Container based simulation of Electric Vehicles charge optimization

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Abstract This paper proposes the exploitation of simulation techniques to evaluate energy optimization strategies in smart micro-grids. In particular, a container based deployment approach allows for running simulations in the Cloud, evaluating multiple scenarios and optimization algorithms. Here we present both the simulator technology and an original two-phases optimization algorithm that computes a sub-optimal solution in real time. We introduce a simple scenario with real data.

1 Introduction

Two of the greatest environmental concerns are pollution and CO2 Emissions due to vehicles. Use electrical vehicles could the solution of both these problems. However, when EVs are charged at home and, even sometimes, when the charging takes place at public or commercial Charging stations, they start to stress the electrical distribution network. On the other hand, Smart Grids have the potential to consider EVs not only as a load, but also as a flexible power source. Smart meters can provide information to carry out an optimal schedule to optimize the available power in the grid. A comparable research study, performed in Portugal, reveals a positive correlation between charging of electric vehicle and solar power [6].

The spread of IoT technologies provides real time data that can be exploited for developing smart solutions, to improve energy utilization in micro-

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grids. The GreenCharge project provides innovative cities with technological solutions and business models for cost-effective implementation and management of charging infrastructures for electric vehicles in smart micro-grids[7]. GreenCharge is testing its innovative solutions in practical trials in Barcelona, Bremen and Oslo. Simulation will be used in the GreenCharge Evaluation Loop to operate the measures in a virtual environment where the Pilots can be extended, overcoming real limitations, and the measures can be easily complemented with missing functionalities[4].

This contribution focuses on the design and implementation of an optimal loads scheduler that exploits charging flexibility of electric vehicles and the potential vehicle to grid capability. The objective of the optimal schedule is to maximize the utilization of energy production by decentralized renewable energy sources and to reduce the power peak. The optimization techniques exploits the load shifting and the control of power level of charged EVs. A software simulator, developed within the activities of the GreenCharge H2020 research project, is used for the experimental activities. Here we present the container based architecture of the simulator and a simple case study that uses real data to reproduce a realistic scenario.

2 The Greencharge Simulator

The GreenCharge simulator reproduces in a virtual environment the events that occur in a real pilot using a collection of real misured data [3]. It is based on the original CoSSMic simulator [1], and allows to extend the evaluation capability in real pilots, which are limited in the heterogeneity and number of devices and in the duration of operating trials. The simulator is based on the discrete-event simulation (DES) model where the system appears as a discrete sequence of events in time [2]. In Fig. 1 the conceptual model of the container based deployment configuration of the GreenCharge simulator is shown. Using both a virtual or a real network many containerized components interoperate trough a loosely coupled integration. The blue boxes represent the simulation engine and its Graphical User Interface (GUI). They use a volume to access simulation input and output data such as the configuration of scenarios, input time-series and output results. The XMPP server provides a peer-to-peer communication overlay for multi-agents distributed implementation. A volume is used to save user-credentials, since the simulator can be used by multiple users who can run their simulations in parallel, in one or in multiple containers. An optimization model can be integrated as Energy Management Systems (EMS) that runs in its own container and uses the Simulator interface to receive simulation events and to return the optimal energy schedule. The GreenCharge project will evaluate two different EMS innovative technological solutions, developed by the University of Oslo and by the Eurecat partner. Here we investigate an alternative solution that is

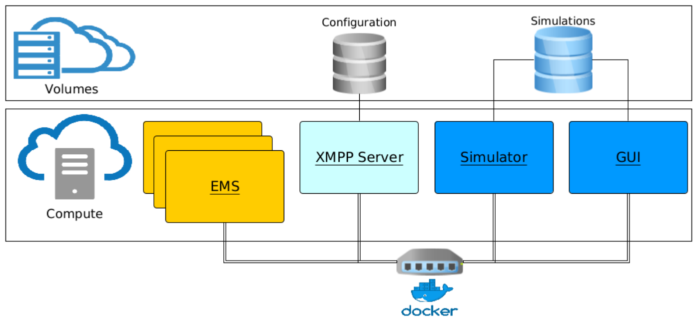


Fig. 1: Container based deployment configuration of GreenCharge Simulator

used to demonstrate how the simulation platform works. The user can access the Simulator GUI by the web interface of the hosting container.

In Fig. 2 the GreenCharge Simulator Graphic User Interface (GUI) is shown. The Control Panel represents a kind of dashboard of the tool to set

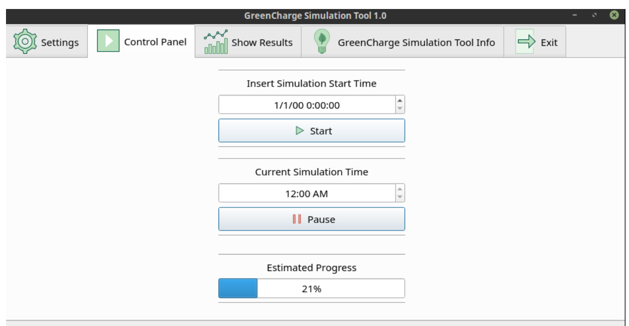


Fig. 2: Simulator GUI

and overlook a simulation session. In this panel, after completing the configuration phase, we can set the day and the starting time of the simulation. Pressing the start button activates all the simulation agents and starts the scheduling process. As the simulation progresses over time, the actual simulation time is updated, allowing the user to keep track of its evolution. The *simulation scenario* is described by two XML files. The *neighborhood.xml* file describes the static configuration of the micro-grid, that means the list of device with their parameters and the topology of their connections. The *loads.xml* file defines the events which will occur during the simulation, such as the start of an EV charge session, the booking of a charge point, the update of prediction of PV energy production, or the planned utilization of a heating-cooling device. The *inputs* include a list of time-series which correspond to the energy profile of devices such as washing-machines or production profile of photo-voltaic panels. The output include a log of the messages exchanged between the EMS and the simulation engine. The remaining results consist of time-series directly uploaded by the EMS or computed by the simulator according to the schedule received from EMS.

3 Formulating the Energy Management Problem

Self-consumption can be defined as the share of total photovoltaic production consumed directly by the owner of the plant [5]. In Fig. 3, areas A and B

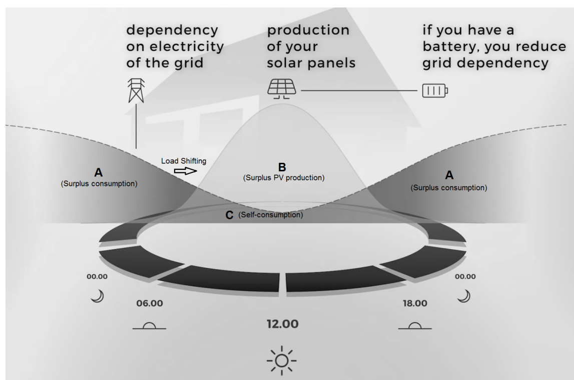


Fig. 3: Self Consumption

correspond to the interaction with the electricity grid in terms of demand and generation, respectively. Area A corresponds to the power absorbed from the electricity network by a building. Area B corresponds to the injection into the electricity grid of the surplus power produced by the photovoltaic system. The overlapping parts, i.e. area C, correspond to the power used directly inside the building. This area is sometimes referred to with the term of absolute self-consumption, but what is usually meant by the term self-consumption is the self-consumed part relating to total production. The increase in self-consumption may provide greater profits of the plants and may decrease the pressure on the electricity distribution network (Grid).

Therefore, the goal of an energy management system here is to find an optimal schedule of energy loads, that maximizes the self-consumption, without violating constraints set by the users about the earliest start time and the latest start time of the appliances. Example of shiftable loads are the ones generated by a washing-machine or a dishwasher.

The formulation of the complete optimization problem, taking into account energy producers, energy consumers and available stotage batteries, aims to maximize the ratio between EC_{res} and EP_{res}, where EC_{res} is the renewable energy consumed in the neighborhood and EP_{res} represents the renewable energy produced. Maximizing this ratio is equivalent to minimizing the energy drained from the grid and the energy exported from the panel to the grid.

Moreover, assuming that storage can either provide or drain energy at one time, and that max charging power is equal to max discharging power, the discrete minimization problem is formulated in Equation 1 .

$$min\Bigg(\sum_{n=0}^{N}\Bigg(\Bigg|\sum_{i=0}^{I}P_{res}^{i}(n\Delta t)-\sum_{j=0}^{J}C_{con}^{j}(n\Delta t)) + \sum_{k=0}^{K}x_k * PMAX_{storage}^{k}\Bigg|\Bigg)\Bigg) : x_{n,k} \in [-1,1]\forall k \in K, \forall n \in N \qquad (1)$$

This formula is valid if and only if the storage can only accumulate the energy produced by the local renewable energy sources. In particular:

- N i the number of discrete time intervals
- I is the number of Producers
- J is the number of Appliances
- K is the number of energy Storage
- $P_{res}^{i}(n\Delta t)$: is the power produced by i-th renewable source at time $n\Delta t$
- $C_{con}^{j}(n\Delta t)$: is the power consumed by j-th appliance at time $n\Delta t$
- $x_{n,k} * PMAX_{storage}^{k}$: power provided by k-th energy storage at time $n\Delta t$.

We also suppose that $J1$ appliance generates shiftable loads, while loads of $J2$ appliance cannot be shifted, such as lights, tv and any other devices that are not monitored and controlled. All these devices represent a background load that can be subtracted to the available renewable production. In Equation 2 we split the contribution of shiftable and not shiftable loads.

$$\sum_{j=0}^{J}C_{con}^{j}(n\Delta t)) = \sum_{j_1=0}^{J_1}C_{Back}^{j_1}(n\Delta t)) + \sum_{j_2=0}^{J_2}C_{Sh}^{j_2}(t_0^{j_2}, n\Delta t)) \qquad (2)$$

with $J1+J2 = J$. In order to simplify the problem, looking for a sub-optimal solution, we propose to address the optimization problem in two steps. First we find the schedule for shiftable loads, than we try to shift and modulate the charging of energy storages.

The first optimization problem is formulated in Equation 3.

$$min\Bigg(\sum_{n=0}^{N}\Bigg(\Bigg|\sum_{i=0}^{I}P^{i}_{res}(n\Delta t)-\sum_{j_1=0}^{J_1}C^{j_1}_{Back}(n\Delta t))$$
$$-\sum_{j_2=0}^{J_2}C^{j_2}_{Sh}(t_0^{j_2},n\Delta t))\Bigg|\Bigg)\Bigg):t_0^{j_2}\in[t^{j2}_{est},t^{j2}_{lst}]\forall j_2 \tag{3}$$

Hence, here we aim at finding the best set of starting times ($\vec{t_0}$) of the shiftable loads that maximizes the self-consumption with t_0^{j2} between the earliest start time t^{j2}_{est} and the latest start time t^{j2}_{lst}. Once the start time of shiftable loads has been assigned we deal with the optimal charging/discharging of the storages. In particular, we address this problem as a linear minimization problem every Δt seconds. In Equation 4, $R_{res}(n\Delta t)$ represents the *Residual power* in the n_{th} time interval, while the k_th x is the real decision variable for each storage. If $x_k > 0$ in the n^th interval, it means that the storage k will charge in that in interval, it will discharge otherwise.

$$min\left(\left|R_{res}(n\Delta t)-\sum_{k=0}^{K}x_{n,k}*PMAX^{k}_{storage}\right|\right):x_k\in[-1,1]\forall k \tag{4}$$

4 Optimization Algorithm

The optimization algorithm works in two phases. In a first phase a Genetic Algorithm is used to find the start time for the load shift. In a second phase a many linear optimization problems are solved, one for each time slot within which the power value of charging EVs is kept constant.

4.1 GA based Load Shifting

To provide results in a defined and certain time, the optimal schedule will be computed using evolutionary optimization techniques, with the addition of specialized genetic operators studied for the type of addressed problem.

In our case, we models an individual as a list of start-time of the loads that must be scheduled. Therefore, the number of genes is variable and depends on the user's real-time needs. The same applies to optimization constraints in terms of load start-time preferences. The less flexible they are, the less there will be room for optimization, making the response time lower.

The optimum is computed without limits of iterations, but using the quadratic norm of the population as a stopping criterion. The quadratic norm (qn) represents an index that measures how much the population is scattered in the research space.

4.2 Linear EV charge optimization

The linear minimization problem of Equation 4 is solved in 144 time interval of 10 minutes each. EVs are modeled as stationary storage. Basically it is possible to use the energy stored in car's battery whenever possible to supply power to the loads present within the neighborhood if necessary. Any intervals where there is not enough self-production to meet the energy demands would be balanced by the battery energy, thus increasing self-consumption On the other hand, if an EV k does not support the V2G capability, the $x_k > 0$ constraint will be set.

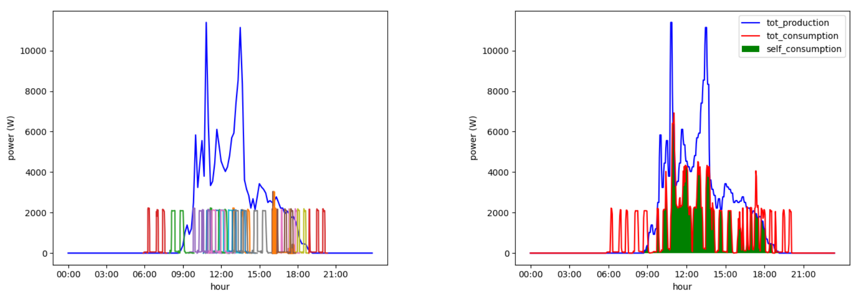
Other constraints limit the maximum amount of energy that can be drained from and to the EV energy storage. Such constraints are defined in Equation 5.

$$\begin{cases} \frac{x_k * PMAX^k_{storage}}{6} \leq E_t - E_n & \text{if } \frac{x_k * PMAX^k_{storage}}{6} > 0 \\ \frac{x_k * PMAX^k_{storage}}{6} \leq E_n & \text{if } \frac{x_k * PMAX^k_{storage}}{6} < 0 \end{cases} \tag{5}$$

Where E_n is the Energy stored in the EV battery at the n_{th} interval and E_t is the total battery capacity. Consequently, $E_t - E_n$ is the energy that can still be charged. The previous constraint states that the energy charged within a ten-minute interval (the sampling step chosen) cannot be greater than the energy necessary for the complete charge of the battery, on the other hand, the Energy discharged within a 10 minute interval cannot be greater than the amount of energy already present in the battery. Moreover, the last constraint is set to avoid that the power peak in each time interval does not overcome the physical threshold. Finally, in order to satisfy the EV energy demand before the departure time, the algorithm dynamically set some x_k values before the linear solver is run. The idea is to leave the car battery free to charge and discharge freely until the last available timeslot after which it would no longer be possible to charge the car up to the necessary level in the desired time even with the maximum charge power. The algorithm, in each time slot, computes the necessary power value to satisfy the charging demand. If the required value, divided by the maximum charging power, belongs to [-1,1], it means that the achievement of the target SoC is still feasible. On the other hand, to avoid that in the next slot is too late to charge at the desired level even if the maximum power is used, then a lower threshold is set for deciding to charge at maximum power in the current interval. Such a threshold value is set equal to 0.9 in the following experiments. A special case of this algorithm is when V2G is enabled. In this case the algorithm prevents the usage of V2G in the i time slot, if it could cause in the i+1 slot that the required power to achieve the target SoC exceeds the maximum value. Logically this procedure also affects the optimal result, because we have inhibited the use of V2G in an slot in advance. Howeve, since the slot duration is only 10 minutes, then the impact is limited.

5 Experimental results

The simulation scenario includes 2 photo-voltaic plants and 16 dishwasher, 2 washing-machines and three EVs. The power profiles of all devices have been extracted from real measured data, but, in order to configure a larger workload, the same device is replicated in the proposed experiment with random EST and LST constraints, whose difference is no more than one hour. The PV plants produces 24.9 kWh from 08 : 00 to 18 : 15. The stopping criterion for computing the theoretical optimum is a value of the quadratic norm equals to 10^{-6}. It is reached on average in 100 iterations. The average value of self-consumption has been 59%, that corresponds to an green energy consumption of $14.7kWh$. Fig. 4a shows the optimal schedule compute by the Genetic Algorithm in a specific run that converged after 81 iterations. In Fig. 4b we see in green the self-consumed energy. It is straightforward to observe that, because of the constraints, some loads consume from the grid before the PV plants start to produce. On the other hand the power peak exceed at the PV power more than once. The blue line corresponds to the PV power consumption In a second phase the linear optimization computes the optimal



(a) Optimal loads shift (b) Self Consumption

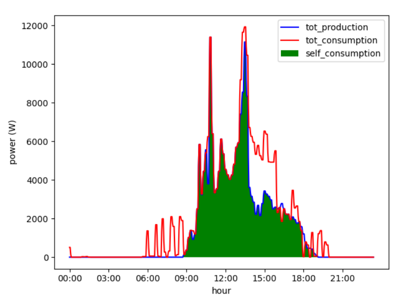
Fig. 4: Optimal schedule after the loads shift.

charge of the three EVs. We considered the real brand and models which have been monitored in trials: two instance of a VW e-Golf with a 24kWh battery and a Peugeot iOn with a 16kWh battery. The maximum charge power for both was limited by the charging point. All the required parameters, including the arrival and departure time, and the status of charge on arrival and the target one, are listed in Table 1. In Fig. 5 it is shown a comparison of results, in terms of self-consumption, with and without V2G support. In Fig. 5a it is shown that the algorithm is able to consume all the energy produced by the PV plants, but it cannot reduce the power peak when it needs to charge the EV to comply with the desired energy level at the departure time. The stacked power of charging EVs in Fig. 5b try to saturate the PV panel in

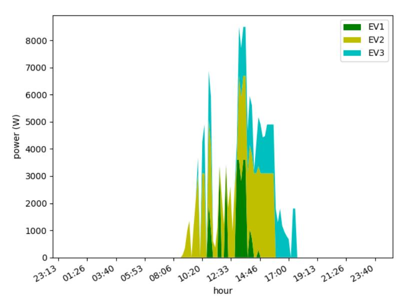
Table 1: Input parameters for the EVs charge optimization.

EV	**Capacity**	**Max Power**	**Arrival (soc, time)**	**Departure**
EV1	24 KWh	3.6 kW	50%;10:40	70%;20:40
EV2	24 KWh	3.1 kW	25%;09:20	90%;17:40
EV3	12 KWh	1.8 kW	25%;08:15	85%;16:16

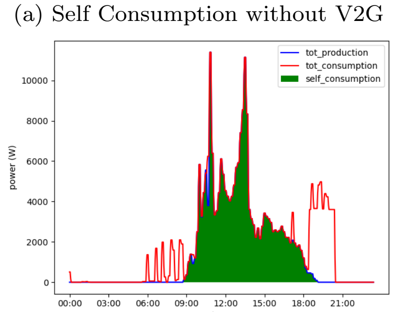
the beginning, but especially EV2 must charge at maximum power before leaving. This behaviour causes a power peak that is partially compensated by the PV production. In Fig. 5c the self-consumption is still 100%, but the algorithm exploits the V2G support to minimize the energy exchange with grid using the available energy stored in the EV batteries. It can be observed that there is not power consumed from the grid while the PV is producing. On the other hand, a higher power peak respect to the the previous case is due to the necessity to charge EV1. In fact EV1 is the last one to leave and the one that provides to the grid most of its energy.



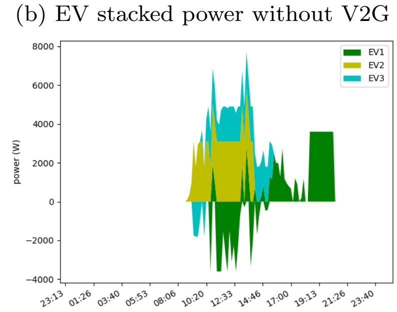
(a) Self Consumption without V2G



(b) EV stacked power without V2G



(c) Self Consumption with V2G



(d) EV stacked power with V2G

Fig. 5: Effects of EV charge on self-consumption with and without V2G.

6 Conclusion

We presented a container based deployment solution for the evaluation of energy management strategies in smart micro-grid scenarios based on simulation. The container based approach allows to speed up the evaluation activities deploying instances of the simulator in a distributed systems, or in Cloud, and running multiple optimization strategies working on different scenarios. We focused on the evaluation of an original optimization algorithm that aims at maximizing the self-consumption of decentralized PV energy production in a smart-microgrid, exploiting the flexibility of EV charging, with and without the support of V2G capability. The experimental results demonstrates the feasibility of the evaluation approach. Further improvements are required to take into account conflicting goals, such as power peak minimization and realistic battery models. Investigation on high performance and scalability issues of the proposed deployment configuration is needed.

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