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Simulation-based Design and Evaluation of a Smart Energy Manager

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Abstract. In this work we describe an advanced development environment for energy management systems using a combination of a Modelica-based simulation tool for multi-physics systems and a controller implemented in the Python scripting language, exchanging information via the FMI (Functional Mockup Interface) standard. As an example, we present the development of a simple but robust Electric Vehicle (EV) charging controller for a smart home with a Photo Voltaic system. The performance of the controller is evaluated using conventional criteria like annual energy costs and peak load plus two newly developed customer satisfaction indicator (CSI) functions.

Keywords: Digital Twin · Energy Management Optimization · Customer Satisfaction Indicators · Smart Home

1 Introduction

The dramatic changes in energy systems towards more and cheaper renewable energies, open up new possibilities for more efficient operation of energy systems. An example we look at in this work is the integration of electric mobility into homes with a Photo Voltaic (PV) system. It is a common problem, that excess PV energy has to be fed back to the grid, reducing the profitability of the system and potentially destabilizing the electricity grid. With a proper control strategy, Electric Vehicle (EV) batteries could be used to store electric energy from the PV system. An energy manager (EM) is used to control the flow of energy between house (PV system) and EV.

Several articles (for example [3, 5]) have already outlined how problems of this type can be solved in an optimal way, however, they require a prediction of future energy demands and production plus substantial computing power. The relatively modest saving potential often does not suffice to compensate for the investment in stronger CPUs and / or cloud computing access. Therefore in practice, often simple rule-based systems are employed, where computing requirements are low, and the rules are easy to understand. Here, we are looking

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at the development of such a rule-based EM for a small building with a PV system and single EV plus charging station. The EM should be operating to minimize energy costs by maximizing self-consumption of PV power, to minimize charging peaks and to maximize customer satisfaction, leading to three separate and conflicting optimization targets. In order to facilitate the development of such a controller, several key components are required that will be outlined in the following:

1. A multi-physics simulation environment that can be used to model a variety of scenarios at a high simulation speed (much faster than real time) while at the same time incorporating all relevant physical effects of the system.
2. A development environment for the energy manager software that is easy to use and capable of supporting advanced tools in the field of AI. We have opted for Python (*www.python.org*) as a platform to develop and test our controller due to the availability of a large number of open-source libraries in the field of machine learning and data mining.
3. A coupling between the simulator and the EM, so that two different software frameworks, both optimized for the task, can be used. The ultimate target is a Software-in-the-loop (SiL) testing framework, where the EM can be connected seamlessly to the real system after it was tested on the simulation system.
4. A definition of the objective functions to be considered. Here it is important to consider the various requirements of the customer. Specifically we need to consider the customer perspective that evaluates the quality of a charging process.

2 Simulation Model

While developing a controller that handles a single objective well is relatively straightforward, finding a good balance for all objectives in many different scenarios is rather challenging. Quite obviously, the development and validation of such a controller can not be done with a real system due to the disturbances to the inhabitants and the limited control over external factors like weather and user behavior. We have therefore decided to employ a simulation system that models relevant physical effects for building and car. Our simulator [1] uses the Modelica language [2] which is well-suited for the modeling of multi-physics systems. In Fig. 1 a view of the model in the simulation tool is shown.

2.1 Simulation-Controller Interface

In order to link a controller written in Python with a detailed physical building simulation we are using the Functional Mockup Interface (FMI) [4]. Originally developed for connecting different simulation tools, FMI is used to link two different programs (Modelica physical simulation and the Python EM logics) via a connecting interface. A view of the different components is shown in Fig.

1. A controller interface block based on Functional Mockup Units (FMUs) is embedded in the simulation model. This serves as an interface to the EM software implemented in Python via a coupling software called SIMBUS.

3 Controller Approaches

In this work we compare four different rule-based EMs of increasing complexity that control the charging of the EV, depending on the following external inputs: current SoC (EV battery state of charge), time to planned departure t_{Remain}, PV surplus power $P_{Surplus}$ (the current power produced by the PV system minus the current energy consumption of the building, excluding the charging system).

3.1 Basic EM: PMax

The most basic control logic (often referred to as 'dumb charging') is to charge the car with maximum power ($P_{Max} = 7.36kW$) as soon as the EV is connected and until it is full. This strategy provides the maximum customer satisfaction but also generates strong peaks and often uses less PV surplus power than other approaches.

3.2 Surplus Charging

This approach only charges the car using PV surplus power, therefore maximizing the self-consumption of PV power. However this comes at the cost of occasional low CSI values, especially, when weather conditions are bad and not enough surplus power is available.

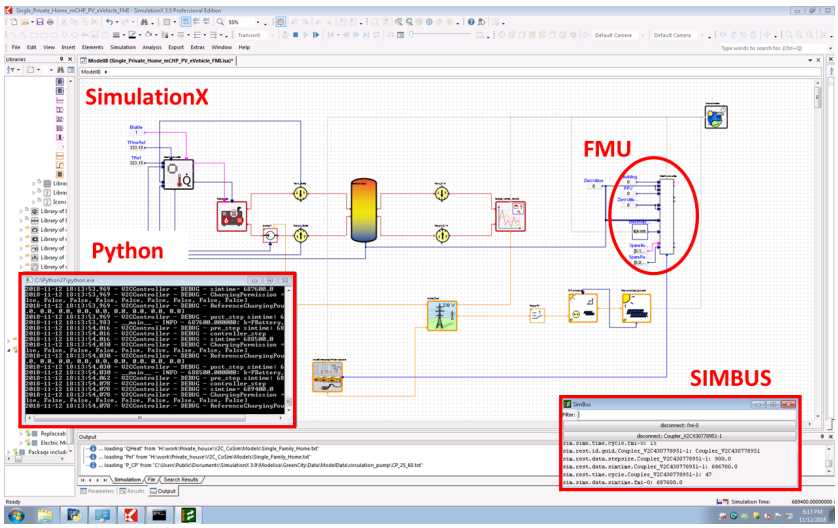


Fig. 1: Schematic view of the simulation environment including FMU coupling.

3.3 Emergency Charging: Last2H

This control approach is a surplus charging strategy, but if the car is not fully charged two hours before planned departure, the EM charges the car with maximum power until it is full. This approach provides a better compromise than the first two methods. However, it still responds poorly under some specific conditions. One example is a customer that arrives in the late afternoon (no more PV surplus) and wants to leave in the morning. The Last2H approach would wait all night (for PV surplus) and then charge with full power in the morning. This would generate substantial peaks in the grid and leave the car at a low SoC level for all of the night.

3.4 New Controller

In order to deal with the issues of the Last2H controller, we add a simple predictive component. Based on historical data (the last 7 days) we predict the amount of PV surplus we can expect in the time till departure ($\overline{P_{Sur}}$). The remaining energy that is probably not going to be provided by the PV system is taken from the grid, but distributed equally over the charging time (P_{Distri}). We also add an emergency charge component that provides the remaining energy evenly distributed in the last 2 hours. This approach combines the merits of the three other approaches and only requires a simple addition to the control structure and hardware (a memory to store PV surplus of the last days.) The flowchart of our new approach is shown in Fig. 2.

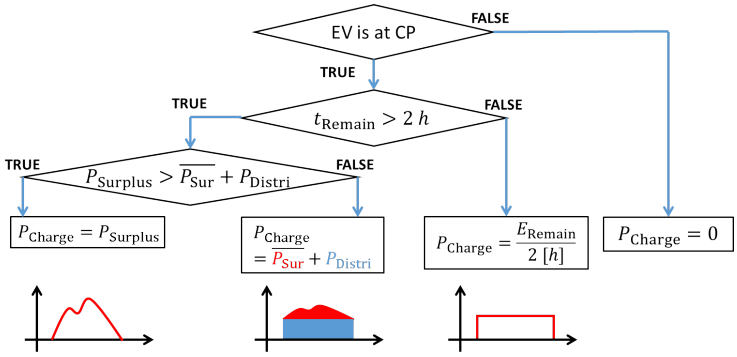


Fig. 2: The flowchart of our new energy management controller logic. The EM first verifies if the EV is at the charging point (CP), then checks if the emergency charging has to be engaged. If the current power surplus is much larger than predicted only surplus power is used, otherwise the controller provides the estimated surplus power plus power from the grid.

In Fig. 3 the differences in charging patterns for the four different control strategies are visualized for one example day.

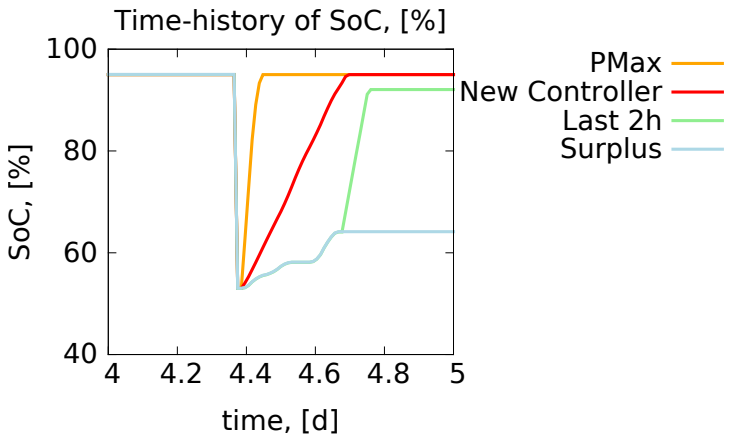


Fig. 3: Typical charging process for each controller during one typical day.

4 Objective Functions

To investigate the performance of a controller one needs to compute a number of performance indicators. The necessary data was generated by the simulation model for a complete simulated year. The simulation covers typical weather patterns and was also tested with different EV usage. The results shown here correspond to a charging scenario where the EV is connected to the charging station during the day, so that it is available when PV surplus energy is generated. The first objective we consider is the annual energy bill:

$$Cost = c_{\text{Buy}} \cdot E_{\text{Grid}} - c_{\text{Sell}} \cdot E_{\text{FeedIn}}. \tag{1}$$

E_{Grid} represents the total amount of energy purchased from the master grid, while E_{FeedIn} represents the total amount of energy sold to the master grid. With reference to general electricity price in Germany, the price for purchased electricity from the grid (c_{Buy}) is set to 30 cents per kWh, and the price for selling electricity (c_{FeedIn}) is set to 10 cents per kWh. The difference in the price between purchased electricity and sold electricity shows that it is more efficient in terms of cost to consume electric power obtained by PV as much as possible within the home.

The second objective is the peak power which represents the maximum purchased power from the master grid in one year. Peak Power is often used as an indicator to be minimized when developing smart home systems and energy management controllers. The larger Peak Power, the higher the load on the grid which might lead to blackouts. Especially in the case when designing systems which include hundreds of EVs, Peak Power must be properly considered. We note that for many customers, peak power also influences the annual electricity bill, but this was not considered in this work.

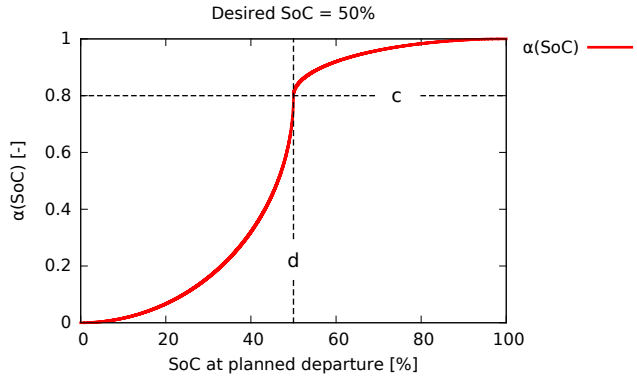


Fig. 4: CSI_α with $SoC_{desired} = 0.5$ and $c = 0.8$.

4.1 Customer Satisfaction Indicator

In order to properly represent the customers' mobility demand, we introduce two new objectives via customer satisfaction indicators (CSI) that compare the user's (modeled) requirements with the result of the charging process. The CSIs consider two different aspects of the charging process:

Final State Of Charge: $\boldsymbol{CSI_\alpha}$ We assume that before the charging commences the customer provides the intended departure time and desired SoC ($SOC_{desired}$). At the time of departure, we compare the desired SoC with the achieved value (SoC) according to the following equation (see also Fig. 4):

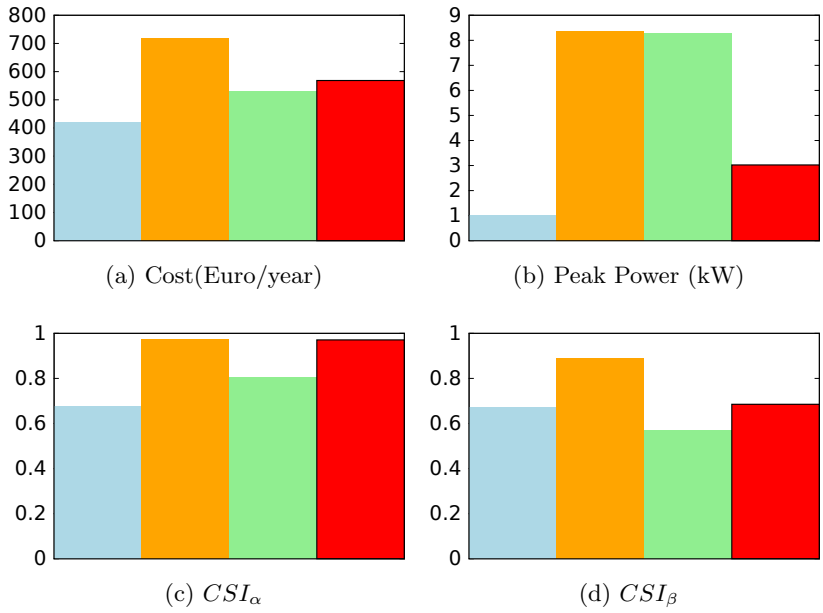
$$CSI_\alpha = \begin{cases} c\left\{1 - \sqrt{1 - \left(\frac{SoC}{SoC_{desired}}\right)^2}\right\} & (SoC < SoC_{\text{desired}}) \\ c + (1-c)\sqrt{1 - \left(\frac{SoC-100}{SoC_{desired}-100}\right)^2} & (SoC \geq SoC_{\text{desired}}) \end{cases} \tag{2}$$

The parameter c represents the customer satisfaction achieved when the car is charged to the intended level. As one can see, providing more energy than requested will lead to relatively small gains in CSI. On the other hand failing to reach the requested value quickly deteriorates the CSI level.

Intermediate State Of Charge: $\boldsymbol{CSI_\beta}$ The second part of the charging CSI considers the SoC level during the charging process. The rationale behind this is that the customer might have to leave earlier than expected and would prefer to have a fully charged car as soon as possible. We therefore compute CSI_β by computing the mean level of SoC during the charging process minus the SoC at arrival.

5 Results

We simulated the operation of our four controllers for one complete year each and compute the performance objectives. In Fig. 5 we see that the surplus controller has the lowest costs and peak power, but also the worst CSI values. The max power charging in contrast provides high customer satisfaction for the charging process but also high costs and peak power. The more advanced Last2H approach provides a better trade-off for the different objectives, but still has high peak load values and low CSI scores. Our new approach has reduced annual costs compared to max power charging, low peak power values, and higher CSI values than Surplus and Last2H. This can also be observed in Fig. 6, which shows a boxplot of CSI values over all charging processes of a year. We see that for Surplus and Last2H strategies, there are occasions where CSI values are extremely low, which would probably lead to a very low subjective evaluation of the EM system. In contrast, CSI values for our new controller approach stay in higher ranges for both CSI types.



(a) Cost(Euro/year) (b) Peak Power (kW)

(c) CSI_α (d) CSI_β

Fig. 5: Comparison of objective functions with four controllers (*from left to right: Surplus, PMax, Last2H,our approach*). CSI are mean values over a year.

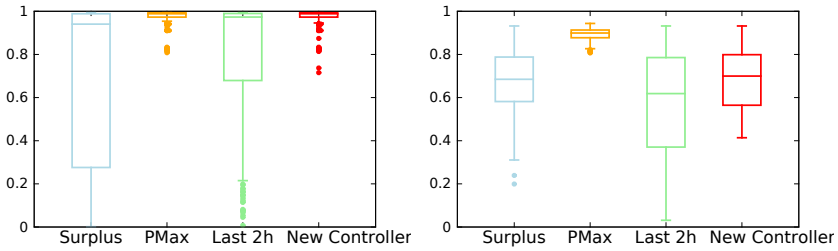


Fig. 6: Boxplot of CSI values (*left:* CSI_α, *right:* CSI_β) for one year.

6 Summary and Conclusion

In this work we have introduced a simulation-based development and test environment for a smart home energy management system. A new controller approach was presented and evaluated for different scenarios. In order to better include the customer's view, we defined two new objective functions, so called customer satisfaction indicators, that evaluate the success of the charging process from a user perspective. We have shown that our new approach exhibits very competitive performance compared to three other controllers, with only a limited amount of extra complexity. Using the simulation approach we could complete the model set-up, controller development, CSI definition, and system tests within a 6 student months project, which is much faster than any development based on real-world pilot studies.

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