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## A coordinated framework for optimized charging of EV fleet in smart grid

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### Abstract

Electric vehicles can be sustainable alternative in contrast to conventional fossil fuel powered vehicles only if the green energy is used to power them. Without coordination among electric vehicles and grid operator, it can imbalance the power production and demand. This paper presents an automated coordinated mechanism among EV fleet and the grid operator that plans a charging strategy for electric vehicles while sustaining the grid capacity constraints. The intelligent planner plans the charging strategy at the cheaper moments and keep the vehicle charged enough to complete its scheduled trips. It suggests a charging pattern for the electric vehicle by using the time dependent electric prices and available power at the given time slots. It also ensures the cheapest charging cost and fulfills the constraints of battery state of the charge. A central power tracker is also introduced which keeps track of the available and required power at each time slot. According to the current market share of the electric vehicles, a fraction of the daily agendas, created by an operational activity-based model, is used to test the framework. Moreover, an experiment has been set up, it makes use of wind and solar renewable energy to power the vehicles.

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**Keywords:** Electric vehicle charging; Grid capacity constrain; charging optimization; Renewable energy;

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## 1. Introduction

Electric vehicles (EVs) can provide sustainable mode of transportation in contrast to conventional fossil fuel powered vehicles<sup>1</sup>. It can impact on the environment by reducing the traffic emission. Driving cost can be reduced using electric vehicles, on the other hand it might increase the  $CO_2$  emissions if conventional electricity generation methods are used to feed the electric vehicles<sup>2</sup>. During recent years, researchers are working to find solutions to integrate the EVs with transportation system and electric grid. EVs can pose huge challenges to regulate the electric grids to balance the demand and production of the electricity, if they are restricted to be powered using renewable energy sources<sup>3</sup>. Without any coordination between grid operator and EV fleet, electricity required to charge EVs can overload the grid and create the sharp load peaks. Power consumed to charging EVs fleet without coordination is shown in Figure 1. It is apparent to note that power demand is higher than available power during periods from 55 to 88, which will cause power breakdown. The EV's usage can be burdensome in order to keep it charged to cover all scheduled trips as EVs have operational challenges (e.g. range anxiety and high battery recharge time).

The research has been carried out to build optimization models of charging strategy for EVs. Most of the research was focused on control charging of EVs by the grid operator. It is suggested to balance the energy demand from EVs at peak hours. Controlled charging strategy can be helpful to improve the grid efficiency and reduce the power losses<sup>4</sup>. EVs can be a good contribution for renewable power usage with load management using grid communication<sup>5</sup>. A smart control strategy based on quadratic programming is also used to minimize the peak load and flatten the overall load profile<sup>6</sup>. Sundstrom and Binding, 2010, present a study to compare linear and quadratic approximation of the EV batteries to plan the charging<sup>7</sup>. Cao et. al, 2012 present a charging model with the time and the price of electricity in regulated markets to control the EV charging load<sup>8</sup>. A flexible charging scheme of EV can create the optimization problem for different stake holders i.e. wind producers, and grid operators<sup>9</sup>. It is unrealistic that the traveler will declare his/her available time at charging location due to privacy reasons. Hence, an optimization process is required which can be used within vehicle to optimize its charging strategy.

In this paper, an automated tool is presented which provides a coordination among grid operator and EVs fleet. Such tool, at grid operator side, regulates the grid operations by keeping the records of energy production and consumption and, on the vehicle side, it guarantees to keep the EV charged required for the scheduled trips. The grid agent keeps record of available energy at the grid. The Vehicle agent, which resides in the EV, communicates to the grid agent and plans a charging strategy for the EV depending upon the scheduled trips of the vehicle and available energy in the grid. The vehicle agent can book the required energy without disclosing the private trip's information to the grid agent. It will only share the time and location (where the energy will be charged) with the server agent.

## 2. Conceptual overview of the framework

The conceptual overview of the framework is shown in Figure 2. It contains three main parts: 1) *central grid agent* 2) *EV agent* 3) *request queue*. *Central grid agent* provides the central role to manage the energy utilization. It takes renewable power production information from power supplier and keeps track of the available and booked power at each time slot. It also receives the time and location based energy price from the power supplier. All vehicles in the electric fleet contain a private *EV agent* which carries out the optimization process. It is responsible for the communication between EVs and *grid agent*. Once the owner of the EV feeds his/her schedule for the next planning period, The *EV agent* starts the optimization process. It first sends the request to the *grid agent* and get the feedback about the available power and price of the energy at each time period. The *grid agent* sends the data about available power and price for each time slot back to the *EV agent*. The *EV agent* uses the information (about trip details, battery capacity, available (not already booked) energy, electricity price, and availability of charger) to optimize the charging strategy for the vehicle for next planning period. A detailed description of charging strategy optimization process is given in section 2.3.1. After the optimization process, the *EV agent* sends a message back to *grid agent* containing the information about all charging events. This message contains the information about charging start time, duration, and energy drawn from the grid for all charging events in the planning period. After receiving the booking message, the *grid agent* updates its track of booked and available power for each charging slot.

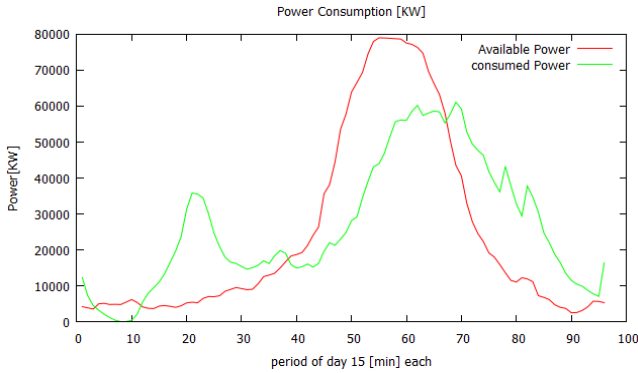


Figure 1 – Power consumption by EV fleet without coordination

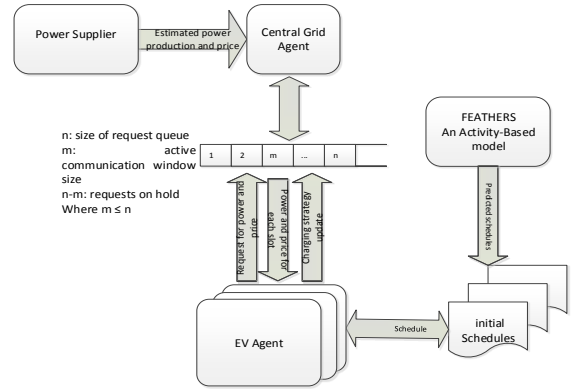


Figure 2 – Overview of the framework

## 2.1. Central Grid Agent

*Grid Agent* has a central role to manage the energy utilization. It takes renewable power production information from power supplier and keeps track of the available and booked power at each time slot. It also takes information about the price from the power supplier. *EV agents* send the optimization requests to the *grid agent*. The *grid agent* will keep these requests on hold, and will grant the optimization token by replying with the information of available power and price at each time slot. When *EV agent* completes the charging optimization process, it will send the booking information for all charging slots for the next planning period. *Grid agent* updates its record about available power. Finally, when all power is consumed at the available slots, it is marked as unavailable.

## 2.2. Request Queue with variable degree of parallel processing

The *EV agent* can start the next day activities from the last home activity. To start the optimization process, the *EV agent* sends the information request about available power and price of the electricity to the *grid agent*. After receiving the information, *EV agent* can start optimization process for the next day. Request generate pattern can outburst and deregulate the booking system at the *grid agent*. All the requests sent from vehicles are stored in the request queue where requests are served on first come first served basis.

Hence, to synchronize the consumed and available power at grid, one option is to respond the requests in a serial order by keeping all other requests on hold until first *EV* completes its optimization process and returns the booked power information back to *grid agent*. This process may keep a large number of requests on hold, resulting very long waiting time for some *EVs*. Hence, optimization tokens are granted to a bunch of *EVs* in parallel where degree of parallel

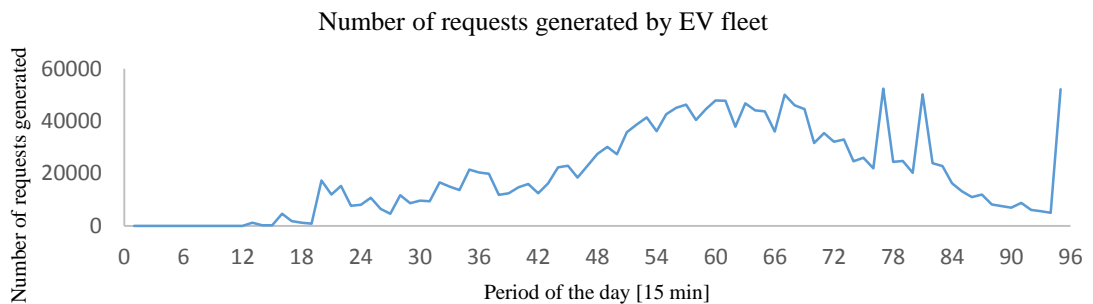


Figure 3 - Number of requested generated over time

processing (DOP) is variable. As shown in Figure 3, the size of the request queue can be a number  $n$ , where  $n$  is the maximum number of requests that can be served by the *grid agent*. Out of  $n$  requests,  $m$  requests are granted the optimization token, where  $m$  is called *active communication window size*. Active window communication size can vary from 1 to  $m$ . The mechanism to find the DOP is described below. All requests which are stored later in the queue are kept on hold until the booking reply is received from the batch of vehicles which were given the optimization token in parallel. In the real context, timeout mechanism is provided since some cars can fail to send a response within a reasonable period. DOP is re-evaluated by the *grid agent* after all requests are processed in the current batch, and new requests are updated in the *active communication window*.

Charging switches used by the EVs have not always the same charging power. In this framework it is assumed that each car already knows each location (i.e. home, work) whether charger will be available to charge or not. It is assumed that each car can charge at its home and work locations only. If the charger is available at any location, car knows its power rating to charge the electricity. Out of all chargers which are available at scheduled activity location, EV knows the maximum charging power  $Ch_{\max}$ . When the *EV* sends the request for optimization token, it also declares the  $Ch_{\max}$  to the *grid agent*. Then *grid agent* calculates the maximum  $Ch_{\max}$  ( $chPower_{\max}$ ) out of all received request. Suppose that  $C$  requests are received, hence,  $Ch_{\max}^c$  is already received for each request. Then  $chSwitch_{\max}$  will be calculated as following:

$$chPower_{\max} = \max_{1 \leq c \leq C} Ch_{\max}^c$$

*Grid agent* marks the time slot as unavailable if all of the power is booked for the particular time slot. While calculating the DOP, *grid agent* finds the time slot with minimum available power  $availPower_{\min}(t)$  out of all available time slots. Using information about time slot with minimum available power and maximum charger power, *grid agent* calculates the active communication window size using following equation:

$$DOP = \frac{availPower_{\min}(t)}{chPower_{\max}}$$

### 2.3. Optimization process at EV agents

Figure 4 shows the state-machine of an *EV agent*. *EV agent* initializes in its idle state until it reads the trips schedule for the next day. Upon reading the schedule, it sends the optimization token request to the *grid agent* and gets into the waiting state until the optimization token is granted to it by the *grid agent*. Optimization process is time bound, and is supervised by the *grid agent*. Upon the successful completion of the optimization process, *EV agent* will update the *grid agent* about scheduled charging events. Each charging event contains the information (i.e. Charging location, power booked, charging start time, and duration).

#### 2.3.1. Charging optimization process

Suppose that car  $C$  receives its traveling schedule  $S$ . upon receiving the optimization token, first, it reads the available energy  $E$  and price  $Prc$  for each period  $p$  [15 min] of the day  $D$ . It is assumed that Car has its battery  $SOC$  at some  $INITSOC$  level at start of the day. For all trips  $T$  in the schedule  $S$  where car  $C$  is used as transport mode, the optimizer ensures that car battery should have enough energy charged so that it does not go below to the minimum level.  $DCD$  level of the battery is used as minimum threshold for battery  $SOC$  for all trips except of the last trip where  $INITSOC$  is used as threshold. In case of battery  $SOC$  goes below to the minimum level after a particular trip, the cheapest time slot is found between two time periods  $t_0$  and  $t_1$ , where  $t_1$  is the last period before trip and  $t_0$  is the last period when battery was full. In case of no battery full event found, starting period of the schedule is used as  $t_0$ . The list of available time slots is scanned and a slot is selected for the car if all following conditions are fulfilled:

- i. The requested amount of power is available at the time slot.

- ii. The vehicle is not traveling completely during the period associated with the time slot. It should have some parking moments during the period.
- iii. The time slot is not already booked for this vehicle.

If any slot is found, car need to determine at what rate energy will be charged. It depends upon the power of the charger that will be used for charging at the found time slot. So, the car first determines the location it will be parked at the found time slot (i.e at home or at work).

If any slot is found, then it determines the location of the car during the time slot period: location determines the power of available charger that will be used to charge the energy at the found slot. Then, it determines the vehicle presence time at this location overlapped with period of found slot. Using this presence time and charger power it calculates the maximum energy  $E_{max}$  which can be charged at this particular slot. Then it calculates the effective energy that is planned to charge at this slot by taking the minimum of required energy to meet minimum energy level constraint, available energy from the grid at this slot, maximum energy that can be charged during this slot, and the amount of the energy that can be charged before the battery gets full during already planned charging in successive slots. This effective energy is added to the battery *SOC*. If this optimization process successfully iterates over all trips to keep the battery *SOC* above minimum level at each point in time, this schedule is marked as “feasible”. In case of feasible charging pattern found, information about charging events is sent back to register at grid agent.

Algorithm 1 shows the main components of the optimizer used by the *EV agent*. Lines 1-4 perform general initialization with data received from *grid agent*. Lines 5-33 determine the optimal set of charging slots. Lines 34-41 specify the required minimum *SOC* at the end of trip *T* before the next trip is processed.

### 3. Test Simulation of the framework

The presented framework of charging optimization process for EVs is simulated in conjugated with activity-based model FEATHERS<sup>10</sup>. FEATHERS predicts the daily trips for all individuals living in the study area (Flanders, Belgium). According to the current market share of electric vehicles<sup>11</sup>, a fraction of daily agendas created by the large scaled activity-based model are used to test the proposed framework. From selected set of schedules, all schedules which contain any trip covering more than predefined maximum distance between two consecutive charging opportunities are dropped. Maximum predefined distance depends upon the battery capacity of the EV. In this test suite, charging is only kept possible at home and work locations using 3.3 kW or 7.2 kW power chargers.

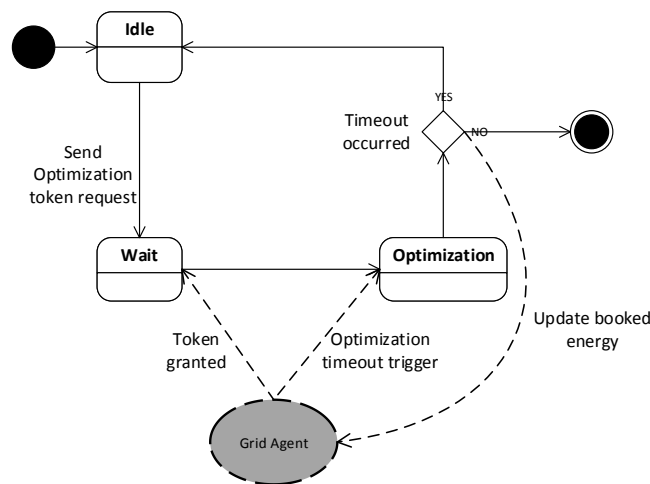


Figure 4 - State-machine diagram of EV agent

Table 1 - Algorithm to optimize the charging plan of an EV

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Input:
1.   for  $p \in D$  do
2.        $E[p] \leftarrow \text{read}()$ 
3.        $\text{Prc}[p] \leftarrow \text{read}()$ 
4.   end for
5.    $C.\text{SOC}[0] = \text{INITSOC}$ 

Begin:
6.   for all  $T \in S.\text{TripSet}()$  do
7.        $t_1 \leftarrow T.\text{startTime}()$ 
8.        $\text{minLevel} \leftarrow \text{minReqdBatteryLevel}()$ 
9.       while  $C.\text{SOCatEndOfTrip}(T) < \text{minLevel}$  do
10.           $t_0 \leftarrow \text{lastTsFullBattPred}(T)$ 
11.           $cs \leftarrow \text{cheapestUsableSlotIn}(t_0, t_1)$ 
12.          if  $cs \neq \text{null}$  then
13.               $S.\text{markAsPlanned}(cs)$ 
14.               $\text{chrgPwr} \leftarrow S.\text{location}(cs).\text{power}()$ 
15.               $E_{\text{req}} \leftarrow \text{energyRequired}(cs)$ 
16.               $\Delta t \leftarrow \text{durationAt}(S.\text{location}(cs))$ 
17.               $E_{\text{eff}} \leftarrow \min(E_{\text{req}}, E[cs], E_{\text{max}}(\text{chrgPwr}, \Delta t), E_{\text{SOC}}(S.\text{SOC}[cs]))$ 
18.               $C.\text{SOC}[cs + 1] \leftarrow C.\text{SOC}[cs] + E_{\text{eff}}$ 
19.               $E[cs] \leftarrow E[cs] - E_{\text{eff}}$ 
20.               $cs.\text{markAsScheduled}(cs)$ 
21.          else
22.              Goto: END
23.          end if
24.           $\text{minLevel} \leftarrow \text{minReqdBatteryLevel}()$ 
25.      end while
26.  end for
27.   $S.\text{mark}(\text{"feasible"})$ 
28.  END:
29.  if  $s.\text{index}(T) = \text{Last}$  AND  $C.\text{DCD} < C.\text{SOCatEndOfTrip}(T) < \text{INITSOC}$ 
30.       $S.\text{mark}(\text{"soft infeasible"})$ 
31.  else
32.       $S.\text{mark}(\text{"hard infeasible"})$ 
33.  end if
34.  Function  $\text{minReqdBatteryLevel}()$ 
35.      If  $S.\text{index}(T) = \text{LastTrip}$ 
36.           $\text{minLevel} \leftarrow \text{INITSOC}$ 
37.      else
38.           $\text{minLevel} \leftarrow C.\text{DCD}$ 
39.      end if
40.      return  $\text{minLevel}$ 
41.  end Function

```

To test the presented framework, data about available renewable power from Elia, Belgium's electricity transmission system operator is used<sup>12</sup>. Using the market share value for BEV of 10% of the total vehicle fleet, total electric demand for one day to charge the EVs in Flanders is 1,815,534 kWh while total available renewable power for a typical day in summer is 20,770,400 kWh. Hence to make the test simulation interesting available power is

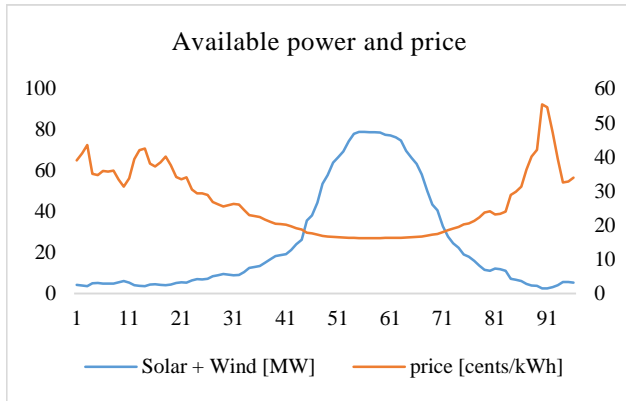


Figure 5 - Available power and price of electricity

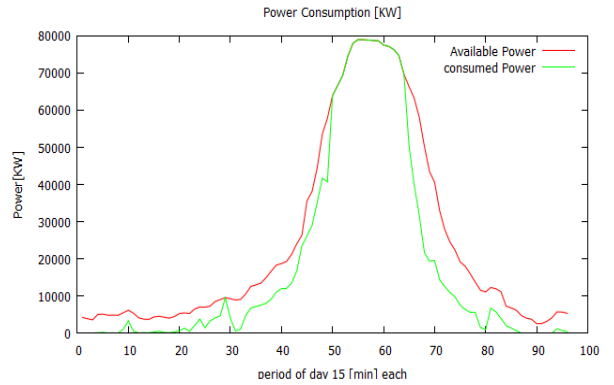


Figure 6 - Consumed power

downscaled 10 times at each 15 min period. Price signal is derived from available power as an indicator of relative cost using the following equation. This price is not absolute price of the energy but it is only a relative price signal.

$$Price_t = \frac{1000}{Power_t} + 20$$

Available power and price used for the simulation are shown in Figure 5.

#### 4. Results

The electric vehicle used for each schedule can start the optimization process till the last moment before executing the schedule. This optimization process depending upon the energy demand for travel and available power, devises the charging strategy for the car. The process creates the charging plan for the EV as a sequence of charging events. Each charging event contains information about start time and duration of charging event, amount of energy charged, location of charging and power at which energy is charged. Optimization process marks the resulting strategy as *feasible*, *soft infeasible* or *hard infeasible*. Information about charging events is sent back to *grid agent* in case of *feasible* or *soft infeasible* strategy, while a negative signal is sent in case of *hard infeasible* strategy. Examples of *soft feasible* is shown in form of battery SOC timeline in Figure 7.

**Feasible strategy:** if battery SOC level at the end of the schedule and at the start of the schedule are equal.

**Soft infeasible:** if initial battery SOC level cannot be prevailed but the SOC at any other time does not violate minimum level requirement.

**Hard infeasible:** if initial battery SOC level cannot be prevailed and the minimum DCD level requirement is violated at least once.

In this test simulation, optimization process is carried out for 90569 EV. Out of them, 85872 BEV succeeded as feasible strategy, 4001 as soft infeasible, and 379 as hard infeasible strategies. The optimization process took 0.63 millisecond for each car on average.

In Figure 1Figure 6, a comparison is presented between available and consumed power for each 15 min period of the day. Power is booked completely during the relatively cheaper moments of the day.

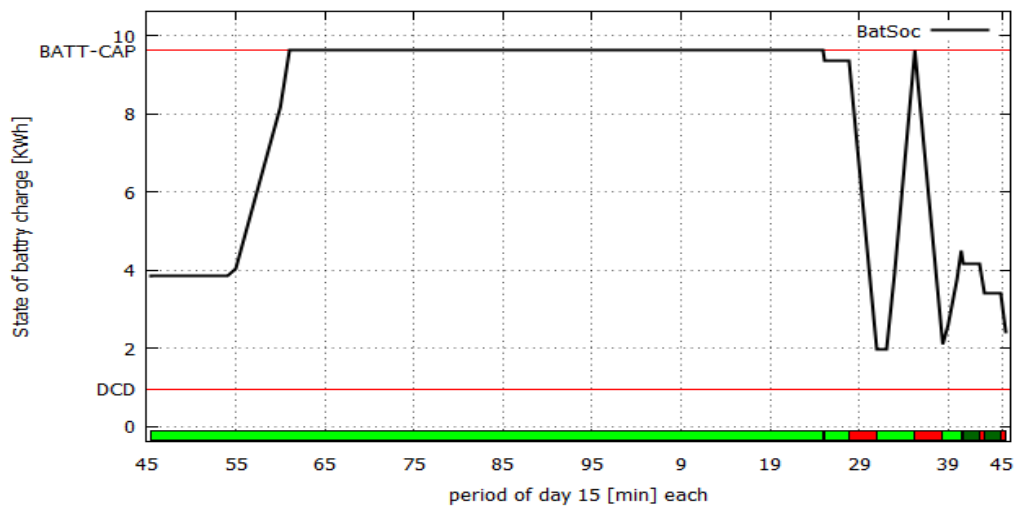


Figure 7 - Soft infeasible charging plan

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