Chapter 19
A House Appliances-Level Co-simulation Framework for Smart Grid Applications

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19.1 Introduction

Renewable energy sources cover a large part of the worldwide energy supply. In 2014 the share was approximately 19.1% [23]. Because of the continued expansion of renewable energy sources, the energy system is moving away from its traditional centralized structure with large producers towards a structure with many distributed generators. While the share of renewable energy in electricity production in 2005 excluding hydropower was 2.6% [24], it was already 4% at the end of 2014.

Due to the expansion of wind energy and photovoltaics (PV), fluctuating energy sources must be integrated increasingly into the system. In 2004, the global installed capacity of wind power was 48 GW, whereas with 370 GW it increased by almost eight times in the year 2014. At the same time, the installed PV capacity increased almost 48-fold from 3.7 GW_p to 177 GW_p [23]. Thus, the classic roles of producers and consumers in the energy system are supplemented by consumers who generate energy, the so-called prosumers. The integration of variable renewables increases the need for centralized and decentralized energy storage. Prosumers equipped with storage systems are also referred to as prostumers.

The increasing use of electric vehicles (EV) leads to a further increase in consumers and storage systems in the grid. Such mobile storage systems can be charged at home and also at charging stations, which intensifies the complexity of the entire system. In 2015 there were 1.26 million EVs worldwide, compared to

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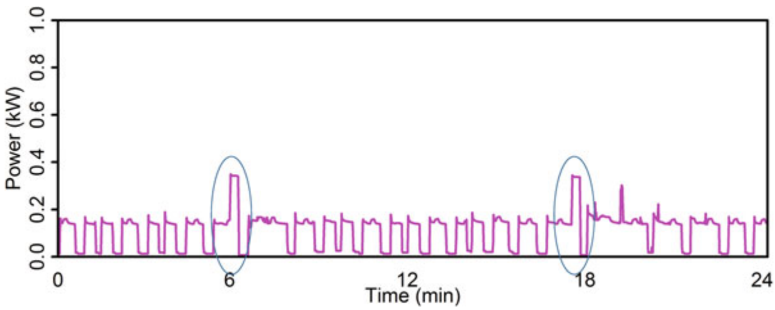


Fig. 19.1 Power consumption of a refrigerator

several hundred EVs in the year 2005 [16]. Therefore, the integration of millions of EVs will be an additional problem in the future. The increasing integration of information and communication technology into the system of consumers, prosumers, and prostumers enables the coordination of such systems and ensuring of grid stability.

Smart grid enables new applications for households such as Demand Response (DR) and Advanced Metering Infrastructure (AMI). Simulation models at appliance level can help understanding the benefits and risks of employing smart grid applications. Figure 19.1 shows the power consumption of a refrigerator. As can be seen, in the morning as well as in the afternoon, there are small increases in the power consumption (small spikes). It is the bulb in the fridge that is causing these spikes which is being captured by these readings. Such readings can be exploited to extract information about the behavior of the household. In [3, 4, 28] we used a co-simulation approach to study CVR and Volt/VAR control. In [5] we presented a short tutorial on using SGsim in electricity distributed networks. In [2] we have explored different methods to preserve privacy. In this work, we present an appliance-level co-simulation framework that enables exploring house-level smart grid applications.

The rest of the paper is organized as follows. At the beginning we present some related works. Then in Sect. 19.3 we introduce SGsim-Home. In Sect. 19.4 we present a case study, and in Sect. 19.4.2, we evaluate the proposed approaches. Finally, Sect. 19.5 concludes the paper.

19.2 Related Work

The use of simulation tools for the evaluation of new technologies and applications is a widely adopted method, and therefore, there is a wide range of tools. Some of these simulation tools have been combined into simulation environments which allow the co-simulation of various domains of a complex system. An overview of the requested requirements of such tools is given in [27]. There, the integration of of-the-shelf simulators for communication systems and electrical power systems into a co-simulation simulation framework is suggested, together with the ability to model control strategies for smart grid applications.

An example of a co-simulation framework is the modular platform mosaik for the evaluation of agent-based smart grid controls [26]. It combines different simulators and simulations and controls the data-flow between them. For this purpose, it defines its own modeling and specification language. It enables the simulation of large-scale smart grid scenarios but lacks the integration of a communication simulator. This problem is addressed with the presentation of a preliminary system architecture of integrating OMNeT++ [10]. Unlike SGsim-Home, this integration is not yet implemented.

Because communication is a key part of smart grid applications, several co-simulation tools are using the discrete-event simulator OMNeT++ [31] for modeling and simulation of communication systems. An example is the co-simulation approach of power systems, communication, and controls presented in [29]. This framework combines the commercial power system analysis software PowerFactory [12] with OMNeT++, whereas SGsim combines the electric power distribution system simulator OpenDSS [13] with OMNeT++, both of which can be used in a non-commercial environment without license fees. Another example is the communication network and power distribution network co-simulation tool for smart grids presented in [18]. There the discrete-event-based simulation of communication systems framework OMNeT++ is coupled with the continuous simulation of power systems tool OpenDSS using a Hypertext Transfer Protocol (HTTP) connection. SGsim-Home, on the other hand, couples the two simulation tools via a more runtime efficient Component Object Model (COM) interface. In addition to the two co-simulation examples, the controller component of SGsim-Home allows the connection to powerful optimizers over the internet.

The agent-based simulation engine of the co-simulation tool GridLAB-D [9], unlike SGsim-Home, has only simple network characteristics integrated like latency, bandwidth, buffer size, or congestion. Instead of using OpenDSS, it is coupled with the power system simulation and optimal power flow tool MatPOWER [33].

The approach of [20] combines three simulation tools for validating flexible-demand EV charging management. GridLAB-D controls the simulation and the charging management of the EV, the battery is modeled with OpenModelica [14], and the distribution grid with PowerFactory [12]. Because of GridLAB-D, the approach can only use simple network characteristics.

All these tools cover different aspects of the smart grid by using co-simulation. SGsim-Home integrates these aspects in one framework combining simulation tools of the power grid and the communication with a connection to an optimizer. It provides models for PV, Battery, EV, and home appliances like refrigerator, Air Condition (AC), and TV.

With SGsim-Home it is possible to analyze and minimize the privacy risk introduced by smart meters. It is shown in [17] that the detection of steady state changes from loads with an on/off switching behavior like refrigerators can identify the appliance. Even from smart meter data with a resolution of 30 min measured over 1.5 years, information about the personal circumstances of the residents can be extracted with a high probability [7].

SGsim-Home allows the analysis of integrated privacy protection and demand response techniques. The work in [22] presents a pre-processing approach to enhance user privacy. The authors have used quantization, down-sampling, and averaging to prevent successful classification of household appliance. An empirical and analytical model to study adding noise to mask smart meter readings has been presented in [6]. Additionally, they used correlation to evaluate the approach. Both methods are focused only on privacy.

Another approach introducing privacy, but this time considering several smart meters, is the homomorphic encryption of aggregated smart grid information presented in [19]. The data aggregation is performed at all smart meters involved in routing the data from the source meter to the collection unit.

In [30] privacy in smart metering systems has been studied from an information theoretical perspective in the presence of renewable energy systems and storage units. The authors describe the system as a finite state model and analyze the impact of a renewable energy system on the privacy. They also investigate the privacy and energy efficiency trade-off, but do not consider power-tariff dependent demand response and optimization.

19.3 SGsim-Home

The framework SGsim-Home is based on the co-simulation framework SGsim [1, 3–5, 28] which is based on two main simulators: OpenDSS [13] and OMNeT++ [31]. The focus of [1, 3, 5] was on transmission and distribution networks. SGsim-Home focuses on simulating home appliances. Two attractive characteristics of OpenDSS make it a suitable candidate for co-simulation. In addition to a stand-alone executable program, OpenDSS provides an in-process Component Object Model (COM) server DLL designed to be driven from an external program. The COM interface makes integrating OpenDSS into other simulators relatively easy. The second reason is the fact that OpenDSS is an open source simulator, and hence, providing this framework as open source for education and research community is possible. OMNeT++ has been selected to implement SGsim. In addition to the basic simulation tools, several frameworks have been developed for OMNeT++. For instance, INET framework has been developed with well-tuned data communication components such as TCP/IP, 802.11, and Ethernet. In order to enable the use of the framework in the field of smart grid applications, we have integrated new components for the electricity distribution network. Figure 19.2 shows the different components of the simulator. Through the COM interface, it is possible to control the execution of the circuit and to change/add/remove different components. Different approaches have been used to simulate the different devices. We have used real data to simulate some devices such as TV and washing machines. Figure 19.4 presents a 10 s resolution power consumption of a TV [15, 25]. At each time step,

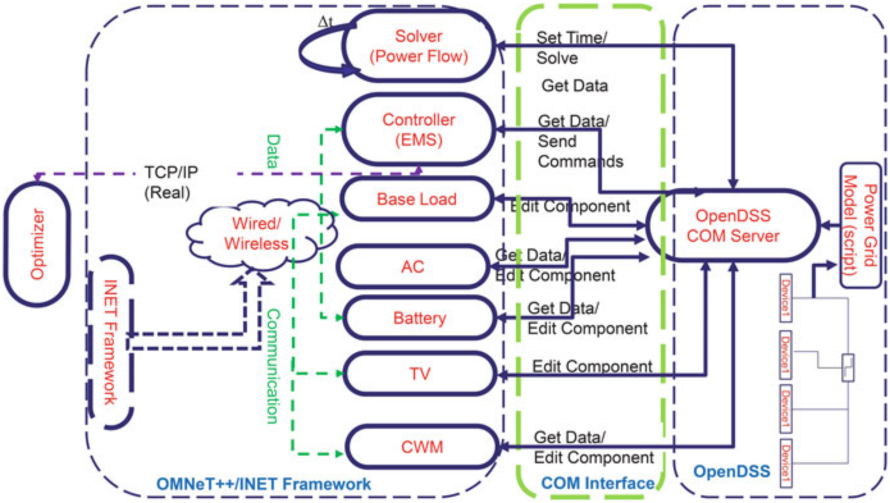


Fig. 19.2 Structure of SGsim-Home with the connections between the different components

the *Edit* command is used to change the parameter of these devices. The database provides data only for 1 h, therefore, the data will be repeated as long as the device is on. A mathematical model has been used to model thermal devices such as AC and refrigerator. The following set of equations represents this mathematical model of a refrigerator, a freezer, or an AC:

$$T(t+1) = \epsilon T(t) + (1-\epsilon)\left(\mathrm{To}(t) - \frac{\mathrm{COP} \times P_{\mathrm{ref}}}{A}\right) \tag{19.1}$$

$$\epsilon = \exp\left(\frac{\delta}{\delta_c}\right), \ \delta_c = \frac{\mathrm{mc}}{A}, \ A = \frac{k \times G}{\mathrm{Th}}$$

where $T(t+1)$ is the temperature inside the room at control period $t+1$, ϵ is the factor of inertia, δ is the duration of the control period, δ_c is the time constant, mc is the total thermal mass in Wh/C, A is the overall thermal conductivity in W/C, $\mathrm{To}(t)$ is the ambient temperature in C at control period t, COP is the coefficient of performance, and P_{ref} is the electrical power demand of the AC in W at control period t. k is the thermal conductivity coefficient, G denotes the area of the room, and Th denotes the thickness of the wall. If the refrigerator door is open, the bulb in the fridge will cause an additional power consumption P_{bulb}

$$P_{\mathrm{Ref}}^{\mathrm{Total}} = P_{\mathrm{ref}} + P_{\mathrm{bulb}} \tag{19.2}$$

OpenDSS provides several models to represent loads. We have used the ZIP-based load model *model 8* to simulate the different loads. This model is very useful when studying smart grid applications such as Conservation Voltage Reduction (CVR). The loads are modeled as ZIP loads with the parameters as in [8, 11]. The ZIP model represents the variation (with voltage) of a load as a composition of the three types of constant loads Z, I, and P which stand for constant impedance, constant current, and constant power loads, respectively. Equations (19.3) and (19.4) give the current active and reactive loads as a function of current voltage (V). The constants P_0 and Q_0 are the design active and reactive power, respectively. The parameter v_0 is the design voltage.

$$P_{Li} = P_{0i}\left[Z_P\left(\frac{v_i}{v_0}\right)^2 + I_P\left(\frac{v_i}{v_0}\right) + P_P\right] \tag{19.3}$$

$$Q_{Li} = Q_{0i}\left[Z_q\left(\frac{v_i}{v_0}\right)^2 + I_q\left(\frac{v_i}{v_0}\right) + P_q\right] \tag{19.4}$$

All devices are equipped with communication capability so that it is possible to control these devices. The INET framework provides the necessary components to simulate several kinds of communication networks such as WiFi and Ethernet.

Figure 19.3 shows a screenshot of the simulator. The devices are connected through a wireless LAN. The Smart Meter (SM) sends the energy usage at a specific frequency (e.g., 1 reading/min). The Home Energy Management System (HEMS)

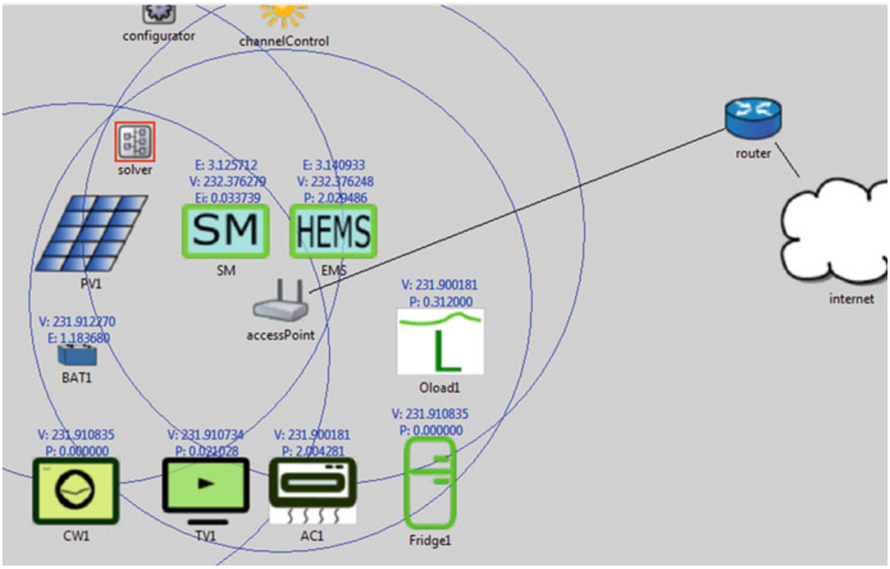


Fig. 19.3 Screenshot of the simulator

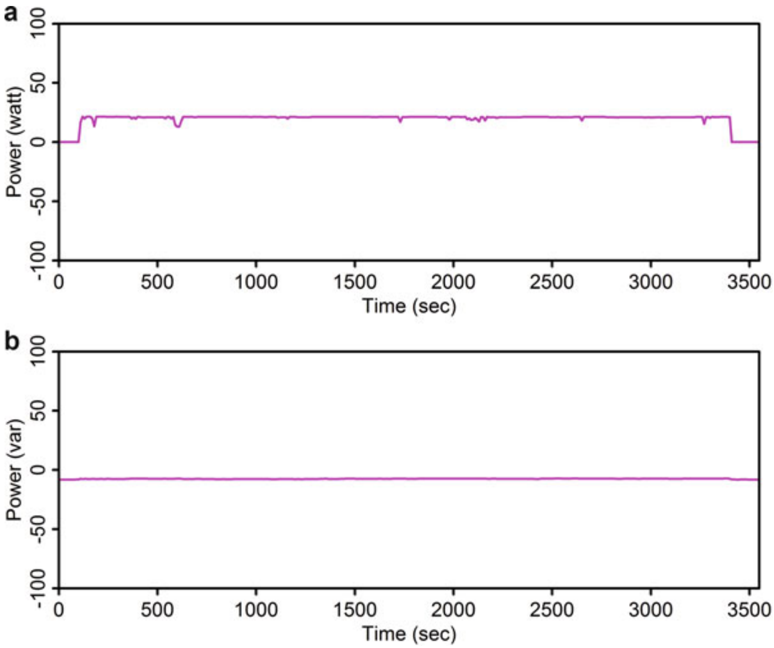


Fig. 19.4 TV active (**a**) and reactive power consumption (**b**)

coordinates the operation of the different devices. For instance, it can find the optimal operation strategy of the devices in order to minimize the electricity costs. The HEMS measures the energy usage at a higher frequency than the SM (e.g., at 1 Hz). The Oload1 represents the basic load and it is non-elastic. V is the voltage value, P represents the power consumption, E is the energy usage, Ei denotes to the last reading from the smart meter. The air condition is considered as an elastic load and the temperature should be maintained within a specific range. The clothes washing machine (CW) is considered also as an elastic load. It consists of several phases which should be run sequentially without interruption. It is possible to control the operation of the battery (charging and discharging periods) by the HEMS (Fig. 19.4).

19.4 Case Study: Integrated Privacy Protection and Demand Response

In this section, we present a case study on integrating privacy protection inside demand response. The HEMS uses the day-ahead price, storage, and load elasticity to minimize the costs. At the same time, it tries to hide load characteristics through a coordinated operation of a battery and elastic loads.

19.4.1 Smooth Consumption

In this approach, we exploit load elasticity and storage device (e.g., battery) to maximize the profit and at the same time to hide household information. The controller tries to maintain a constant power consumption level throughout the whole day through coordination between the different household appliances. Additionally, the controller tries to prevent power consumption spikes.

The main idea is to use the day-ahead price, the electricity demand, and the battery to find the optimal strategy to be followed to minimize the electricity costs and minimize privacy risks. The controller uses the day-ahead price and demand forecast to solve an optimization problem to find the optimal amount of energy to be sold, charged/discharged in/from the energy storage unit, and the amount of electricity to be imported from the main grid. Additionally, it finds the optimal time slots to run elastic loads such as washing machines. Furthermore, it controls the thermal devices (e.g., AC) to hide load characteristics. The controller solves a linear optimization problem for 1 day (i.e., $T = 1440$ min with a resolution of $\delta = 1$ min). Then, according to the results, it changes the current operating parameters of the system. We have formulated the optimization problem using the general algebraic modeling system (GAMS) and then solving the problem using the solver CPLEX.

The objective of the controller is to minimize the costs $C(t)$ and the privacy risks $\mathrm{PR}(t)$, therefore, the objective function can be written as below:

$$\min \left\{ \sum_{t=1}^{T} \lambda 1 C(t) + \lambda 2 \mathrm{PR}(t) \right\} \tag{19.5}$$

$\lambda 1$ and $\lambda 2$ are constants that emphasize the importance of costs or privacy, respectively. The costs come from importing energy from the grid.

$$C(t) = \mathrm{EP}(t) \delta P_b(t) \tag{19.6}$$

$\mathrm{EP}(t)$ is the electricity price, $P_b(t)$ is the power imported from the grid.

The above maximization problem is subject to system constraints. We considered the electrical balance constraints which can be written as:

$$P_d(t) + P_b(t) - P_l(t) - P_e(t) - P_c(t) = 0 \tag{19.7}$$

where P_d denotes power discharged from the battery, P_l represents the base load (non-elastic), P_c is the power charged in the battery, and $P_e(t)$ denotes the amount of allocated power in this time slot from the elastic energy.

The energy balance in the battery can be modeled as:

$$E(t+1) = (1-\alpha)E(t) + \delta \eta_c P_c(t) - \delta \frac{P_d(t)}{\eta_d} \tag{19.8}$$

$$E^{\max} \geq E(t) \tag{19.9}$$

E is the state of charge of the battery, α represents the self-discharge rate from the battery, and η_c and η_d are the charge and discharge efficiencies of the battery, respectively. $E^{\max}$ is the capacity of the battery. We have also considered the following limitations in the system:

$$P_d^{\max} \geq P_d(t),\ \ P_c^{\max} \geq P_c(t),\ \ P_e^{\max} \geq P_e(t) \tag{19.10}$$

$P_c^{\max}$, $P_d^{\max}$,$P_e^{\max}$ denote the maximum amount of power allowed to charge, to discharge, and to allocate an extra load at each time step, respectively.

The next set of equations guarantees that the battery is either in charge or discharge state.

$$P_d^{\max} x(t) \geq P_d(t) \tag{19.11}$$

$$P_c^{\max}(1 - x(t)) \geq P_c(t) \tag{19.12}$$

$$P_e^{\max} \geq P_e(t) \tag{19.13}$$

$$x(t) \in \{0, 1\} \tag{19.14}$$

The elastic load EL should be served in a specific period, which can be written as:

$$\sum_{t=T_1}^{T_2} \delta P_e(t) = \mathrm{EL} \tag{19.15}$$

where $[T_1, T_2]$ is the period where the elastic load should be run. If the load should be carried out continuously and it consists of several phases (e.g., washing machine), the following constraints should be added:

$$P_e(t) = w(t) P_{\text{phases}}(k) \quad \forall k \tag{19.16}$$

$$y(t) + w(t) \geq w(t-1) \tag{19.17}$$

$$y(t) \geq y(t-1) \tag{19.18}$$

$$w(t) \in \{0, 1\} \tag{19.19}$$

Equation (19.16) models whether an energy phase (k) is being processed during time slot t. Equation (19.17) ensures that the process will not be interrupted after it starts. Equation (19.18) ensures sequential processing of the phases.

We define the following function for privacy. The first term tries to maintain a constant consumption throughout the whole day, while the second term tries to minimize the changes of the power consumption.

$$\mathrm{PR}(t) = |P_b(t) - P_{\mathrm{Avg}}| + |P_b(t) - P_b(t-1)| \tag{19.20}$$

Additionally, the following constraint prevents sudden changes in the power consumption.

$$|P_b(t) - P_b(t-1)| \le \Delta P \tag{19.21}$$

19.4.2 Evaluation

In order to explore the capability of the approach to preserve the privacy, we have used the constant consumption approach to hide an EV charging signal. Hiding such a signal is more challenging than hiding refrigerator cooling cycle or turning on a bulb. We evaluated the proposed methods by examining the capability of the algorithm proposed in [32] to disaggregate EV charging signals from aggregated real power signals. The methods presented in [32] can effectively mitigate the interference coming from an AC, enabling accurate EV charging detection and energy estimation under the presence of AC power signals. It is a non-intrusive energy disaggregation algorithm of EV charging signals. It has five steps. In the first step, a threshold is applied to obtain a rough estimate of the EV charging load signal. Then in the second step, it filters the AC spikes. Then it removes the so-called residual noise. Then, in the fourth step, it classifies the type of each filtered segment. In the last step, it performs the energy disaggregation based on the effective width and the effective height of a segment. We have used the same data set that has been used in [32], which came from the Pecan Street Database [21]. This database collects raw power signals recorded from hundreds of residual houses in Austin, Texas. Ten houses using EV were randomly chosen from the database. Each aggregated power signal is generally a combination of about twenty power signals of various appliances, such as EV, AC, furnace, dryer, oven, range, dishwasher, cloth-washer, refrigerator, microwave, bedroom-lighting, and bathroom-lighting. The ground-truth power signals of these appliances are also available in the database. Thus, the database is very suitable to test algorithms' performance in practice. Table 19.1 summarizes the simulation parameters. Figure 19.5a shows the non-elastic power consumption of the house and electricity price. The EV charging process occurs in the afternoon. The house tries to minimize the power usage costs through optimal allocation of an elastic load and storing energy in a battery when it is cheap (e.g., at early morning) for future usage when the electricity is expensive (at afternoon). We assumed that the house owns a 1 kWh battery and a 2 kW AC. Figure 19.5b shows the power usage of the house when coordinating the usage to maintain a constant electricity usage. The house gets the day-ahead price and calls the optimizer. Using this price signal, the optimizer finds the optimal allocation of the elastic loads and the battery charging and discharging period to minimize the costs. At the same time, it tries to maintain a constant power consumption during

Table 19.1 Parameters

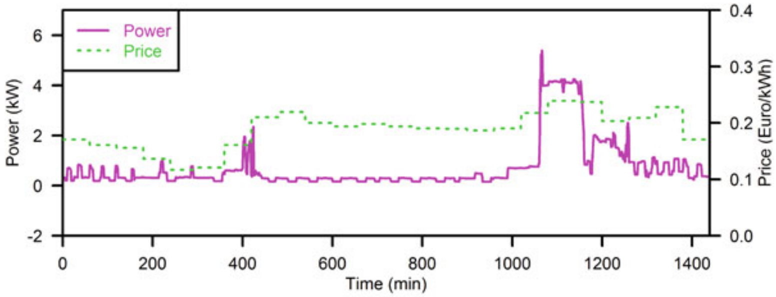
Parameter	Value
Battery	1, 5 kWh
ΔP	50 W
$\lambda 1 = \lambda 2$	1
δ	1 min
T	1440 min
$P_d^{max} = P_c^{max} = P_e^{max}$	3 kW
$\eta_c = \eta_d$	90%
ϵ	0.99
A	300 Wh/C
COP	3.5

the day. The controller can adapt the operation to react to new load signals. We have repeated the same experiment for ten houses with EV charging signal. Only in one case it was possible to detect the charging time. Increasing the battery size makes it possible for the controller to further flattening of the power consumption as can be seen in Fig. 19.5c, where we tested a 5 kWh battery. Using the available components, it is possible to produce a misleading charging signal. As depicted in Fig. 19.5d, the controller has produced a consumption profile that looks similar to an EV charging signal at midday.

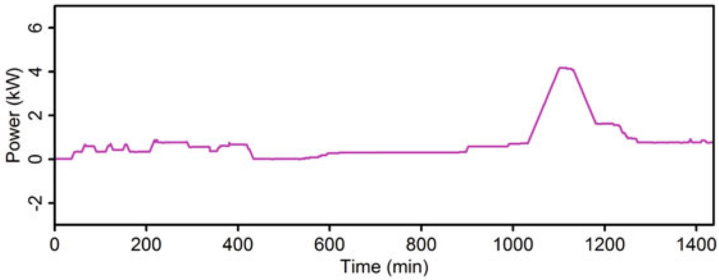
Based on the price signal, charging the EV in the afternoon is not the optimal charging time. In fact, the EV charging process can be considered as an elastic load which should be done in a specific period (e.g., before 8 AM). If we consider only the electricity costs, i.e., $\lambda 2 = 0$, the controller will select time slots in the early morning as an optimal charging period as can be seen in Fig. 19.6.

19.5 Conclusion

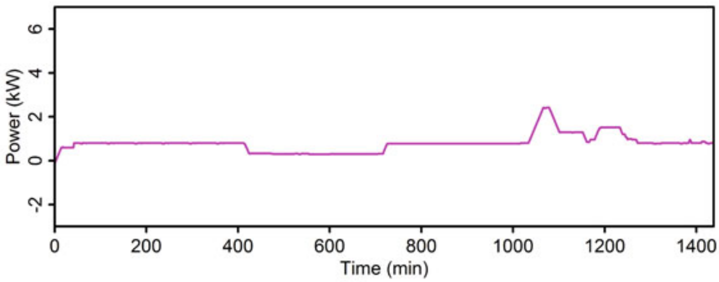
In this work, we have presented a home-appliance co-simulation framework. The simulator is able to capture the electricity as well as the ICT capabilities of smart appliances. Different components have been implemented and simulated. Additionally, the operation of the components can be adapted during the simulation (e.g., the operating parameters can be changed). This way, it is possible to simulate smart grid applications at home-appliances level. Through a case study, we have presented the possibility to integrate privacy protection into an important smart grid application, namely into the demand response. The results have shown the ability to hide load information through coordination between different components. Similarly as with SGsim, we are planning to provide this framework as open source for the academic community.



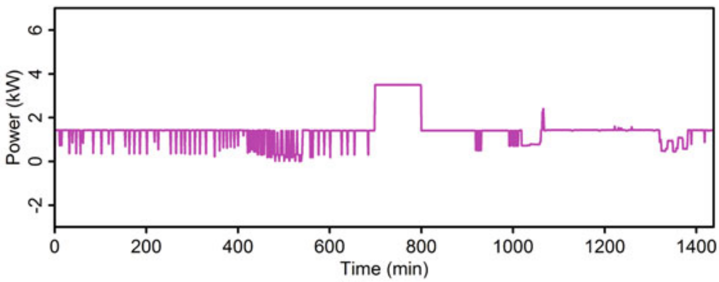
(a)



(b)



(c)



(d)

Fig. 19.5 Non-elastic load (**a**), load after smoothing with a 1 kWh battery (**b**), load after smoothing with a 5 kWh battery (**c**), and load after smoothing and adding a misleading charging signal (**d**)

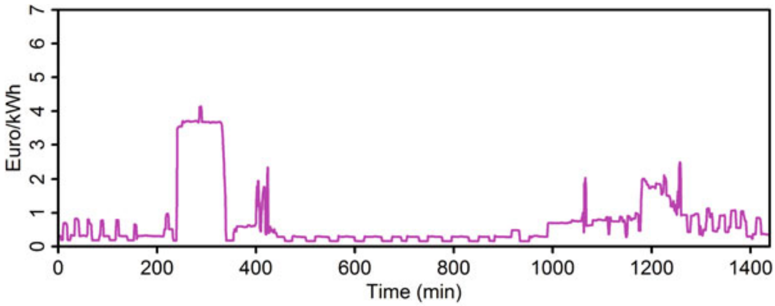


Fig. 19.6 Optimal allocation of EV charging

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