V). However, the chargers aren't perfect, as they suffer from energy losses. Charging and discharging efficiency has a set value, $eff \in (0, 1)$ and is the same for all the chargers in the CS. Energy that passes through a charger is multiplied by eff in order to determine the energy that reaches its destination. For simplicity's sake, we assume that energy losses happen only because of the chargers and are solely dependent to the number of chargers involved. In the case of G2V energy transfer, a single charger is used and the losses of this transaction are $(1 - eff) \times en$, where en the initial energy. In contrast, V2V involves energy transfer via two chargers and in this case the losses are $(1 - eff^2) \times en$ (i.e., if energy en is transferred via V2V, the energy that reaches the second EV is $(en \times eff) \times eff$, so the lost energy is $en - (en \times eff) \times eff = (1 - eff^2) \times en$). The CS knows about the chargers' efficiency and seeks the optimal solution. Also, the chargers have an upper limit on the transmission rate (electric power), denoted by the variable $ch^{rate} \in \mathbb{R}^+$ measured in kW.

The energy itself can come from two main sources: 1) From the grid that is produced by non renewable means and thus its cost is elevated, but is available on demand, so it can be considered unlimited for the scope of our setting. 2) From photovoltaic (PV) panels that harvest solar power and is cheaper and environmentally friendlier. The energy from RES might be produced by designated PV panels, or as a portion of larger scale production. Thus, the CS has incentives to consume the energy from RES, rather than the energy from non-renewable sources, while managing the charging of the EVs. As the non-RES production is always present, there isn't need to use V2V to transfer that kind of energy. Thus, V2V is used solely to increase RES energy utilization.

The production from PVs isn't known ahead of time as it directly relates to cloud coverage and other factors that are challenging to predict. As a result, the CS schedules the EV (dis)charging based on the forecasted production of PVs. In case this amount is higher than the actual one, some of the energy could be wasted. In the opposite case, where the forecasted amount is lower than the actual production, it is possible that the (dis)charging schedule requires a larger amount of energy than the available. To compensate that amount, energy from expensive non-RES (i.e., fossil fuels) is being used, administering a slightly increased cost. While incorporating uncertainty via the forecast, the scheduling becomes more challenging and produces sub-optimal results.

IV. Offline Optimization

The problem of the optimal EV charging scheduling is formulated as a Mixed Integer Programming (MIP) one and is solved using CPLEX 12.6.2. This formulation is based on a previous work of ours [12], however a number of improvements have been made. In contrast to [12], here the charging efficiency is introduced and charging rate is more flexible as it can have real values. This means that the updated algorithm can schedule to charge any amount of energy, as opposed to handling only integer energy units. Moreover, two different kinds of RES forecast are incorporated, instead of fixed RES production values. Also, the chargers' availability becomes more direct, as now each parking spot has a dedicated charger, instead of sharing few chargers. Finally, all EVs must be charged and the possibility that some EVs solely sell energy was removed as it is considered unlikely.

Offline optimization has all the information about EVs (i.e., p_i) available in advance. Moreover, it has information about the RES production, either the actual values, or the available forecast at t^{start}. Using this information, the charging/discharging schedule that covers all the TPs, is optimized.

A. MIP Formulation of the Problem

The offline formulation is presented in this subsection, starting with the decision variables and following with the objective function and the constraints. Moreover, some parameters that are required in the formulation are presented in Table I.

Decision Variables:

1) $VtoV_{i,i',t} \in [0, ch^{rate} \times |TP|]$ is the amount of energy the EV i transfers to i', during time point t.

TABLE I
PREREQUISITE PARAMETERS

Parameters	Description
$\|TP\|$	Duration of one TP in hours
$c = \frac{cost(nonRES_{energy})}{cost(RES_{energy})}$	Cost relation between the two energy sources
$b > c$	b penalizes residual energy demand. It must be greater than c to ensure full charging
$RESprod_t^{t^{start}}$	Energy production from RES per TP
$t^{start} = 0$	Starting TP of the offline scheduling is always the first TP
$t^{end} = \|T\|$	Ending TP of the schedule of the offline scheduling is always the last TP

2) $REStoV_{i,t} \in [0, ch^{rate} \times |TP|]$ is the amount of energy from RES given to EV i during time point t.
3) $nREStoV_{i,t} \in [0, ch^{rate} \times |TP|]$ is the amount of energy from non-RES given to EV i during t.
4) $enDem_i \in [-SoC_i^{max}, SoC_i^{max}]$ is the absolute energy demand that EV i has after the end of the optimization process. Negative demand can occur only when virtual demand exists (see subsection V-A).

Objective Function:

$$minimize\Bigg(\sum_{i\in A_{t^{start}}} b \times enDem_i + \sum_{t=t^{start}}^{t^{end}} \sum_{i\in A_{t^{start}}} (REStoV_{i,t} + c \times nREStoV_{i,t})\Bigg) \tag{1}$$

Constraints:

$$\forall i \in A, SoC_{i,t=0} = SoC_i^{init} \tag{2}$$

$$\begin{aligned}&\forall i \in A, \forall t \in [t^{start}+1, t^{end}+1]:\\ &SoC_{i,t} = SoC_{i,t-1} +\\ &\Big(REStoV_{i,t-1} + nREStoV_{i,t-1}\Big) \times eff +\\ &\sum_{i'\in A}\Big(VtoV_{i',i,t-1} \times eff^2 - VtoV_{i,i',t-1}\Big)\end{aligned} \tag{3}$$

$$\forall i \in A : enDem_i = \Big|SoC_i^{req} - SoC_{i,t^{end}}\Big| \tag{4}$$

$$\forall t \in [t^{start}, t^{end}] : \sum_{i\in A} REStoV_{i,t} \le RESprod_t^{t^{start}} \tag{5}$$

$$\forall i \in A, \forall t \in [t^{start}, t^{end}] : \sum_{i'\in A} VtoV_{i,i',t} \le ch^{rate} \times |TP| \tag{6}$$

$$\begin{aligned}&\forall i \in A, \forall t \in [t^{start}, t^{end}] : \Big(REStoV_{i,t} + nREStoV_{i,t}\\ &+ \sum_{i'\in A} VtoV_{i',i,t}\Big) \le ch^{rate} \times |TP|\end{aligned} \tag{7}$$

$$\forall t \in T, \forall i \in A : VtoV_{i,i,t} = 0 \tag{8}$$

$$\begin{aligned}&\forall i \in A, \forall i' \in A, t < t_i^{arr}, t < t_{i'}^{arr}, t > t_i^{dep}, t > t_{i'}^{dep} :\\ &VtoV_{i,i',t} = 0\end{aligned} \tag{9}$$

$$\begin{aligned}&\forall i \in A, t < t_i^{arr}, t > t_i^{dep} :\\ &REStoV_{i,t} = 0, nREStoV_{i,t} = 0\end{aligned} \tag{10}$$

Next we comment on the constraints and the objective:

Constraints (2) and (3) define how the current state of charge is computed at any t. Equation (2) shows that at the first TP SoC receives the value of EV's initial energy, while Equation (3) describes how SoC is computed for all subsequent TPs. The current SoC is equal to the SoC during previous TP plus the energy the EV received, minus the energy the EV provided. Note that the received energy suffers loses defined by the chargers' efficiency. Especially, the energy received from another EV is truncated twice(i.e., once for every charger involved) and thus, the losses are squared ($\times eff^2$).

Equation (4) sets the energy demand an EV has, after all the scheduled actions take place. Energy demand is defined as the absolute difference between the required SoC and the SoC at the end of the time horizon, as it was calculated by (2) and (3). In the offline scenario, as opposed to online, energy demand is guaranteed to be zero at the end of the optimization cycle, which means that all the EVs will get the required energy by their departure time. This is guaranteed because there is always available energy form non-RES and because the EVs don't require more energy than they can receive within their parking time, according to their charging rate ch^{rate}.

Inequality (5) constraints the amount of energy the RESs can discharge during a TP to be less or equal to their production. Given that the offline scheduling takes place before the actual charging of the EVs, it is possible that the forecasted production from RES varies from the actual one. Thus, when the EVs arrive to the station to charge, there is a correction of the available energy based on the actual values of production and any energy deficit is completed by non-RES.

Constraint (6) bounds the maximum amount of energy an EV can give to any other during a TP. This limit is imposed by the charger's charging/discharging rate (ch^{rate}). Moreover, charging rate also sets an upper bound to the amount of energy one EV can receive during a TP, where the energy can be from RES, non-RES, or other EVs (Inequality (7)). Simultaneous charging and discharging of one EV isn't prohibited by the constraints, but the charging efficiency always makes this case more costly, and thus, it can never occur within this formulation. For example, $Grid \rightarrow EV_1 \rightarrow EV_2$ is always more costly than $Grid \rightarrow EV_2$, because of chargers' efficiency.

Objective function (1) breaks down to two parts: The first summation aims to minimize the total energy demand of the EVs, as it is calculated by (4), which is equivalently the summation of Manhattan distance to the desired energy level, for all the EVs. Note that the energy demand from equation (4) refers to the energy demand at the end of charging schedule (i.e., the distance between the desired SOC and the actual one). As a result of non-RES being practically unlimited, all vehicles are able to reach their required SoC and this distance ends up being zero (provided the requirements respect the limitations of charging rate). So, any concerns about treating EVs unevenly are dissolved. The second part of the objective function aims to minimize the overall amount of energy used, both from RES and non-RES. Constant c expresses the cost ratio $\frac{cost(nonRES_{energy})}{cost(RES_{energy})}$ and makes CS prefer using RES rather than the alternative non-RES for charging the EVs, as we set $c > 1$. Value $b : b > c$ multiplies the residual energy demand in order to penalize it and while its value is greater than c, it is ensured that the cost of not having the desired energy level is greater than the cost of non-RES energy. That results in always charging the EVs to required level, even if the more costly (but unlimited) non-RES energy is used. Unnecessary energy transfers are avoided due to the objective function that minimizes the energy used, alongside with constraint (3) that denotes that there are energy loss caused by chargers' efficiency.

Finally, Equation (8) bans energy transfers from one EV to itself. Equation (9) makes sure that energy transfers between two EVs (V2V) occur only if both of the EVs are present at the CS at t, meaning that t must be after the arrival and before the departure of both EVs. Similarly, constraint (10) allows energy transfer from the grid (either RES or non-RES) to take place only if the recipient EV is present at t.

In the next section, we present an online solution to the EV charging scheduling problem.

V. Online Optimization

Knowing EV information ahead of time, isn't usually possible. Thus, we formulate an online algorithm that optimizes the charging schedule while having information only about the EVs that are present at the CS. Moreover, in this scenario, only the forecast of RES production is assumed, so the scheduling deals with imperfect RES production knowledge.

In more detail, the charging schedule is optimized periodically, using the information that is currently available regarding the PV power output forecast and the present number of EVs. Each optimization iteration covers a range that is calculated by a method similar to a sliding window, whereas the width isn't necessarily constant. The *start* of the sliding "window" (t^{start}) slides a constant number of TPs denoted by variable $interval$. Given the starting TP of one cycle, the following cycle will start on $t^{start} = t^{'start} + interval$, meaning $interval$ TPs after previous start. The end of each optimization cycle (t^{end}) is when all the EVs that are present at the CS during t^{start} leave the station and there is no more charging to be done. So, in order to calculate t^{end} we denote the set of EVs $A_{t^{start}}$ that are present at the CS at t^{start}. Then, the end of each optimization cycle is when all the EVs that belong in $A_{t^{start}}$ depart from the station, or $t^{end} = max(t_i^{dep}), \forall i \in A_{t^{start}}$. In the special case where no EVs are present in the CS when an optimization cycle is due to start, then calculation of t^{start} is overridden, and the start is postponed until one EV arrives. Also, the scheduling uses only the known information about the RES production ($RESprod_t^{t^{start}}$), which is the forecast that is available at the starting time of each optimization cycle. Finally, note that the greater the value of $interval$ is, the more EV idling may occur as they wait to enter the next optimization cycle. In contrast, small values of the variable denote frequent rerun of the optimization cycle, overall resulting in a trade-off between computational cost and EV charging delay.

At the end of each optimization cycle, the new SoC of the EVs is computed, using only the actions (from the schedule) that are between the start of current iteration and the start of the new iteration. During this procedure, the real production from RES is checked whether is enough to cover the scheduled actions. If the production isn't sufficient, non-RES energy compensates, so that the scheduled actions are ensured to take place. After this process, the SoC_i^{init} is updated with the current charge, as it represents the state of charge when the current optimization cycle begins.

For every optimization cycle, the formulation of Section IV is used while altering the objective function, in order to mitigate the negative effects of the uncertainty that is introduced. The modification of the objective function requires knowledge of the $interval$ variable, as well as the range of the more accurate forecast, denoted $forecastAcc$. The forecast breaks down to two distinct forecasts, the first is more accurate but has limited range ($forecastAcc$) and the second predicts the production for later TPs but is less accurate ($forecastFuzzy$). The new objective function is:

$$minimize\Bigg(\sum_{a_i \in A_{t^{start}}} b \times enDem_{i,t^{end}} + \sum_{t=t^{start}}^{t^{end}} \sum_{a_i \in A_{t^{start}}} (w \times REStoV_{i,t} + c \times nREStoV_{i,t})\Bigg) \tag{11}$$

Where:

$(t < t^{start} + interval) \rightarrow w = 1$

$(t > t^{start} + interval) \wedge (t < t^{start} + forecastAcc) \rightarrow w = w_2$

$(t > t^{start} + forecastAcc) \rightarrow w = w_3$

The new version of the objective function has a multiplier w on energy that comes from RES. The aim of the multiplier is to cause RES energy to be used earlier by applying a penalty to actions that are scheduled for later, and its value can be one of the three: 1) When the current TP is up to $interval$ TPs after the start of the optimization cycle, then, multiplier $w = 1$ i.e., there is no penalty on those actions. 2) For the immediately following TPs but while the RES production is covered by the accurate forecast ($forecastAcc$), $w = w_2 > 1$, i.e., a small penalty is applied. RES usage within those TPs is possible to be disrupted by newcomer EVs that will be included in the next optimization cycle resulting in worse RES utilization, thus, the penalty applied. For example, if the CS postpones charging one EV with RES energy until more EVs arrive, it is possible that when the new EVs arrive the RES energy will not suffice for the accumulated demand and result in unnecessary non-RES consumption. 3) For even later TPs the multiplier is $w = w_3 > w_2$, i.e. an even greater penalty is applied. In that case, beyond the possibility of newcomer EVs disrupting the schedule, RES production is given by the less accurate forecast, so is expected to result in even worse RES utilization. For example, if more RES production is predicted than the actual amount, then the CS could postpone using RES, with the false expectation of upcoming RES production. In this case, when the charging is scheduled there might not be enough RES energy, once again resulting in unnecessary non-RES usage. The multiplier must always be $w < c$, because RES energy is preferred to non-RES, even if some waiting is needed, so the different values are connected with the inequality $1 < w_2 < w_3 < c$. Overall, the multiplier encourages RES energy to be used the earlier possible to avoid disruption by newcomer EVs and worse RES forecast. Also, it is assumed that $interval < forecastAcc$, meaning the new optimization cycle begins before the accurate forecast expires.

Consecutive optimization cycles are separated by a number of TPs, thus potentially resulting in EVs idling instead of charging. This can happen if an EV arrives at the CS on the period between two consecutive optimization cycles; in that case it will wait up to $interval - 1$ TPs to be considered in the next charging schedule. In the worst case, the EV might miss $(interval - 1) \times ch^{rate} \times |TP|$ kWh, of RES energy that won't be available in the future. So, in order to mitigate this energy loss, we applied greedy EV charging for the "dead" time until the next optimization cycle begins. Greedy charging takes place only if all the actions ordered by the schedule leave unused RES energy, in which case the energy is divided equally to the EVs that arrived after the current optimization cycle. Moreover, note that greedy charging uses only RES, because the aim is to minimize usage of expensive non-RES, thus lowering the charging cost.

A. Virtual EV

The above formulation uses the available information in order to find the best solution for the *online* charging problem, but does so in a shortsighted way that optimizes the objective function for each iteration while not considering future possibilities. This shortsightedness wastes RES energy that could be used to charge future EVs via a series of V2V actions, and thus, leads to greater overall cost as more expensive non-RES energy is used instead. In order to alleviate this problem, we propose the introduction of a virtual EV, that the CS assumes will arrive in the future, whose demand incentivizes real EVs to store RES energy for later actions. In essence, the virtual EV represents the EVs that are about to arrive and its demand depends on the prediction about future energy demand.

In order to determine virtual EV's demand (also called *virtual demand*), it is needed to extrapolate the amount of energy from non-RES that is used per TP, called *deficit*. That amount shows how much energy from RES could be used, if it was available, on each TP. We ran repetitively scheduling simulations with RES data from different days without the virtual EV in order to derive the deficit value per TP. Using those values, we determine the projected deficit per TP ($dfct_t$) for the current day, using a *similar day* approach. In detail, the deficit vector is the mean of the three more similar days to the current, i.e. the mean of the 3-nearest neighbors. Three nearest neighbors were selected after experimentation with different values, as it yielded the best prediction. The similarity is determined using Euclidean distance between the forecast of the current day and the RES production of past days. The Virtual EV's demand primarily depends on the accumulated deficit for a number of future TPs, but it is also limited by the RES forecast production. The virtual demand isn't the first priority (the real demand must be satisfied first), so when the production isn't enough, the virtual demand is lowered.

Overall, the virtual EV is defined by the tuple $p_v = \{t_v^{arr}, t_v^{dep}, SoC_v^{max}, SoC_v^{req}, SoC_v^{init}\}$, where $t_v^{arr} = t^{start} + interval$, i.e., it arrives when the next optimization cycle is going to start, so that it will never actually receive any energy, as only the scheduled actions for the first TPs are actually applied. Departing TP ($t_v^{dep} = t^{end}$) is when the current optimization cycle ends. The required energy $SoC_v^{req} \in [0, SoC_v^{max}]$ is calculated using the deficit and the production forecast. The upper bound of the charging capacity is $SoC_v^{max} = M$, where M is a very large number, as it is only a virtual EV and there is no point in limiting its capacity. In practice, M could be equal to infinity, but in order to be used in optimization a real value is required. Initial energy is zero, ($SoC_v^{init} = 0$) and when $t_v^{arr} \geq t_v^{dep}$, the virtual EV strategy cannot be applied; this happens if the current optimization cycle has duration at most equal to $interval$ TPs.

B. Virtual Demand Algorithm

The calculation of virtual demand requires knowledge on the following variables in order to comply with the energy production limitations and successfully support the RES utilization:

$$rsrv^{t^{start}} = \sum_{a_i \in A_{t^{start}}} \left(max(0, SoC_i^{init} - SoC_i^{req}) \right) \quad (12)$$

$$dem^{t^{start}} = \sum_{a_i \in A_{t^{start}}} \left(max(0, SoC_i^{req} - SoC_i^{init}) \right) \quad (13)$$

$$dfct^{t^{start}} = \sum_{t=t^{start}+interval}^{min(t^{start}+n, |T|)} \left(deficit_t \right) \quad (14)$$

$$tRESprod^{t^{start}} = \sum_{t=t^{start}}^{t^{end}} \left(RESprod_t^{t^{start}} \right) \quad (15)$$

$rsrv^{t^{start}}$ (12) (reservoir) denotes the excess energy that is stored in all present EVs at the start (t^{start}) of the optimization cycle. An EV has excess energy when the current SOC is greater than the required (i.e., needs to discharge). $dem^{t^{start}}$ (13) expresses the energy demand of EVs, excluding those that have excess energy. $dfct^{t^{start}}$ (14) is the sum of the deficit for the next n TPs, excluding the first $interval$ TPs. These are excluded as there is no need to force storing for the EVs that are already present at the CS, as they can receive energy directly. The value n denotes how far ahead the deficit should look, and depends greatly on the type of RESs. The deficit variable is used for determining the maximum energy that the EVs should store as virtual energy for future EVs. Finally, $tRESprod^{t^{start}}$ (15) is the total energy production from RES for the current optimization cycle, calculated from the forecast available at t^{start}.

The value of virtual demand can cause actions in three different ways. Initially, it can affect the charging by causing the present EVs to store enough energy to cover the future deficit. However, this requires that the RES production is enough to cover the real demand plus the deficit. Otherwise, it would use more energy than the available for satisfying the real EVs, thus forcing non-RES consumption unnecessarily.

Second distinctive virtual demand case is when the production is more than the actual demand, but not enough to satisfy both actual demand plus future deficit. In that case, the virtual demand is the maximum amount that the RES production can cover, after the actual demand is satisfied. Finally, the last way it affects the charging is when the RES production doesn't meet the actual requirements. Then, the already stored excess energy from previous optimization cycles (reservoir), comes into play by giving back some of that stored energy. When the virtual demand is lower than the stored energy (reservoir), then the difference between them returns back to the system and subsequently participates in charging real EVs. It is important to note that this energy never reaches virtual EV, but only its demand causes real EVs to potentially store more energy than they need and later provide it to charge other EVs. Also, it is impossible for EVs to receive non-RES energy to store, because it is preferable to schedule direct charging instead of using V2V as an intermediate step, avoiding V2V losses.

Algorithm 1 Algorithm for calculating virtual demand

Output: $virtual^{t^{start}}$ *: Virtual EV's demand*

{If production plus stored energy is enough to cover the default virtual demand.}

1: **if** $(prod^{t^{start}} + rsrv^{t^{start}} \geq \frac{dfct^{t^{start}}}{eff^4})$ **then**

2: $\quad virtual^{t^{start}} = \frac{dfct^{t^{start}}}{eff^4}$

{If production is not enough to cover the default value, but enough to cover the real demand, then apply the greater amount available.}

3: **else if** $(prod^{t^{start}} > dem^{t^{start}})$ **then**

4: $\quad virtual^{t^{start}} = rsrv^{t^{start}} + (prod^{t^{start}} - dem^{t^{start}})$

{If production does not cover real demand, set virtual demand lower than the reservoir, to return back some of the stored energy to supplement real demand.}

5: **else if** $(prod^{t^{start}} \leq dem^{t^{start}})$ **then**

6: $\quad virtual^{t^{start}} = rsrv^{t^{start}} - (dem^{t^{start}} - prod^{t^{start}})$

7: **end if**

8: **if** $virtual^{t^{start}} < 0$ **then**

9: $\quad virtual^{t^{start}} = 0$ {*Virtual demand cannot be negative.*}

10: **end if**

Algorithm 1 shows how the virtual EV's demand ($virtual^{t^{start}}$) is calculated, for each optimization cycle that starts on t^{start} and ends on t^{end}. Initially, condition in line 1 is true when the RES production plus the reserved energy in current EVs is enough to cover the default virtual demand $\frac{dfct^{t^{start}}}{eff^4}$. In that case, virtual amount receives the default value, which is the total deficit for the next n TPs, divided by the chargers' efficiency to the power of 4 (line 2). The amount is divided by the charging efficiency in order to cover losses from two consecutive V2V transactions, as the CS is not aware and cannot account for those potential future losses. The efficiency of one V2V is eff^2, thus the energy that reaches the destination is multiplied by the same value. So, if two V2V were to take place the final energy would be $energy^{final} = energy^{init} \times eff^2 \times eff^2$. Thus, dividing the deficit by eff^4 causes slightly more energy to be stored, in order to cover for the losses of two consecutive V2V steps. Otherwise, when the RES production isn't enough to completely cover the demand plus the deficit (line 3), then virtual demand is the maximum available. The updated virtual demand is equal to the already stored energy ($rsrv^{t^{start}}$) plus the difference between production and actual demand ($prod^{t^{start}} - dem^{t^{start}}$), as shown in line 4. Finally, when production is less than actual demand (line 5), then the stored energy should be decreased in order to give back some energy. So, the resulting $virtual^{t^{start}}$ is equal to the reservoir value minus the difference between real demand and production (line 6). Lines 8-9 ensure that virtual demand cannot have negative value, since that would mean that the virtual EV should give energy, which isn't plausible. This happens when the deficit is greater than the stored energy plus production and means that some non-RES energy intake will be necessary. Lines 3-6 could be condensed into one condition and one statement, but for the sake of discriminating the different use cases, we present them separately.

Concluding, virtual demand causes an increase in overall demand when deficit in RES energy is predicted for the next n TPs. In doing so, present EVs store more energy than they need, with the purpose of giving it to the virtual EV which represents future EVs. When the RES production isn't sufficient, the virtual demand decreases and portion of the stored energy is returned to currently charging EVs. It is possible that some EVs will depart with more energy than required, if there aren't EVs to receive the excess energy. This extra charge is regarded as cost in the evaluation, although in our scenario where one organization pays for the charging of all EVs, this error would not have any consequences.

VI. Evaluation

In this section a number of experiments are conducted in order to evaluate the formulations and algorithms from sections IV and V. The time horizon begins at 6:00 am and ends 48 hours later, so the number of TPs is $|T| = 192$ (each TP is 15 minutes). The duration was selected to be two days, so that energy transfer between consecutive days is enabled, while the execution time is not too inflated. Moreover, the increased duration should validate the robustness of the formulation and algorithm and enable potential energy propagation via V2V for longer duration.

Renewable energy in the context of this research comes from solar power and production data are from solar panels in Belgium,[1] while the values are scaled down so that the maximum production is 75 kW or almost 19 kWh per TP. Data are from 28 different random days so that they cover a range of different production fluctuation profiles. Beyond the actual energy production per TP, two different production forecasts are provided by the same source, day-ahead forecast and intra-day, where the second one is more accurate but with more limited range. In our formulation, the accurate intra-day forecast is denoted by $forecastAcc$ and the day-ahead is $forecastFuzzy$. In the scope of our experiments, when no perfect knowledge is assumed, the known energy production is a combination of the two types of forecast. Given the starting time t^{start} of an optimization cycle, the production

[1] http://bit.ly/1ADOxaL

for TPs up until 24 hours later is approximated by intra-day forecast, while for the following TPs the production is approximated by day-ahead forecast. Thus, the optimization is calculated according to the production forecast and for this reason the charging schedule may have inconsistencies. If the scheduled amount is greater than the actual production, the grid compensates; otherwise, if the actual production is greater, there might be an opportunity cost but no action is required. The cost relation between the two energy sources is $c = \frac{cost(nonRES_{energy})}{cost(RESe_{energy})} = 2$, which means the cost of energy from non-RES is double than that from RES.

The EVs' arrival time is generated using parking occupancy data from the SFpark program in San Francisco.[2] Given the number of occupied parking slots per TP, the difference between two consecutive TPs ($occupancyVector_t = [\frac{\Delta(occupancy)}{\Delta(t)}]$) was extracted and normalized in the range $[0.1, 1]$. Those values were used via roulette sampling in order to decide the arrival time of each EV, causing more EVs to arrive during TPs when parking occupancy increased and fewer EVs when it decreased. No EVs are assumed to arrive during the last 3 hours (maximum $t_i^{arr} = |T| - 12$), so that they have time to finish charging.

The bidirectional chargers that the CS is equipped with are level-2 chargers with max charging rate $ch^{rate} = 6.6kWh$ [4]. Their efficiency is $eff = 0.93$, which means that 7% of the transferred energy is wasted (in charging and discharging).

Time spent at the CS is drawn from a Gaussian distribution with median $\mu = 32$ and standard deviation $\sigma = 10$, meaning that 96% of the EVs will stay at the CS for a duration in the range of $[12, 52]$ TPs or $[3, 13]$ hours. As the EVs are assumed to be driven by employees of a company, the duration is given by Gaussian distribution with mean being 8 hours (=32TPs), the typical duration of a workday. Moreover, some drivers have to travel during their shift while others do overtimes, resulting in more variable behavior. The departure time is calculated via the duration spent in the CS, i.e. $t_i^{dep} = t_i^{arr} + duration@CS$, while respecting the time horizon limit.

In order to make the scenario more diverse and realistic, EVs with three different battery capacities are considered: 1) Small with $SoC_i^{max} = 19kWh$, 2) medium with $SoC_i^{max} = 30kWh$, and 3) large with $SoC_i^{max} = 60kWh$. The percentage of EVs that have small batteries is 30%, medium 50%, and large 20%. Upon arrival, the EVs have an initial battery level SoC_i^{init} which is drawn from uniform distribution within the EV's battery range. Moreover, each EV has a required energy level SoC_i^{req}, which is also drawn from uniform distribution and has to be greater than the initial energy level. Uniform distribution is selected because the probability of any initial energy level is expected to be similar, within the acceptable range, and similarly for the required energy. We assume that the required energy amount is always feasible, meaning the duration spent in the CS must be enough to charge the EV.

Four different configurations are evaluated. 1) Offline Real Production (ORP): The first configuration is offline, so the optimization is as described in section IV. All the information about EVs (arrival and departure times, initial SoC, required SoC) is known in advance. Moreover, the CS has the real RES production values available, instead of the forecast. The virtual demand algorithm isn't applicable in the offline case, so it isn't active in this configuration. As a result, *Offline Real Production* finds the optimal scheduling, as full prior knowledge is granted, and thus, it acts as the upper limit and comparison point for the rest of the configurations. 2) Offline Forecast (OF): This configuration is also offline, exactly one optimization cycle occurs that covers the whole time horizon and the EV information is available a priori, similarly to the previous configuration. In this case though, the real RES production data aren't available. Thus, the optimization is expected to produce a worse schedule than in the case of ORP. 3) Online (ON): Next configuration is online, so multiple optimization cycles occur, as described in Section V. The CS has information only about the EVs that have arrived on the station so far and it can use only the forecast of RES production, with the inherent error it causes. Virtual demand is not used in this configuration. 4) Online Virtual (ONV): Finally, *Online Virtual* extends the previous configuration with virtual demand, while using only the available EV information and the RES production forecast. The variable n that is used on virtual demand algorithm has value $n = 48$TPs.

[2]http://bit.ly/2ysz69w

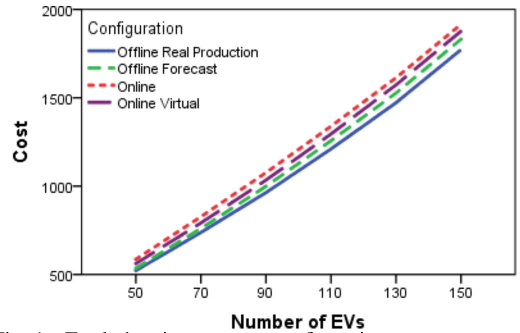

Fig. 1. Total charging cost per configuration

A. Experiment - Cost Comparison

Figure (1) shows the cost for charging the EVs, calculated using the known relation between the cost of RES and non-RES (called c). Values on vertical axis do not represent a particular currency, but are consistent for all the configurations and so is a valid way of comparison. As the figure illustrates, the total charging cost is lowest for the ORP as it has the highest amount of information and finds the best solution. The OF configuration follows with somewhat higher cost, as expected. The two online configurations result in even more costly charging, although ONV consistently outperforms ON. Overall, comparing to ORP as upper limit, OF has 3.3% greater cost, ONV has 7% and ON 10.7% on average. Those results show that more information provides, unsurprisingly, a better solution. Also, virtual demand manages to lower the cost compared to the simple online solution, with a decrease in cost of more than 3%. Paired-samples T test shows that there is a statistically significant difference between the ONV and ON, with $sign. > 0.99$. The specific T test compares the performance of the configurations for every given day and shows that consistently ONV produces lower cost schedule than the ON's, on the same day.

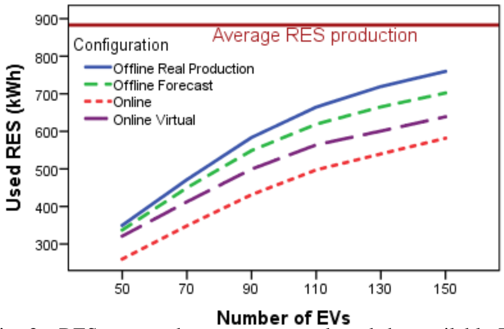

Fig. 2. RES energy that got consumed, and the available RES production

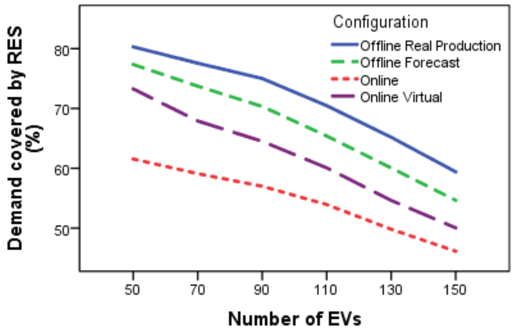

Fig. 3. Percentage of demand satisfied via RES

B. Experiment - RES energy used

Figure (2) shows the average consumption of RES energy. RES consumption depends on the total demand and the ability of the configuration to utilize the available RES production. RES consumption rises almost linearly for up to 90 EVs, but later it starts leveling off. This is because while the demand increases with the number of EVs, the production doesn't suffice to cover the demand for more than 110 EVs. Also, when the overall consumption increases, the production that corresponds to high demand periods is consumed quickly, thus, energy that is produced on less demanding periods may be used but in a less effective manner, resulting in reduced RES utilization. For example, if there is excess RES production early in the day and all the present EVs are already satisfied, it might be impossible or too costly to store the energy for future use during the night, causing this way suboptimal RES use. Overall, this figure shows the inverse ranking to the cost (fig. 1), the configurations that use more RES have lower charging cost. Moreover, when the RES consumption decelerates, the cost increases more steeply. OF uses on average 6.5%, the ONV 13.5%, and the ON 23.5% less solar energy compared to ORP. Virtual demand achieved a significant increase in solar utilization (12%), in relation to the simple online scenario, verified by paired-sample T test ($sign. > 0.99$).

C. Experiment - Energy demand covered by RES

Figure 3 illustrates the percentage of demand satisfied from RES energy. The rest of the demand is covered by non-RES, adding up to 100%, as the EVs are guaranteed to charge as required. Also, this graph is related to figure 2, but in this case the effect of charger inefficiency is also taken into consideration, as it measures how much RES energy ends up to the batteries. Comparing the two figures gives insight about the lost energy due to chargers' inefficiency. When there are a few EVs, a great deal of the demand is covered

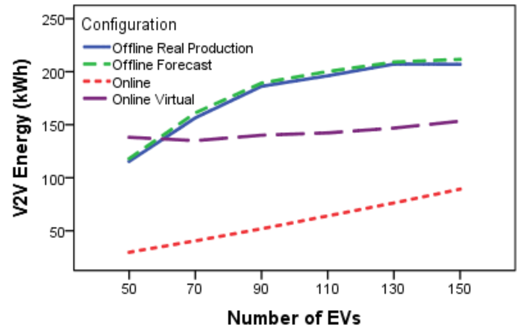

Fig. 4. Energy transferred via V2V

by the RES reaching up to 80%. One important reason that renders impossible to reach 100% coverage by RES is the fact that many different production profiles from various days were used. These profiles result in some days not having enough RES production to cover the demand. Comparing with figure 2, configurations ORP, OF, and ONV have a larger gap between them, for fewer EVs. This means that while the absolute RES consumption is very close among the three, the actual RES energy that ends up in the batteries is significantly lower for OF and ONV. This indicates that RES is used less effectively in those cases. Finally, comparing the two online configurations, it is apparent that virtual demand is more useful when the production is greater than the demand (i.e., for fewer EVs). So, when there is surplus of RES production, virtual demand is more useful, because it exploits excess RES energy for storing it for future usage.

D. Experiment - V2V usage

Figure 4 shows the amount of energy that is transferred via V2V, which can also be interpreted as the impact V2V capabilities have. The two offline configurations have almost identical V2V use, which is increasing for up to 90 EVs, while for more EVs the growth is minimal. This indicates that when there are many EVs, the need for V2V is lower, as more EVs mean more options to consume RES energy directly. Thus, there is less available energy for V2V consumption as the production is limited. Also, the similarity between the offline configurations shows that the superiority of ORP is the result of better immediate RES utilization (Fig. 3), instead of using more V2V to transfer RES energy through time. The online configuration ON uses the fewer V2V transactions, which is easily explained due to the lack of knowledge about future demand. So, most of RES that is used goes directly towards EVs, although it is possible to use V2V in a specific scenario: when the forecast predicts RES production in the close future, it is possible for some EVs to support EVs that are about to leave, with the promise to receive back the energy from RES. This would normally happen in the morning when hasty EVs could charge from other EVs that have the opportunity to charge from RES in the future. Last configuration, ONV, uses great deal more V2V than ON (2.8 times more on average), which evidently results in lower cost (Fig. 1). The reason for the increased V2V usage is that the EVs store temporary RES energy which later is transferred via V2V to other EVs. This difference between ON and ONV highlights that the V2V operation is helpful in reducing the overall cost, in combination with proactive scheduling via virtual demand.

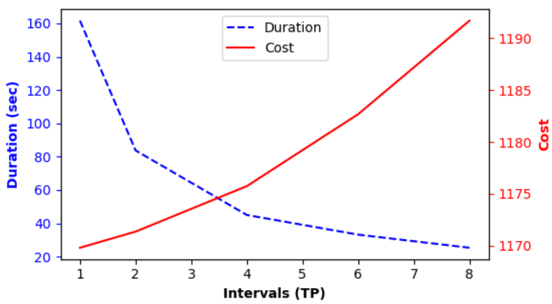

Fig. 5. Execution duration and cost in relation with variable *interval*

Overall, for the ONV configuration the V2V usage is relatively unchanged for different numbers of EVs, which is a result of the limited RES production. While the offline configurations have the knowledge to transfer energy way down the line, ONV takes into consideration a specific window ahead of time, so V2V possibilities are limited (i.e., 16% less V2V than ORP). The reason ONV has relative shortsightedness is to avoid excess loss due to uncontrolled V2V. Finally, note that for all algorithms the execution time remains low as it never exceeds 90 seconds for 150 EVs.

E. Experiment - Interval

Figure 5 presents the effects of different values of the variable *interval* upon execution duration and total charging cost. The experiment was conducted using 100 EVs that were charged according to ONV configuration. This configuration was selected because only on online configurations is the variable *interval* used and virtual demand was applied in order for it to be tested under different circumstances. The experiment shows that the execution time reduces with rate which correlates with the number of optimization cycles. The value of *interval* defines how many cycles will be initiated throughout the optimization horizon with the expression $|cycles| \approx \frac{|TPs|}{interval}$. Together with the fact that the duration of each cycle does not vary greatly (let it be d), we can approximate the execution time with the expression $duration \approx d \times |cycles| \approx \frac{d \times |TPs|}{interval}$, which is an hyperbolic function. The cost increases along with the value of *interval*. The reason for that is the idling of the EVs until the aggregator includes them to the optimization procedure. For example if one EV arrives to the CS one TP after the optimization cycle begins, then it will wait $interval - 1$ TPs until the aggregator includes it. As a result of this waiting, the aggregator has less EVs to utilize for the optimization, which limits the optimizations abilities, and subsequently the cost worsens.

F. Experiment - Various distributions

We tried experimenting with alternative distributions, regarding the duration the EVs stay at the CS in order to examine the effectiveness of the model and the algorithms. We assume that the vehicles are probable to stay either for a few hours or for an extended duration. We represent the short duration as a Gaussian distribution with $\{\mu = 10, \sigma = 5\}$ (TP) and the longer duration as another Gaussian distribution with $\{\mu = 32, \sigma = 5\}$ (TP). In order to test how the online algorithm and its augmentations perform under different patterns of EVs we conducted experiments with different percentages of EVs split between the two Gaussian distributions described above. Three different splits between the two distributions we tried, (1) 75% of EVs at the CS for duration described by the first Gaussian and 25% by the second Gaussian, (2) 50-50% and (3) 25-75%. Also the results from the original method, (4) Gaussian $\{\mu = 32, \sigma = 10\}$ are presented for comparisons sake. The experiment was conducted with 100 EVs. Table II shows that the order does not change in any case; ORP retains the lowest cost, followed by OF, ONV and ON, in this order. The average total cost changes for each different split, which is a direct result of the total energy demand. As EVs stay at the CS for shorter duration their demand adopts and is lowered as to not ask for unobtainable SOC. Overall, this experiment proves that virtual demand augmentation lowers the cost, under a variety of different patterns of EV behavior.

TABLE II
CHARGING COST

	ORP	OF	ON	ONV
(1) 75-25	738	745	832	816
(2) 50-50	814	832	916	877
(3) 25-75	858	881	990	938
(4) Original	1072	1119	1197	1136

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed an MIP-based algorithm to schedule the charging of EVs. The algorithm's objective is to minimize the total charging cost for the EVs and to encourage RES usage, while not knowing in advance the arrival and departure time of the EVs, as well as their energy demand. Moreover, the scheduling refers to a single CS that utilizes RES with cheaper energy but uncertain production levels. Prerequisite for the online algorithm is the formulation of the offline optimization. A novel technique called Virtual Demand was proposed that aims to improve the online scheduling. The goal is to integrate the prediction about future demand into the MIP formulation and consecutively, take advantage of the V2V capabilities, so that the use of cheaper energy is promoted, reducing that way the overall charging cost. Our evaluation shows that the simple online algorithm has 10.7% increased charging cost, because of the unannounced EVs and the imprecise RES forecast, in comparison with the optimal offline scenario. However, the Virtual Demand technique managed to increase solar energy utilization by 12% and decrease the cost by 3.3% in relation to the simple online scenario. Moreover, in all cases RES is utilized in great extent while the execution time remains scalable.

As a future improvement the prediction of energy deficit can be calculated using more advanced Machine Learning techniques. Instead of nearest neighbors, it is possible that other more powerful algorithms would be more effective and accurate in predicting the deficit vector, given the solar radiation forecast. Another future improvement could be the extension of the problem's scope, by adding more CSs and incorporating vehicle mobility patterns throughout an area, so that virtual demand technique gets tested within a larger scale.

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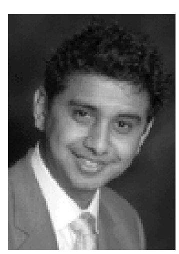

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