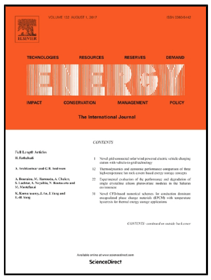
Accepted Manuscript



Cost optimal sizing of smart buildings' energy system components considering changing end-consumer electricity markets

Henryk Wolisz, Thomas Schütz, Tobias Blanke, Markus Hagenkamp, Markus Kohrn, Mark Wesseling, Dirk Müller

PII:	S0360-5442(17)31019-8
DOI:	10.1016/j.energy.2017.06.025
Reference:	EGY 11033
To appear in:	*Energy*
Received Date:	15 October 2016
Revised Date:	19 May 2017
Accepted Date:	01 June 2017

Please cite this article as: Henryk Wolisz, Thomas Schütz, Tobias Blanke, Markus Hagenkamp, Markus Kohrn, Mark Wesseling, Dirk Müller, Cost optimal sizing of smart buildings' energy system components considering changing end-consumer electricity markets, *Energy* (2017), doi: 10.1016/j. energy.2017.06.025

Cost optimal sizing of smart buildings' energy system components considering changing end-consumer electricity markets

Henryk Wolisz[a], Thomas Schütz[a], Tobias Blanke[a], Markus Hagenkamp[a], Markus Kohrn[a], Mark Wesseling[a], Dirk Müller[a]

[a] *RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, 52074 Aachen, Germany, hwolisz@eonerc.rwth-aachen.de*

Abstract:

Managing the electricity system becomes increasingly challenging, calling for modifications of the current electricity market. High fluctuations in power generation could make the introduction of dynamic end-consumer electricity pricing reasonable. Furthermore, the prediction of end-consumers' power consumption would get easier when charging the maximum power capacity, instead of the consumed energy. Thus, this paper discusses the capability of smart buildings to cope with such market models and evaluates how the design of the electrical and thermal energy system of a modern German building is affected. Therefore, cost optimal sizing of the main supply system components is carried out based on a hybrid MILP and a heuristic optimization algorithm. The results indicate that local photovoltaic generation is beneficial in almost all market conditions, while except for the capacity market, batteries are only economical if prices decrease by more than 60%. The identified electricity price dynamics are too low to incentivize investments into load shifting capable supply or storage systems. Nevertheless, if an installed heat pump and the associated thermal storage have smart home capabilities, they support the maximization of PV self-consumption and reduce electricity cost.

Keywords:

Electricity market, cost optimization, dynamic electricity pricing, capacity market, smart grid, demand side management

1. Introduction

The vastly growing renewable energy sector induces the challenge of highly fluctuating and unpredictable renewable energy generation (e. g. from photovoltaic (PV) and wind). Due to the current inflexibility of electricity demand, it is not always possible to match the renewable energy generation with the demand. The rising share of wind and PV in the total energy portfolio will further aggravate that challenge in the upcoming years [1]. Residential and commercial buildings, which are accountable for up to 30% of Germany's final energy consumption [2], can provide flexibility to counter these imbalances between supply and demand in the electrical grid [3, 4]. However, there are several technical and energy political boundary conditions which strongly impact this potential. Technical challenges mainly arise from the energy demand of buildings, which is driven by space heating and supply of domestic hot water (DHW). Therefore, electricity driven heating systems (e. g. heat pumps, direct electric heating) are required to effectively utilize energy flexibility offered by buildings [3].

Furthermore, the energy only market (EOM) currently established in Germany and many other European countries, does not provide any motivation for flexible, grid supportive electricity consumption. Market models have to change in order to provide incentives for customers to change their consumption behavior. Grid compatibility could be encouraged by market models comprising dynamic electricity pricing dependent of the currently available electricity generation, while market operability could be increased through capacity-based pricing, which limits the maximal power being drawn by an individual customer to a contract based level [5, 6].

Both concepts are already known in the European electricity market. France, Austria, Switzerland, Luxembourg and Germany are operating a mutual power trading platform, the European Power Exchange in Paris (EPEX) since 2008 [7]. Several electricity-based products with a granularity of up to 15 minutes are traded there. This is already very close to the concept of real time pricing, however, a minimum power capacity of 0.1 MW hast to be traded currently at the EPEX. Such capacities could be easily reached in the future by aggregators representing a larger group of end-customers. Similarly, capacity driven pricing is common for large industrial customers for a long time, since the impact of sudden load changes at high capacities has already induced high challenges for the electricity providers in the past [5]. Thus, in face of the increasing challenges in balancing the electricity market both approaches might play a role in the future end-consumer market and it is hard to predict in which direction the market may develop.

Previous works have analyzed optimal sizing and operation of building energy systems, but neither investigated nor compared the influence of different electricity market models. Athari and Ardehali [47], for example analyze the performance of energy storages with time-varying electricity prices. However, their study does not involve the sizing of energy conversion or storage units and they do not investigate different market models, such as capacity markets. Celik et al. [48], investigate optimal sizing and operation of residential photovoltaic energy systems with battery storage at fixed EOM. In contrast, Ren et al. [49], analyze the economic optimization of residential photovoltaic systems with dynamic prices. Other studies [50-52] further extend the optimization and also include sizing and operation of thermal generation systems, like combined heat and power units or boilers, but limiting their analyses to either fixed EOM or dynamic EOM.

Existing studies on electricity market and pricing structures typically do not account for optimal design, sizing and operation of energy systems. Laws et al. [53] analyze the spread of PV and PV with battery systems for three different utilities' pricing structures and their effect on retail prices on a regional level. Darghouth et al. [54] similarly model the adoption of PV systems based on different pricing structures. They also analyze how PV systems affect utilities' retail prices.

This paper contributes to this field of research by analyzing how different electricity market models (table 1) affect the sizing of thermal and electrical supply components of a residential building in Germany. Among others, the future role of battery storage and solar energy in the residential sector is discussed. Also, the future role of widespread technologies like thermal buffer storages will be discussed, especially as a measure of increasing the demand flexibility. Finally, based on the outcomes of the analysis, it is discussed which developments of the electricity market could be favorable in a complex future power grid with high fluctuation of renewable energies. Thereby, not only a radical change of the market model is observed but also potential variations of the current system or hybrid market models are discussed.

2. Approach

This analysis is based on thermal and electrical simulations of a generic modern residential one family house. This house comprises a photovoltaic system (PV), a battery (Batt), an inverter (Inv), a heat pump (HP) and a hot water thermal storage tank (TS), which are analyzed in this paper. It is assumed that in this house, a control unit and required measuring equipment enable the system to use all these components automatically and efficiently, while reacting to changing boundary conditions dynamically. The ability of this building system to manage the house's energy demands and the ability to optimize when and how these demands are covered is summed up in the term "smart home". The influence of different electricity market models on the sizing and usage of these components will be evaluated.

The different observed electricity market models are two versions of the EOM and one capacity market (table 1). In the conventional EOM, the electricity is traded at a fixed price at all times combined with an also constant feed-in tariff for electricity produced by the PV system. This corresponds to the current end-consumer market situation in Germany and therefore boundary conditions of this market are chosen in compliance with the current German electricity market [8]. In the dynamic EOM, electricity is traded with a linkage to the European Power Exchange. Thus, the electricity price is based on the dynamic trading prices of the stock exchange plus the end-customer taxes and levies as applicable in Germany [8]. Therefore, prices of the intra-day-auctions of the EPEX are used as a realistic input data set for the dynamic EOM [9]. The German construct of the "market premium" [8] is used for the calculation of the revenues generated by the PV systems electricity generation.

In the evaluated capacity market, the end-consumer pays the energy provider a fixed price according to the maximal power capacity, which can be drawn from, or fed into the grid. Below that capacity limit electricity can be obtained at all times without additional cost. Above the capacity limit a very high price for each kWh applies. PV generation can be sold to the grid according to the same rules as in the conventional EOM, however the feed-in capacity is also restricted by the limit.

Table 1 - Analyzed market models

A coupled hybrid optimization model is created to evaluate the influence of these electricity market models on the building's supply components. This model varies the supply components in size to minimize the sum of acquisition and grid interaction costs. Thereby one algorithm optimizes the choice of supply components, while a second algorithm performs a one-year optimization of the total system to find the resulting costs of operation. Where applicable, the results are compared to an optimized reference building without PV, inverter and battery system. Additionally, several input parameters of the optimizations are varied as a measure of sensitivity analysis. Thus, to evaluate the impact of component prices and enable the discussion of system changes in face of different price developments, components prices are varied by +/- 20%. Similarly, also the electricity prices and PV feed-in tariffs are varied. Additionally, the impact of changing the price input for the dynamic EOM from the intra-day-auctions to the day-ahead-auctions of the EPEX is analyzed. Variations of the electrical load as a measure of demand side management (DSM) are also investigated. Therein the flattening of electrical peak loads by 50% and the possibility to relocate 20% of the daily load to other times of the day is evaluated and compared to a 10% increase of the total load. Market specific sensitivities as the discontinuation of feed-in compensation or the introduction of wildcards for the capacity limit are also considered. Wildcards are defined as the number of hours per year where the capacity limitation has not to be met. Different quantities (12, 24, 48 and 120) of such exception hours per year are investigated.

3. Modelling

3.1. Building model

The analysis is performed based on thermal simulations of a generic residential one family house with 145 m² heated floor area constructed according to the German insulation standard EnEV 2009 [10]. This standard is chosen since it represents a large share of the modern German building stock constructed or retrofitted between 2009 and 2015. Also, it can be expected that future retrofits of existing buildings will often result in a similar thermal standard. The thermal building model is scripted in the modelling language Modelica [11] and used in the simulation environment Dymola. The developed model builds upon the HouseModels Library which is part of AixLib Library[1] which is made publicly available by the Institute for Energy Efficient Buildings and Indoor Climate [12]. The HouseModels Library was validated with several test cases, for example with the ASHARE Standard 140 [13]. Table 2 and table 3 give the dimension of the envelope and the thermal properties

[1] https://github.com/RWTH-EBC/AixLib

of the main construction components respectively, while figure 1 presents a sketch of the modelled building from the east and the layout of the first floor. In addition to the thermal heating demand obtained from the dynamic simulation, a domestic hot water demand is calculated with the software DHWcalc [14], based on the requirements of a four-person household. The resulting thermal demands for space heating and domestic hot water are presented in figure 2. Even though all values are simulated in hourly time steps, figure 2 presents the average daily power demands for better visualization. Accordingly, figure 3 presents the average daily electricity demand. The underlying weather inputs for this analysis are based on the region 5 of the German test reference year (Lower Rhine region) [15]. The average daily ambient temperatures from the TRY weather file is presented in figure 4.

Table 2 - Properties of the building envelope

Table 3 - U-values of the main building components

Fig. 1 - Sketch of the modelled building from the east (left) and layout of the first floor (right)

Fig. 2 – Average daily thermal power required by the modelled building

Fig. 3 – Average daily electrical power required by the modelled building

Fig. 4 – Average daily ambient temperatures of the TRY weather file for region 5

3.2. Supply system components

The supply system of the building is modelled with an air to water heat pump, a thermal buffer tank and a direct electric resistance heater. Furthermore, it is also equipped with models for photovoltaic electricity generation, the associated inverter and a battery system. The appropriate sizing of these components in different electricity markets is one of the main outcomes of this study, however the boundaries for sizing were chosen based on market researches (table 4). In figures 5 through 7 the main not size dependent parameters of the battery, the inverter and the PV system are presented.

Fig. 5 – Cycle loss of battery capacity in dependence of the depth of discharge

Fig. 6 – Inverter efficiency in dependence of the applied fraction of nominal power

Fig. 7 – Average daily generation of the PV system in kWh per kW_p

The costs for heat pump, inverter and thermal storage are chosen with respect to the component size according to a descending quadratic price curve, which is based on a current review of online retailers [16-18]. Similarly, the battery and the PV system costs are based on linear price curves resulting from an online review [19]. The components are depreciated based on assumptions about typical functional service lifetime. The service lifetime of the heat pump [20-22], the thermal storage [23] and the battery [24] is assumed to be 20 years. The service lifetime of the PV is estimated to 25 years [25-27] and the inverter service lifetime to 15 years [26, 28]. The battery is an exception since its service lifetime depends besides of the calendric aging also strongly on the deterioration induced by the usage [14, 29]. Therefore, it is depreciated by the expected service lifetime based on both effects [29]. In the further analysis, the sum of these component costs and the electricity costs resulting from the operation of these systems will be the main driver for the evaluation of any system configuration. Formulas (26-31), in Appendix A, present the exact calculations of the yearly component costs.

3.3. Optimization

A three-layer structure (figure 8) is implemented for evaluating the impact of different electricity market models on the sizing and operation of building energy components. In the top-layer, a genetic algorithm is used for selecting a set of components. Furthermore, in this layer, the annual performance of each of these sets is evaluated. The mid-layer provides data inputs such as electrical and thermal demands and costs for the selected components. The bottom-layer executes an optimization of one full year of system operation based on a mixed integer linear program.

The separation into different layers has also been suggested in [30]. In this manner, the nonlinearities arising in the simultaneous sizing and operation optimization are largely avoided and an efficient analysis of the high number of possible component configurations is achieved.

Fig. 8 - Three-layer structure of the numeric algorithm

3.3.1. Top-layer – genetic algorithm

The top-layer uses a genetic algorithm [31, 32] to dimension five components of the residential building, the photovoltaic system, the battery, the inverter, the heat pump and the thermal storage. These components are available in different sizes between the chosen boundaries at the given discretization steps (table 4). Furthermore, the chances for mutation within the genetic algorithm are given in table 4. The chance of mutation and the discretization steps are chosen based on the total distance between upper and lower bounds as well as on accuracy's manageable by the optimization. The resistance heater is not adapted dynamically in this analysis, since its cost is very low and has just a very small correlation with the power rating.

Table 4 - Supply component technical and heuristic parameters

To dimension these components, the algorithm creates a random start population of 30 system configurations named 'individuals'. Each of the individuals consists of a full set of randomly sized components in component specific discretization steps (table 4). The individuals are assessed by the mid- and bottom-layer and attributed with their annual costs. Depending on the resulting costs the algorithm chooses and saves the best performing individual before further mutations and crossings are performed. All other individuals take part in a tournament selection. Therein, a new group of 30 individuals consisting of members of the start population is chosen, while the chance to be selected for the new population scales with the performance in the previous evaluation.

In this way high rated individuals are likely to appear several times in the new population while low ratings may lead to complete disappearance. Afterwards, the algorithm applies a two-point-crossover [33, 34] on the new population with a chance of 50% for each individual to be crossed. The remaining population is (again with a probability of 50%) exposed to a polynomial bound mutation. If an individual is selected for mutation, there are different chances for each component to mutate (table 4). Thus, a new start population is formed from the mutated and crossed individuals of the last one. Based on previous test optimizations the iteration limit is set to 30 iterations. Afterwards, the best performing individual represents the optimal system configuration of supply components and the lowest associated operation costs in the investigated electricity market model [35].

3.3.2. Mid-layer – data aggregation

The mid-layer receives a given set of the five supply components chosen by the top-layer and allocates them with component and demand specific data for the analyzed case. Demand specific data includes hourly electricity, space heating and DHW demand profiles. Component specific data comprises:

- hourly PV generation, which is scaled according to the selected PV system size & weather [29]
- the inverter's efficiency curve, which is scaled according to the selected nominal power [29]
- the battery system's aging, which is adapted according to the chosen capacity [29]
- the heat pump's COP matrix, which is interpolated from available COP matrices according to the selected nominal power [36]
- the surface area of the thermal storage, which describes thermal heat losses, is calculated according to its volume

Moreover, the underlying investment costs for all selected components are calculated within the mid-layer (formulas given in Appendix A).

3.3.3. Bottom-layer – linear optimization

The bottom-layer consists of a mixed integer linear program, which optimizes the operation of all selected components for a full year with respect to the resulting total costs. It is modelled in Python and solved with the Gurobi optimizer [37]. The model considers various options for routing energy flows and covering electrical and thermal demands within the building (figure 9). The optimization minimizes the annual energy costs of the system. Since a full year optimization in one step is computationally very expensive, a rolling horizon scheme is implemented. The chosen rolling horizon scheme first optimizes the system for a scope of five days with a time step of one hour. However, afterwards only the first day of the optimization is considered for the results and the procedure is repeated for every single day of the year. Such an approach is required to ensure a reasonable usage of the available storage capacities, since the cost minimization algorithm unloads all storage capacities by the end of the optimization scope. The following section presents the target function and the detailed constraints of the linear optimization. Additionally, for better comprehension of the entire optimization process figure 10 summarizes all performed steps in a flow chart.

Fig. 9 - Energy system of the house model

Fig. 10 – Flow chart of the optimization process

The target function of the optimization (1) is the reduction of the grid interaction costs (C_{grid}) and the battery aging costs (C_{aging}). The detailed calculation of C_{grid} is explained in section 3.3.4. These costs depend on the grid interaction, thus upon the sold (P_{sell}) and bought (P_{buy}) electrical energy. The following section describes the underlying constraints in the performed optimization.

$$\min(C_{grid} + C_{aging}) \tag{1}$$

The grid interaction has to be equal to the sum of the demands of domestic appliances and lighting (P_{el}), the power of the HP (P_{HP}), the power of the resistance heater (P_{heater}), the power for the inverter ($P_{AC \rightarrow INV}$) and the power from the inverter ($P_{INV \rightarrow AC}$):

$$P_{buy} - P_{sell} = P_{Inv \rightarrow AC} - P_{AC \rightarrow Inv} - P_{el} - P_{HP} - P_{heater} \tag{2}$$

An ideal resistance heater is assumed, thus all electricity is transformed into heat ($\dot{Q}_{heater}$):

$$P_{heater} = \dot{Q}_{heater} \tag{3}$$

The heat generation of the heat pump ($\dot{Q}_{HP}$) is calculated according to an ambient temperature (T_A) sensitive COP and the electrical heat pump power (P_{HP}). Additionally, a binary variable (b) is used to limit the heat pump to two states (on and off) [38]:

$$\dot{Q}_{HP} = b \cdot COP(T_A) \cdot P_{HP} \tag{4}$$

The energy level of the thermal storage (Q_{TS}) depends on the given water mass (m_{TS}), the storage temperature (T_{TS}) and the heat capacity of water (c_p). Together with the heat generation of the heat pump and the resistance heater, the thermal storage has to cover the space heating demand ($\dot{Q}_{SHD}$) and the domestic hot water ($\dot{Q}_{DHW}$) at all times. Furthermore, heat losses of the thermal storage ($\dot{Q}_{loss}$) are calculated depending on the surface area (A_S) and the thermal transmittance coefficient (U_{TS}) of the storage envelope as well as the storage temperature (T_{TS}) and the surrounding temperature of the storage which is approximated with the buildings indoor temperature (T_I).

$$m_{TS} \cdot c_p \cdot (T^t_{TS} - T^{t-1}_{TS}) = \left(\dot{Q}^t_{HP} + \dot{Q}^t_{heater} - \dot{Q}^t_{SHD} - \dot{Q}^t_{DHW} - A_S \cdot U_{TS} \cdot (T^t_{TS} - T^t_I)\right) \cdot dt \tag{5}$$

The inverter has a logarithmic efficiency curve (n_x; n_y) [29] describing the energy losses of the energy conversions from AC to DC ($P_{AC \to Inv}$; $P_{Inv \to DC}$) and DC to AC ($P_{DC \to Inv}$; $P_{Inv \to AC}$). The logarithmic efficiency curve has been implemented using continuous weighting variables ($w_{AC \to DC}$; $w_{DC \to AC}$). A Special Ordered Set of type Two (SOS 2) constraint is forced upon these weighting variables, which allows for piecewise linear interpolation within both sets $w_{AC \to DC}$ and $w_{DC \to AC}$ [39]:

$$P_{Inv \to DC} = \sum (w_{AC \to DC} \cdot n_x) \tag{6}$$

$$P_{AC \to Inv} = \sum (w_{AC \to DC} \cdot n_y) \tag{7}$$

$$1 = \sum (w_{AC \to DC}) \tag{8}$$

$$P_{Inv \to AC} = \sum (w_{DC \to AC} \cdot n_x) \tag{9}$$

$$P_{DC \to Inv} = \sum (w_{DC \to AC} \cdot n_y) \tag{10}$$

$$1 = \sum (w_{DC \to AC}) \tag{11}$$

The battery can be charged ($P_{DC \to Batt}$), discharged ($P_{Batt \to DC}$) or stay unchanged in every time step. The PV generation (P_{PV}) is injected into the DC grid of the house and can be used to either charge the battery, or be converted to AC and fed into the grid or used for electric appliances within the house.

$$P_{DC \to Batt} = P_{PV} + P_{Inv \to DC} - P_{DC \to Inv} \tag{12}$$

$$P_{Batt \to DC} = P_{DC \to Inv} - P_{PV} \tag{13}$$

The PV generation depends on the size of the PV system (A_{PV}) and current weather conditions. Furthermore, the current weather conditions depend on the time and date (t), and include the required information about current direct solar radiation, diffuse solar radiation and ambient temperature:

$$P_{PV} = f(weather^t; A_{PV}) \tag{14}$$

$$weather^t = f(rad^t_{direct}; rad^t_{diffuse}; T^t_{ambient}) \tag{15}$$

The costs induced by the battery degradation (C_{aging}) depend on the relative battery costs (k_{rel}), the capacity of the new battery ($E_{Batt\,new}$), the minimal battery energy level ($E_{Batt\,min}$) and the current capacity of the battery (E^t_{Batt}). The loss of capacity of the battery depends on the logarithmic capacity loss curve (m_x; m_y) [29]. This is also implemented through continuous weighting variables (w_{Batt}) using SOS 2 constraints for a piecewise linear interpolation [39], which depend on the depth of discharge (DOD):

$$C_{aging} = E_{Batt\ new} \cdot k_{rel} \cdot \frac{E_{Batt\ new} - E^{t}_{Batt}}{E_{Batt\ new} - E_{Batt\ min}} \quad (16)$$

$$E^{t}_{Batt} = \sum (w_{Batt} \cdot m_x) \cdot E_{Batt\ new} \quad (17)$$

$$DOD = \sum (w_{Batt} \cdot m_y) \quad (18)$$

$$1 = \sum (w_{Batt}) \quad (19)$$

$$DOD = \frac{\sum_{t=1}^{t_n} E^{t}_{Batt}}{E_{Batt\ new}} \quad (20)$$

3.3.4. Electricity markets

In this analysis, three different electricity market models are evaluated, two different EOMs and one capacity market. In the conventional EOM model, electricity is delivered to the end-customers at a fixed price of 0.2913 €/kWh ($k_{fix\ price}$) at all times during the entire year [40]. This price is the average end-consumer price in Germany for the year 2014. The exported PV energy is compensated at a fixed feed-in tariff of 0.1302 €/kWh ($k_{fix\ feed}$), which is the average of the monthly feed-in tariffs for new PV systems installed in 2014 in Germany [41].

$$C_{grid} = \sum_{t} \left(P^{t}_{buy} \cdot k_{fix\ price} - P^{t}_{sell} \cdot k_{fix\ feed}\right) \cdot dt \quad (21)$$

The dynamic EOM model is coupled to the dynamics of the European Power Exchange. In this case, end-customer prices are based on the dynamic electricity prices resulting from the intra-day-market of the EPEX Spot SE [42]. The power can be sold ($k_{flex.\ feed}$) or bought ($k_{flex.\ price}$) at fluctuating prices, which encourage increased electricity consumption when electricity is abundant and available at a low price and motivate reduced consumption and export when the market prices are high. The feed-in tariff is granted according to current German regulations ("market premium concept") [8]. This guarantees the end-customer average feed-in revenue slightly above the regular fixed feed-in tariff, but electricity has to be sold at the varying prices of the stock exchange in the first place. Discrepancies between stock exchange revenues and guaranteed feed-in compensation level are subsequently reimbursed in a second step.

$$C_{grid} = \sum_{t} \left(P^{t}_{buy} \cdot k^{t}_{flex\ price} - P^{t}_{sell} \cdot k^{t}_{flex\ feed}\right) \cdot dt \quad (22)$$

In the capacity market model, the end-customer pays for the maximal available power capacity (in kW) instead of the consumed energy (in kWh) as in the EOMs. Thus, this model can be described as an electricity flat rate with the charge depending on the required bandwidth. If at some point in time, the end-customer requires a higher capacity than agreed with the energy provider, the consumed energy exceeding the limit $\left(P^{t}_{over\ limit}\right)$ has to be purchased separately at a high price (k_{high}). The high price is chosen as the fiftyfold of the conventional EOM price. The relative capacity price (k_{cap}) has been derived from previous reference simulations to 1.44 €/W. At this relative capacity price, the grid interaction costs of the reference simulation in the conventional EOM are equal to the capacity markets flat rate price. Furthermore, the ability of selling electricity (P_{sell}) to the power grid is also restricted by the chosen capacity limit ($P_{max.\ cap}$) and not only by the actual energy production of the PV system (P_{PV}). Latter restriction is required to prevent the consumer from re-selling his flat rate electricity to the grid. The exact restrictions applied in the calculations are given below.

$$C_{grid} = P_{max\ cap} \cdot k_{cap} + \sum_{t} \left(P^{t}_{over\ limit} \cdot k_{high} - P^{t}_{sell} \cdot k_{fix\ feed}\right) \cdot dt \quad (23)$$

$$P^{t}_{sell} + P^{t}_{buy} \leq P_{max\ cap} \quad (24)$$

$$P_{sell}^{t} \leq P_{PV}^{t} \quad (25)$$

4. Results

Within this analysis hundreds of optimizations were performed. Therefore, it is not possible to present the detailed optimization outcomes and the convergence behavior for all optimized cases. In the following sub-chapter the most important and substantial outcomes for the three analyzed market scenarios will be presented. Additionally, figure 11 presents exemplarily the convergence curve of the performed optimization for the main scenario of the dynamic EOM. It can be seen that both, the best individual as well as the average fitness of the optimized population is clearly converging without considerable variations towards the final iterations.

Fig. 11 – Convergence curve for the dynamic EOM scenario

4.1. Conventional EOM

In the conventional EOM, the PV system is dimensioned with its maximum size of 60 m², while a battery is not selected at all. The thermal storage is sized to a volume of 550 l. Both, the nominal thermal power of the heat pump and the electrical power of the inverter are set to 4.5 kW. The resulting total system costs sum up to 2,200 € per year, as compared to 2,712 € for the reference house without PV.

In the sensitivity analysis, component price increases or decreases of 20% (in case of PV, heat pump, thermal storage) and 33% (in case of battery) only affect the total costs but do not influence the optimal component sizing. A battery would only be integrated in the system if the costs go down by 58% of the current costs, thus below 250 €/kWh. Also, the variation of feed-in tariff by 20% does not affect the chosen components. Only a general discontinuation of feed-in tariffs leads to changes. Thereby, the area of the PV system would be reduced to 38 m² (-37%) and the inverter would be scaled down to 2 kW (-56%). In addition, the nominal power of the heat pump would slightly decrease to 4 kW (-12%) and the thermal storage volume would increase to a size of 700 l (+27%). The redistribution of the electrical load by measures of DSM only marginally influences the sizing of the thermal storage volume which increases by 50 l (+9%).

In comparison, the reference building with just a HP and a thermal storage, would be equipped with a smaller thermal storage tank of 450 l (-19%) while keeping the same nominal power of the HP. Due to the reduced amount and size of supply systems the component costs in the reference building decrease by 36%, while total costs are 23% higher due to the missing revenues of PV feed-in. All other performed variations do not affect the optimal choice of supply system components.

4.2. Dynamic EOM

In the dynamic EOM, the optimization results in similar component sizing as in the conventional EOM. Solely a decrease of the electricity costs by 2% (as compared to the conventional EOM) is the benefit from the optimized use of the dynamic electricity price. However, in this market model, variations of the boundary conditions significantly affect the component sizing. In case of a 20% reduction of the feed-in tariff as well as in a case of 20% reduction of thermal storage costs, a layout with a 750 l (+36%) thermal storage tank and a heat pump with 4 kW (-11%) nominal power is chosen. Such setup is also chosen if dynamic prices are based upon the day-ahead-market instead of the intra-day-market. In the dynamic EOM, the battery is only selected if the installation costs are reduced by 62% to 230 €/kWh.

Again, the redistribution of the electrical load by measures of DSM only increases the thermal storage volume by 50 l (+9%). The optimal size of the PV system and the inverter are insensitive to all tested variations. In the reference scenario (just a HP and a thermal storage) evaluated for the dynamic market, the thermal storage volume is increased to 600 l (+9%) while the HP nominal power is reduced to 4 kW (-12%) resulting in 24% higher total costs than the optimized case. All other performed variations do not affect the optimal choice of supply system components.

4.3. Capacity market

In the capacity market, the PV system is sized to 44 m² and a battery with a capacity of 7 kWh is selected. The thermal storage is sized to 1,400 l, the inverter is scaled to 3.5 kW and the heat pump's nominal power is 4.5 kW. The maximum required capacity of grid interaction is 1.65 kW. The resulting total system costs sum up to 3,037 € per year.

The sensitivity analysis reveals that the determined component sizing is just sensitive to some variation of the boundary conditions. While cost variations do not have great influence on the system, the variations of the electrical loads induce changes. Thus, a 10% increase of electrical loads results in a 6% increase of the required maximal capacity and 4% increased total costs.

When flattening the electrical peak loads, the required capacity can be reduced by 3% resulting in 6% lower total costs. Also, in the case of peak load flattening, the battery's capacity can be reduced to 5 kWh (-29%) while the thermal storage volume is increased to 700 l (+25%). For the case of combined peak load flattening and general load increase, the battery's capacity is reduced to 4.5 kWh (-36%) and the thermal storage volume increases to 600 l (+11%) respectively, yielding an overall cost reduction of 3%. In both cases, the inverter's nominal power is approximately halved. The dynamic redistribution of the daily loads results in diverse component variations, however the capacity limit remains unchanged. Still, the redistribution yields a total cost reduction of 3%.

Without a feed-in tariff, the PV system is completely omitted and the required maximal capacity is increased by 6%. Furthermore, the influence of a given number of hours without power limitation is also investigated. The cases with 12 or 24 such one hour wildcards, both allow for reducing the required capacity limit by 9%, and lowering total costs by 4% and 7% respectively, without changing any component sizing. For higher numbers of wildcards (48, 120) the PV system size, the thermal storage capacity and the heat pump size tend to decrease, in contrast to a growing battery. With 120 wildcards, the maximum required capacity can be reduced by 27%, leading to total cost savings of 10%. Table 5 gives an overview of the optimal choice of components and the resulting costs for the three presented market scenarios. An overview of all optimization results including the outcomes of the sensitivity analysis is given in Tables 6-8 in Appendix B.

Table 5 - Main optimization results

5. Discussion

5.1. Conventional EOM

For the conventional electricity market, the simulation underlines the high profitability of the PV systems. The main reason for that is the fixed feed-in tariff of 0.1302 €/kWh, which is well above the calculated PV electricity generation cost of about 0.0866 €/kWh (in case of the smart building observed in this study with a 60 m² PV system, 25 years of service lifetime). Thus, the generation costs are 33% lower than the feed in-tariff, making the PV system even profitable if it is not used to cover any of the electricity demand of the house. Moreover, the relative costs of PV systems decrease with the system size. As a consequence, the possible profit increases with the system's size and is only limited by the available roof area (which was set as a boundary condition to 60 m² in this analysis).

Increasingly PV systems are offered in combination with a battery storage. However, purchasing a battery system in the present market is not favorable at all. First, the savings due to an increase of PV self-consumption, which can be reached using a battery, do not outweigh the very high investment costs. And second, there is no incentive to store electricity from the grid in a battery, when it can be purchased at the same price at any time.

The required thermal storage size is determined by different influences. First, to enable coordination of the building's dynamic heat demand with the cycling operation of the heat pump, a minimal storage volume of 150 l is inevitable. Second, the comparison with the reference simulation shows, that the existence of a PV system increases the thermal storage by 22%. This indicates, that the thermal storage is an economically reasonable measure to increase PV self-consumption. Third, the use of a large thermal storage as a buffer tank allows reducing the nominal power of the installed heat pump, since demand peaks can be covered by the storage. However, fourth, the heat loss of the thermal storage increases with the size and reduces the attractiveness of a large storage.

The heat pump has an average COP of 3.4, which describes the amount of heat delivered per unit electrical power ($\dot{Q}/ P_{el}$). This means, that on average the heat pump is 3.4 times more efficient than the resistance heater and is consequently the preferred heat source. Still, it is not reasonable to dimension the heat pump for the rarely occurring peak loads. Therefore, the balance of purchasing costs and operation costs is found at a nominal power of 4.5 kW_{el}. The inverter is dimensioned with 4.5 kW and therefore capable of handling the PV generation in 99.5% of the time, even though the PV peak generation power is at 5.67 kW. Due to the lack of electrical storage, the options of a smart home are limited. Only the thermal storage is used to increase the self-consumption of solar power. Additionally required energy is obtained from the grid demand-driven due to the constant price. Excess PV generation is also injected to the power grid immediately.

5.2. Dynamic EOM

The introduction of dynamic electricity pricing does not induce any changes to the optimal system configuration of the conventional EOM. This is mainly due to the various taxes and levies in the German market [40], which sum up to 85% of the end-consumer electricity price and do not depend on the actual trading price. Therefore, the resulting variance of the final end-consumer price is very low (+/- 6.5%). While these fluctuations have some impact upon the operation of the building's supply systems, they are not sufficient to provide a real financial incentive for changing the optimal component configuration, particularly not for purchasing battery storage. Therefore, the possibilities to react on price fluctuations are very limited and the dynamics of the electricity tariff are solely exploited through the thermal storage, which is charged by the heat pump. As a consequence, the smart home also does not fully reach its potential in this electricity market. However, the identified slight electricity cost reduction of 2% supports the upcoming development towards dynamic operation of smart interconnected heat pumps coupled with thermal storage.

5.3. Capacity market

There are entirely different challenges for a smart home in a capacity market compared to the EOM situation. Consequently, the system's layout is also significantly different. Since a low capacity limit is cost-critical, the increased use of storage technology is essential. The battery is now dimensioned to a capacity of 7 kWh, as compared to no battery in the EOMs. Similarly, the thermal storage capacity increases from 550 l in the EOMs to 1400 l in the capacity market. The benefits of these changes become obvious when focusing on the capacity limit. The maximum hourly capacity required by the smart building is as low as 1.65 kW, while the highest electrical capacity required for the reference building is 5.12 kW, not even taking into account the electricity demand for the heating system. The evaluation of the capacity limit is performed, as the rest of the optimization, with a one-hour time step and does therefore not take into account the real dynamics of domestic electricity consumption, with its frequent, short and high demand peaks. However, it can be expected that the large battery system installed in a smart building participating in a capacity market would be capable of efficiently flattening such peaks.

The profitability of PV on the other hand decreases in the capacity market. Instead of the total roof area as in the EOMs, the optimal PV area decreases to 44 m². Mainly, because the possible feed-in is now also restricted by the capacity limit. Therefore, revenues no longer increase proportionally to the

PV system's size. However, PV is still profitable generating revenues from the feed-in tariff. Additionally, the local PV generation allows for reducing the required capacity limit by 6%. The inverter's nominal power output also decreases in comparison to the EOMs. On the one hand, this is the direct result of the reduced PV system size. On the other hand, the sum of the inverter's nominal power and the capacity limit matches the maximum electrical load of the building. In this way, even in peak load situations the electricity demand can be covered without exceeding the capacity limit.

Sizing of the heat pump does not change in comparison to earlier market scenarios, since the large capacity of the storage tank is generally required for load shifting purposes and does not leave potential for generation capacity reductions. In general, the smart home concept is of major importance in the capacity market. Electrical and thermal loads have to be covered at all times with a possibly low capacity limit. Therefore, a well-coordinated interplay of the different components as well as an intelligent and proactive usage of the given energy storage options is essential.

5.4. Sensitivity analysis

Further conclusions about chances and challenges of the market models can be derived from the sensitivity analysis. It is shown that in both analyzed EOMs, approximately 60% lower battery prices (< 250 €/kWh) would be crucial to justify such an investment. However, further improvement of the expected battery service lifetime and reduction of the capacity loss due to deterioration could increase the profitability of batteries even at slightly higher costs. Still, even with the expected rapid battery price decline, such low end-customer prices are unlikely to be reached in the upcoming years [43]. Therefore, currently batteries are just installed for ideological reasons and under very special circumstances, like for example in systems, which have the capability to operate in island mode. Investigation of DSM redistributing 20% of the daily electrical load indicated better utilization of the local PV generation and results in electricity cost reductions of 5% in both EOMs. Thereby, mainly consumption peaks occurring in the evenings are mitigated and relocated to earlier times of the day, as presented in figure 12. However, even without DSM, the self-consumption plays a major role. Even without feed-in compensation, a PV system with 63% of the maximum size would be selected under conventional EOM conditions.

Fig. 12 – Daily distribution of electrical load with and without DSM

In the capacity market, flattening of electrical peak loads as a crucial impact factor is investigated. It turns out that such change in consumption dynamics is sufficient to operate the building with a smaller capacity limit (1.60 kW) and in such way reduce costs significantly (-6%). Similarly, the redistribution of loads is beneficial, yielding total cost reductions of 3%. This underlines the assumption that the capability of a smart home to decouple the electricity demand and electricity usage significantly contributes to cost savings in a capacity market. The PV self-consumption proves to be beneficial for reducing the required capacity limit, still the profitability of the system relies on the feed-in tariff. Therefore, in case of total discontinuation of feed-in tariffs, a system configuration without a PV system would be selected, resulting in a capacity limit increase of 6% and a 30% higher grid interaction balance. The evaluated concept of wildcards in the capacity market is meant to increase practicability of this market scenario, offering a possibility to cope with seldom occurring unpredictable high loads. It is shown that already 24 wildcard hours per year (about 0.3% of the year) are sufficient to reduce the overall cost by about 7%. Figure 13 exemplary demonstrates the distribution of these 24 hours among the year along with a relative indication of the associated electricity load. It can be seen that the wildcards are distributed relatively equal among the heating period, without distinct aggregation on special days. Thus, the general concept of exceptions from the strict capacity limitation seems very promising. Still, it must be ensured that a massive synchronous use of wildcards along the end-consumers is prevented. However, the well-distributed usage of individual wildcards among the winter season, as presented in in figure 13, indicates that the risk that different systems will select exactly the same wildcard hours is limited.

Fig. 13 – Distribution of wildcard hours (depicted by red vertical lines)

5.5. Strengths and weaknesses of the market models

In the conventional EOM model the consumer pays a clear and well predictable amount just for the actually used electricity. However, there is no incentive to adapt the demand to the increasing fluctuations of the electricity generation. Therefore, the smart home concept can be hardly established under such market conditions, since it is limited to maximizing the PV self-consumption. In contrast, a dynamic EOM could in general promote demand elasticity since consumers are given incentives to adapt through the electricity price fluctuations. However, under the current German market conditions, the relatively small fluctuations of the end-consumer price cannot justify investments in storage technologies. Therefore, the extent of the smart home concept is limited. Nevertheless, the existing thermal storage in combination with the heat pump is now beneficially used for thermal load shifting. Still, to create an incentive for flexible and grid compatible smart homes comprising the required storage technologies, at least parts of electricity taxes and levies must adapt dynamically as well. Furthermore, the implementation of a dynamic EOM requires the dissemination of smart meters, smart home getaways and interconnected supply system components.

In contrast, the introduction of capacity market model would directly generate significant incentives towards smart home systems, yielding more uniform power consumption. In this way, the fluctuations of the grid load would be reduced, facilitating the manageability and predictability of the system for the grid operators. This could be of major value especially in rural not intermeshed power grids, which are challenged strongly by the high peak loads of consumption and PV feed-in at given times. However, there is no incentive for the adaption of demand to current renewable generation and there is risk of an overall consumption increase due to the flat rate character of this market. Also, further clarification is required concerning the feed-in of PV generation in a capacity market. To prevent re-selling of flat rate electricity as PV generation, it would be necessary to couple the permitted feed-in to the current generation of the PV system. Also, strictly limiting the permitted feed-in capacity, even in times when the power grid is not overloaded but requires electricity, would be counterproductive for the electricity market. Thus, in comparison to the dynamic EOM, the capacity market requires more complex definition of the market conditions as well as a sophisticated management and control system. Furthermore, the adaption of a building to this market model is more complex and expensive while the benefits for end-consumers are not foreseeable in advance.

5.6. Outlook on potential market model modifications

Both, the markets with flexible electricity prices, as well as the capacity market have a distinct potential to promote the dissemination of the smart home concept and thus impact the electricity consumption patterns of buildings. However, both also require adaptions within the energy system and investment in smart home equipment. Especially, the capacity market is not suitable for direct implementation by end-consumers due to the necessary high investments and the required complex regulatory system. Nevertheless, some promising aspects of these market models could be implemented with reduced expenses. As such, the capacity limit could be applied just for the feed-in of PV generation in the first step. Furthermore, instead of a fixed capacity limit, the maximum capacity could be modified in dependence of the load situation of the power grid. Alternatively, a dynamic electricity price could be applied within the limits of a capacity cap, to prevent overreactions to price signals. In this way, the benefits of the capacity market, yielding a more uniform consumption could be combined with the incentives for adapting local demand to the generation induced by the flexible pricing.

Furthermore, especially the capacity market could be strongly facilitated if consumers are aggregated within a city district or rural area. In this way, regional grid overloads could be still effectively prevented without strict capacity limit regulations for every single individual. Also, the required storage capacities could be established and utilized at district level, reducing the investment costs for each building. As shown by the evaluation of the wildcard approach, just very few exceptions to a strict capacity limit can reduce the total system cost significantly.

Thus, the coordination of interconnected smart buildings within a district would strongly facilitate managing such exceptions locally without violating the regional capacity limit. Therefore, while dynamic pricing could be established successfully for every single end-consumer, it would be preferable to establish a capacity market rather on a district level.

6. Conclusion

In this paper, the effect of different electricity market models on the sizing of supply system components and the smart home capability of a residential building was analyzed. In both analyzed energy only markets, PV was highly profitable for both, self-consumption and feed-in to the grid. Therefore, in most system configurations, the PV system's size was maximized. In contrast, battery systems require a cost reduction of approximately 60% to become economically feasible under EOM conditions. Today, thermal storages are the only economical source of demand flexibility in residential buildings, in particular improving the performance of heat pumps. Still, it turns out that without an adaption to the currently imposed taxes and levies, the electricity price dynamics in the end-consumer market are too low to promote any investments into storage systems for load shifting. This corresponds to former research on the profitability of storage systems [44]. In the case of a capacity market, the smart home concept offers a great potential in flattening and redistributing daily local electricity demands, if equipped with the necessary storage technologies. Widespread implementation of capacity markets could be simplified by defining capacity limits for aggregated regions instead of individual customers. Further, selective dynamic capacity limits (e.g. on PV feed-in) could be combined with a dynamic electricity price in future markets.

In general, the operation of smart residential buildings can be well adapted to different electricity market models, generating savings for the residents and offering flexibility to the power grid. However, the impact is very limited if the optimal configuration of building supply and storage systems is selected according to the current market conditions. Stronger incentives or regulations are required to encourage investments in load shifting supporting smart home systems. Building supply systems have service lifetimes of 20 years on average. Thus, it is crucial to timely disseminate such systems for reaching the governmental goals of 55-60% renewable electricity generation in Germany by the year 2035. Future work should further focus on possibilities to provide electrical demand flexibility through energy systems in buildings. Especially, on the development of predictive control algorithms, enabling storage based load shifting and demand flexibility while maximizing efficiency and minimizing system operation costs. Furthermore, since there is only very limited economic motivation to invest in domestic storage systems, the promising concept of utilizing the intrinsic thermal mass of buildings as a thermal storage should be further analyzed [4, 45, 46].

Appendix A – Yearly costs of supply system components

PV system
$$C_{\mathrm{PV}} = \frac{184\frac{€}{m^2} \cdot A_{\mathrm{PV}} + 1061\ €}{25\ a} \tag{26}$$

Thermal storage
$$C_{\mathrm{TS}} = \frac{-\,0.0001\frac{€}{l^2} \cdot V_{\mathrm{TS}}^2 + 1.16\frac{€}{l} \cdot V_{\mathrm{TS}} + 682\ €}{20\ a} \tag{27}$$

Battery
$$C_{\mathrm{Batt}} = 600\frac{€}{kWh} \cdot E_{\mathrm{Batt\ new}} \cdot \max\left(\frac{1}{20}, \frac{E_{\mathrm{Batt\ new}} - E_{\mathrm{Batt}}^{\mathrm{t}}}{E_{\mathrm{Batt\ new}} - E_{\mathrm{Batt\ min}}}\right) \cdot \frac{1}{a} \tag{28}$$

Heat pump
$$C_{\mathrm{HP}} = \frac{-\,1.6\frac{€}{kW^2} \cdot \dot{Q}_{\mathrm{HP,nom}}^2 + 484\frac{€}{kW} \cdot \dot{Q}_{\mathrm{HP,nom}} + 3182\ €}{20\ a} \tag{29}$$

Inverter
$$C_{\mathrm{Inv}} = \frac{-\,2.1\frac{€}{kW^2} \cdot P_{\mathrm{Inv}}^2 + 165\frac{€}{kW} \cdot P_{\mathrm{Inv}} + 517\ €}{15\ a} \tag{30}$$

Total component costs
$$C_{\mathrm{component}} = C_{\mathrm{PV}} + C_{\mathrm{Batt}} + C_{\mathrm{TS}} + C_{\mathrm{HP}} + C_{\mathrm{Inv}} \tag{31}$$

Appendix B – Full optimization results

Table 6 - Results conventional EOM

Table 7 - Results dynamic EOM

Table 8 - Results capacity market

Appendix C – Further parameters

Table 9 – Parametric values

Nomenclature

Abbreviations and symbols

A	Area, m²	$k_{[\_]}$	Costs related to subscript
AC	Alternating Current	kW	Kilowatt
COP	Coefficient of Performance	kWh	Kilowatt hour
c_p	Heat capacity, J/(kg K)	kW_p	Kilowatt peak
C	Costs, € or € /a	m	Mass, kg
DC	Directed Current	P	Power, W or kW
DHW	Domestic Hot Water	PV	Photovoltaic (-system)
DOD	Depth of discharge (battery), %	$\dot{Q}$	Heat flow rate, W
DSM	Demand Side Management	Q	Thermal energy / heat, J or kWh
E	Battery Capacity, kWh	T	Temperature, °C
EOM	Electricity Only Market	TS	Thermal storage
EPEX	European Power Exchange	U	thermal transmittance
HP	Heat pump	V	Volume, l

Subscripts and superscripts

A	Ambient	high	Very high electricity price if capacity limit is exceeded
A → B	Indication: flow from A to B		
aging	Battery aging	Inv	Inverter
Batt	Battery	loss	losses (thermal or electrical)
Batt new	New battery	max cap	Maximal capacity
buy	Electricity from the power grid	nom	Nominal
cap	Capacity	over limit	Above capacity limitation
component	Supply system component	rel	Relative
el	Electric appliances and lighting	sell	Remunerated feed in
flex price	Flexible price	S	Surface
flex feed	Flexible feed in tariff	t	Time step
fix price	Fixed price	TS	Thermal storage
fix feed	Fixed feed in tariff	x / y	First / second component of matrix / table
grid	The power grid		
heater	Electrical resistance heater		

References

[1] T. Boßmann, I. Staffell, The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain, Energy, Volume 90, October 2015, Pages 1317-1333, http://dx.doi.org/10.1016/j.energy.2015.06.082.

[2] Federal Ministry for Economic Affairs and Energy, Energy-data-and-forecasts, 01.01.2016. Available at: http://www.bmwi.de/EN/Topics/Energy/Energy-data-and-forecasts/energy-data.html. [accessed 24.01.2016].

[3] H. Wolisz, C. Punkenburg, R. Streblow, D. Müller, Feasibility and potential of thermal demand side management in residential buildings considering different developments in the German energy market, Energy Conversion and Management Volume 107, January 2016, Pages 86-95, http://dx.doi.org/10.1016/j.enconman.2015.06.059.

[4] J. Le Dréau, P. Heiselberg, Energy flexibility of residential buildings using short term heat storage in the thermal mass, Energy, Volume 111, September 2016, Pages 991-1002, http://dx.doi.org/10.1016/j.energy.2016.05.076.

[5] J. Bower, D. W. Bunn und C. Wattendrup, A model-based analysis of strategic consolidation in the German electricity industry, London, UK, 2001.

[6] Xiao Hui Li, Seung Ho Hong, User-expected price-based demand response algorithm for a home-to-grid system, Energy, Volume 64, January 2014, Pages 437-449, http://dx.doi.org/10.1016/j.energy.2013.11.049.

[7] EPEX SPOT SE, European Power Exchange, Available at: http://www.epexspot.com/en/.

[8] M. Frondel, N. Ritter, C. M. Schmidt und C. Vance, Economic impacts from the promotion of renewable energy technologies: The German experience, Essen, 2010.

[9] EPEX SPOT SE, intraday market, Available at: https://www.epexspot.com/en/market-data/intradaycontinuous/intraday-table. [accessed 22.07.2015].

[10] Federal Ministry for Economic Affairs and Energy (BMWi), The German Energy Saving Ordinance, EnEV, Berlin, 2013.

[11] Modelica Association, Modelica, Available at: www.modelica.org.

[12] M. Fuchs, A. Constantin, M. Lauster, P. Remmen, R. Streblow, D. Müller, Structuring the building performance Modelica library AixLib for open collaborative development, in: 14th IBPSA Building Simulation Conference, Hyderabad, India, 2015.

[13] Constantin, R. Streblow, D. Müller, The Modelica HouseModels Library, Presentation and Evaluation of a Room Model with the ASHRAE Standard 140, in: 10th International Modelica Conference, Lund, Sweden, 2014.

[14] U. Jordan, DHWcalc: Program to generate domestic hot water profiles with statistical means for user defined conditions, ISES Solar World Congress, Orlando (US), 2005.

[15] Federal Institute for Research on Building, Urban Affairs and Spatial Development, Test Reference Year 2011 Region 5.

[16] Thermal storage costs were selected based on a review of the current retail prices on following websites available at: www.klimaworld.com; www.heizungsdiscount24.de; www.unidomo.de; www.ofenseite.com. [accessed 28.07.2015].

[17] Heat pumps costs were selected based on a review of the current retail prices on following website available at: www.klimaworld.com, www.unidomo.de. [accessed 18.05.2015].

[18] Inverter costs were selected based on a review of the current retail prices on following website available at: www.mg-solar-shop.de, www.mastervolt.com/mastervolt-pricelist/. [accessed 3.08.2015].

[19] Photovoltaic system costs were selected based on a review of the current retail prices on following websites available at: www.energieagentur.nrw.de; www.solaranlagen-portal.com; www.solarworld-solarsromrechner.de. [accessed 18.05-30.07.2015].

[20] Dimplex Heat Pumps, Product Information, Available at: http://www.dimplexrenewables.com/ brand/DIMPLEX-HEAT-PUMPS. [accessed 18.05.2015].

[21] H. Lund, B. Möller, B.V. Mathiesen, A. Dyrelund, The role of district heating in future renewable energy systems, Energy, Volume 35, March 2010, Pages 1381-1390, http://dx.doi.org/10.1016/j.energy.2009.11.023.

[22] A. Zottl, M. Lindahl, R. Nordman, P. Riviére und M. Miara, Evaluation method for comparison of heat pump systems with conventional heating systems, SEPEMO-Build, Europa, 2011.

[23] I. Dincer und M. Rosen, Thermal Energy Storage: Systems and Applications, West Sussex, UK, John Wiley & Sons Ltd., 2011.

[24] Power THRU, Lead Acid Battery working - Lifetime Study, Livonia, USA.

[25] A. Budenzer und J. Luther, Photovoltaics Guidebook for Decision-Makers - Technological Status and Potential Role in Energy Economy, Berlin, Germany, Springer, 2003.

[26] K. Komoto, C. Breyer, E. Cunow, K. Megherbi, D. Faiman und P. van der Vleuten, Energy from the Desert 4: Very Large Scale Photovoltaic Power - State of the Art and Into the Future, Oxford, UK, Routledge, 2013.

[27] SolarWorld AG, The linear performance guarantee, Available at http://www.solarworld.de/en/service/linear-performance-guarantee/. [accessed 18.05.2015].

[28] Mastervolt, Lifespan of Solar inverters, Available at http://www.mastervolt.com/news/lifespan-of-solar-inverters/. [accessed 3.08.2015].

[29] A. Schmiegel, P. Knaup, A. Meissner und C. Jehoulet, The Sol-ion System: A Stationary PV Battery System, 2010.

[30] S. Fazlollahi, F. Maréchal, Multi-objective, multi-period optimization of biomass conversion technologies using evolutionary algorithms and mixed integer linear programming (MILP), Applied Thermal Engineering, Volume 50, February 2013, Pages 1504-1513, http://dx.doi.org/10.1016/j.applthermaleng.2011.11.035.

[31] F. Rainville, F. Fortin, M. Gardner, M Parizeau, C. Gagné, DEAP: A Python Framework for Evolutionary Algorithms, *in: Genetic and Evolutionary Computation Conference, Philadelphia, USA* 2012.

[32] M. Mitchell, An Introduction to Genetic Algorithms, Massachusetts, USA, MIT Press 1996.

[33] I. Gerdes, F. Klawonn und R. Kruse, Evolutionäre Algorithmen, Wiesbaden, Germany, Vieweg, 2013.

[34] E. Schöneburg, F. Heinzmann und S. Feddersen, Genetische Algorithmen und Evolutionstrategien - Scientific Computing: Eine Einführung in Theorie und Praxis der Simulierten Evolution, Addison-Wesley Verlag, Bonn, Germany, 1994.

[35] J. Smith, F Fogarty, Self adaptation of mutation rates in a steady state genetic algorithm, in: IEEE International Conference on Evolutionary Computation, Nagoya, Japan, 1996.

[36] Dimplex Datasheets, LA6TU. LA9TU, LA12TU, LA17TU, Available at: http://www.dimplex.de/en/downloads/. [accessed 27.07.2015].

[37] Gurobi Optimization. Available at: http://www.gurobi.com/products/gurobioptimizer. [accessed 27.05.2015].

[38] T. Schütz, H. Harb, R. Streblow, D. Müller, Comparison of models for thermal energy storage units and heat pumps in mixed integer linear programming, in: 28th international conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, Pau, France, 2015.

[39] H. Williams, Model Building in Mathematical Programming, West Sussex, UK, John Wiley & Sons Ltd., 2013.

[40] Federal Association of Energy and Water Industry (BDEW), BDEW Strompreisanalyse 2014, Berlin, Germany, 2014.

[41] Bundesnetzagentur, Degressions- und Vergütungssätze Januar 2014 bis Dezember 2014: für PV Anlagen 2014, Bonn, Germany, 2014.

[42] EPEX SPOT SE, day ahead market, Available at: http://www.epexspot.com/en/market-data/dayaheadauction/auction-table/2014-01-01/DE/24. [accessed 20.08.2015].

[43] International Renewable Energy Agency, Battery storage for renewables: Market status and technology outlook, International Renewable Energy Agency, Abu Dhabi, United Arab Emirates 2015.

[44] H. Wolisz, D. Sepoetro, R. Streblow und D. Müller, Competitiveness and Economic Efficiency of Thermal Energy Storage for Balancing Renewable Electricity Generation, in: Eurotherm Seminar #99, Lleida, Spain, 2014.

[45] H. Wolisz, P. Block, R. Streblow, D. Müller, Dynamic Activation of Structural Thermal Mass in a Multi-Zonal Building with Due Regard to Thermal Comfort, in: 14th IBPSA Building Simulation Conference, Hyderabad, India, 2015.

[46] H. Wolisz, P. Block, R. Streblow, M. Wesseling, D. Müller, Implementation of an experimental setup for the analysis of transient thermal comfort in buildings with dynamic heating operation, in: 9th International Windsor Conference, Windsor, UK, 2016.

[47] M.H. Athari, M.M. Ardehali, Operational performance of energy storage as function of electricity prices for on-grid hybrid renewable energy system by optimized fuzzy logic controller, Renewable Energy, Volume 85, January 2016, Pages 890-902, http://dx.doi.org/10.1016/j.renene.2015.07.055

[48] A.N. Celik, T. Muneer, P. Clarke, Optimal Sizing and Life Cycle Assessment of Residential Photovoltaic Energy Systems With Battery Storage, Progress in Photovoltaics: Research and Applications, Volume 16, 2008, Pages 69-85, DOI: 10.1002/pip.774

[49] H. Ren, W. Gao, Y. Ruan, Economic optimization and sensitivity analysis of photovoltaic system in residential buildings. Renewable Energy, Volume 34, Issue 3, March 2009, Pages 883-889, http://dx.doi.org/10.1016/j.renene.2008.06.011

[50] T. Schütz, L. Schiffer, H. Harb, M. Fuchs, D. Müller, Optimal design of energy conversion units and envelopes for residential building retrofits using a comprehensive MILP model, Applied Energy, Volume 185, January 2017, Pages 1-15, http://dx.doi.org/10.1016/j.apenergy.2016.10.049

[51] T. Schütz, H. Harb, M. Fuchs, D. Müller, Optimal design of building energy systems for residential buildings. In: 12th REHVA world congress. CLIMA 2016. p. 1–10. URL <http://vbn.aau.dk/files/233774153/paper_157.pdf>.

[52] T. Wakui, H. Kawayoshi, R. Yokoyama, Optimal structural design of residential power and heat supply devices in consideration of operational and capital recovery constraints. Applied Energy, Volume 163, 2016, Pages 118-133, http://dx.doi.org/10.1016/j.apenergy.2015.10.154

[53] N. D. Laws, B. P. Epps, S. O. Peterson, M. S. Laser, G. K. Wanjiru, On the utility death spiral and the impact of utility rate structures on the adoption of residential solar photovoltaics and energy storage. Applied Energy, Volume 185, 2017, Pages 627-641, http://dx.doi.org/10.1016/j.apenergy.2016.10.123

[54] N. R. Darghouth, R. H. Wiser, G. Barboser, A. D. Mills, Net metering and market feedback loops: Exploring the impact of retail rate design on distributed PV deployment, Applied Energy, Volume 162, 2016, Pages 713-722, http://dx.doi.org/10.1016/j.apenergy.2015.10.120

Tables:

Table 1 - Analyzed market models

Model	Basis for billing	Electricity tariff	Feed-in remuneration
Conventional EOM	consumed electric energy	constant	constant
Dynamic EOM	consumed electric energy	dynamic	dynamic
Capacity market	maximum power capacity	flat rate	constant

Table 2 - Properties of the building envelope

in m²	North	East	South	West
Outer walls	40	39	37	37.5
Windows	3	9	6	10.5

Table 3 - U-values of the main building components

Building element	U-value according to EnEV 2009 in W / (m²·K)
Outer wall	0.28
Floor towards ground	0.35
Separation ceiling/attic	0.20
Saddle roof	0.20
Window	1.30
Outer door	1.80

Table 4 - Supply component technical and heuristic parameters

Component	Chance of mutation	Dimension size	Boundaries	Discretization steps
Photovoltaic system	30%	area	0-60 m²	2 m²
Battery	20%	capacity	0-10 kWh	0.5 kWh
Thermal storage	30%	volume	200-2,000 l	50 l
Heat pump	20%	nominal thermal power	0-10 kW_{th}	0.5 kW_{th}
Inverter	20%	electrical power	0-10 kW_{el}	0.5 kW_{el}

Table 5 - Main optimization results

Component/cost	Unit	Conventional EOM	Dynamic EOM	Capacity market
Photovoltaic system size	m²	60	60	44
Battery capacity	kWh	0	0	7
Thermal storage size	l	550	550	1,400
Heat pump nominal power	kW_{th}	4.5	4.5	4.5
Inverter power	kW_{el}	4.5	4.5	3.5
Capacity limit	kW_{el}	---	---	1.65
Grid interaction costs	€	1,304	1,281	2,018
Component costs	€	896	896	1,019
Total costs	€	2,200	2,177	3,037

Table 6 - Results conventional EOM

Case	Value Unit	A_{PV} m²	E_{Batt} kWh	V_{TS} l	$\dot{Q}_{HP,nom}$ kW_{th}	P_{Inv} kW_{el}	C_{grid} €	$C_{component}$ €	C_{total} €
Optimized case		60	0	550	4.5	4.5	1,304	896	2,200
Without PV and battery		-	-	450	4.5	-	2,386	326	2,712
Electricity costs +20%		60	0	550	4.5	4.5	1,633	896	2,529
Electricity costs -20%		60	0	550	4.5	4.5	968	896	1,864
PV feed-in tariff +20%		60	0	550	4.5	4.5	1,234	896	2,130
PV feed-in tariff -20%		60	0	550	4.5	4.5	1,376	896	2,272
Without PV feed-in tariff		38	0	700	4.0	2.0	1,778	705	2,483
PV system costs -20%		60	0	550	4.5	4.5	1,304	800	2,104
Battery costs +33%		60	0	550	4.5	4.5	1,304	896	2,200
Batter costs -33%		60	0	550	4.5	4.5	1,304	896	2,200
Heat pump costs +33%		60	0	550	4.5	4.5	1,304	949	2,253
Heat pump costs -33%		60	0	550	4.5	4.5	1,304	843	2,147
Thermal storage costs +20%		60	0	550	4.5	4.5	1,304	909	2,213
Thermal storage costs -20%		60	0	550	4.5	4.5	1,304	883	2,187
20% load redistribution		60	0	600	4.5	4.5	1,241	899	2,140

Table 7 - Results dynamic EOM

Case	Value / Unit	A_{PV} m²	E_{Batt} kWh	V_{TS} l	$\dot{Q}_{HP,nom}$ kW_{th}	P_{Inv} kW_{el}	C_{grid} €	$C_{component}$ €	C_{total} €
Optimized case		60	0	550	4.5	4.5	1,281	896	2,177
Without PV and battery		-	-	600	4.0	-	2,307	399	2,706
Day-ahead-market		60	0	750	4.0	4.5	1,306	895	2,201
Battery costs +33%		60	0	550	4.5	4.5	1,281	896	2,177
Batter costs -33%		60	0	550	4.5	4.5	1,281	896	2,177
PV system costs -20%		60	0	550	4.5	4.5	1,281	799	2,080
PV feed-in tariff +20%		60	0	550	4.5	4.5	1,223	896	2,119
PV feed-in tariff -20%		60	0	750	4.0	4.5	1,345	895	2,240
Heat pump costs +20%		60	0	550	4.5	4.5	1,281	950	2,231
Heat pump costs -20%		60	0	550	4.5	4.5	1,281	843	2,124
Thermal storage costs +20%		60	0	550	4.5	4.5	1,281	909	2,190
Thermal storage costs -20%		60	0	750	4.0	4.5	1,285	880	2,165
20% load redistribution		60	0	600	4.5	4.5	1,212	896	2,108

Table 8 - Results capacity market

Case	Value / Unit	A_{PV} m²	E_{Batt} kWh	V_{TS} l	$\dot{Q}_{HP,nom}$ kW_{th}	P_{Inv} kW_{el}	$P_{max.cap}$ kW_{el}	C_{grid} €	$C_{component}$ €	C_{total} €
Optimized case		44	7.0	1,400	4.5	3.5	1.65	2,018	1,019	3,037
Battery costs +33%		40	7.5	1,400	4.5	3.5	1.65	2,030	930	2,960
Battery costs -33%		44	7.0	1,400	4.5	3.5	1.65	2,009	1,089	3,098
Load increase +10%		42	7.0	1,450	4.5	3.5	1.75	2,134	1,016	3,150
Flattening peak loads		40	5.0	1,750	4.5	2.0	1.60	1,923	930	2,853
Load increase and Peak flattening		28	4.5	1,550	4.5	1.5	1.65	2,135	813	2,948
20% load redistribution		34	6.0	1,100	5.0	2.5	1.65	2,035	904	2,939
Without PV feed-in tariff		0	4.0	1,350	5.0	3.0	1.75	2,629	567	3,196
No PV feed-in limit		60	5.5	1,450	5.0	3.5	1.65	1,704	1,106	2,810
12 wildcard hours		44	7.0	1,400	4.5	3.5	1.50	1,860	1,046	2,906
24 wildcard hours		44	7.0	1,400	4.5	3.5	1.50	1,780	1,059	2,839
48 wildcard hours		26	7.5	950	3.5	3.5	1.50	1,927	857	2,784
120 wildcard hours		36	9.0	1,100	4.0	3.0	1.20	1,733	1,007	2,740

Table 9 – Parametric values

Name	Value	Unit
Lifetime heat pump	20	a
Lifetime battery	20	a
Lifetime photovoltaic	25	a
Lifetime thermal storage	20	a
Lifetime inverter	15	a
Specific heat capacity - c_p	4,180	J/(kg K)
Thermal transmittance of the TS - U_{TS}	1.1189	W/(m² K)
Used time step - dt	3,600	s
Water mass in TS per liter - m_{TS}	1	kg
EOM fixed electricity price - $k_{\text{fix price}}$	0.2913	€/kWh
Fixed feed-in remuneration - $k_{\text{fix feed}}$	0.1302	€/kWh
Capacity price - k_{cap}	1.44	€/W
Electricity price above capacity limit -k_{high}	14.5650	€/kWh
Relative battery costs - k_{rel}	600.00	€/kWh

Figures:

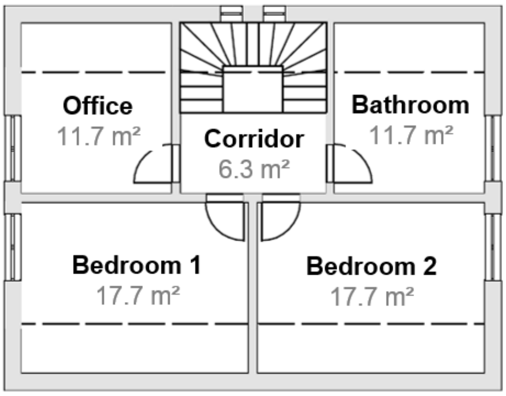


Fig. 1 - Sketch of the modelled building from the east (left) and layout of the first floor (right)

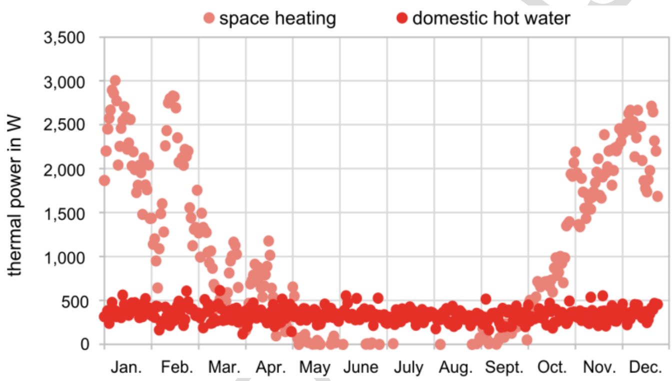


Fig. 2 – Average daily thermal power required by the modelled building

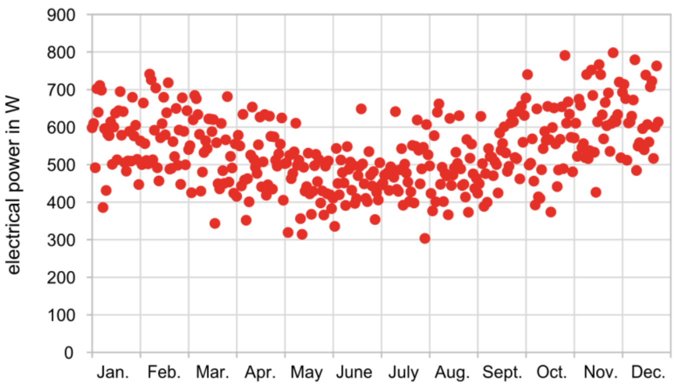


Fig. 3 – Average daily electrical power required by the modelled building

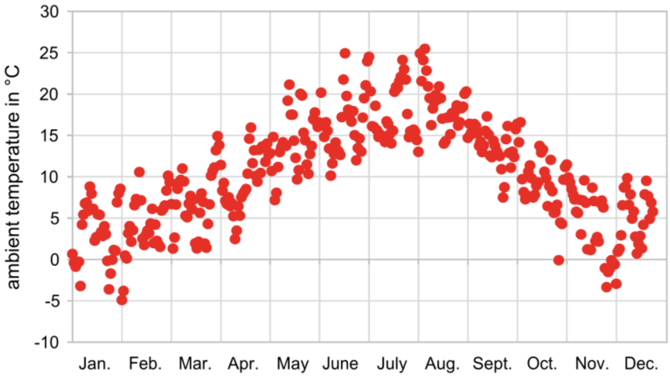


Fig. 4 – Average daily ambient temperatures of the TRY weather file for region 5

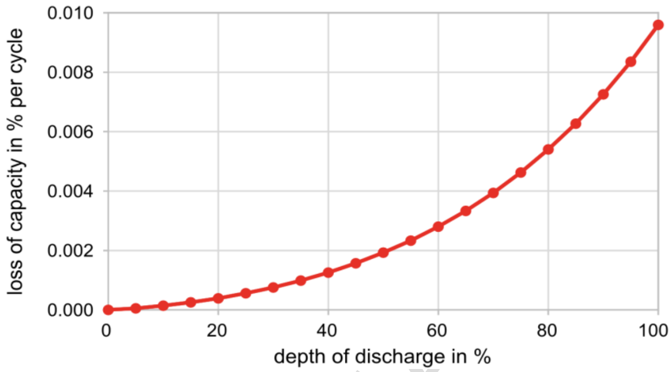


Fig. 5 – Cycle loss of battery capacity in dependence of the depth of discharge

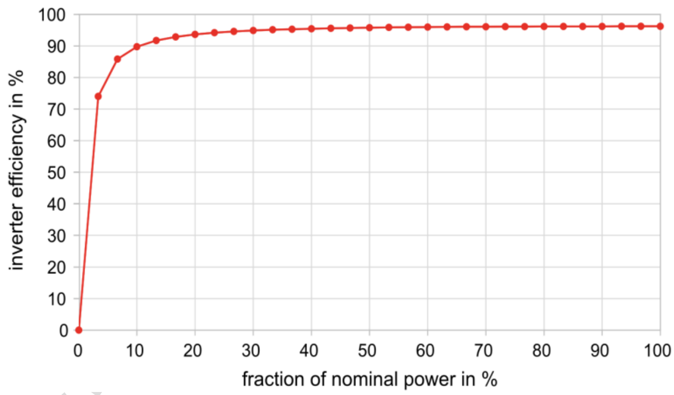


Fig. 6 – Inverter efficiency in dependence of the applied fraction of nominal power

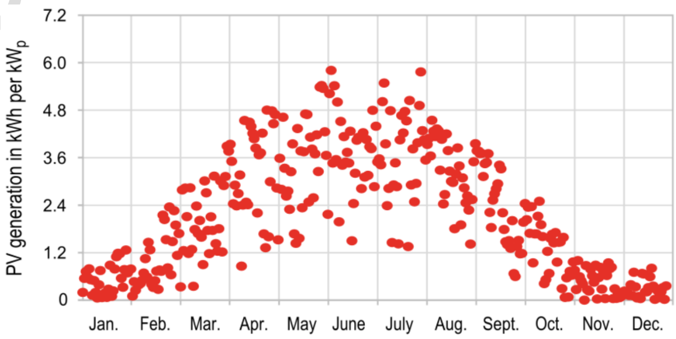


Fig. 7 – Average daily generation of the PV system in kWh per kW_p

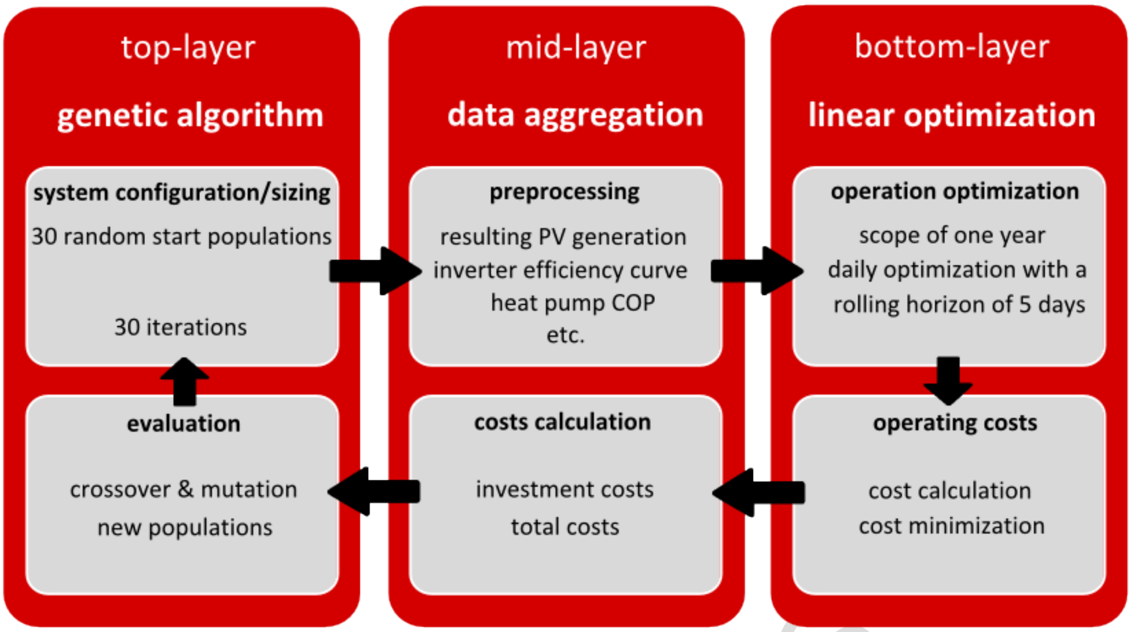


Fig. 8 - Three-layer structure of the numeric algorithm

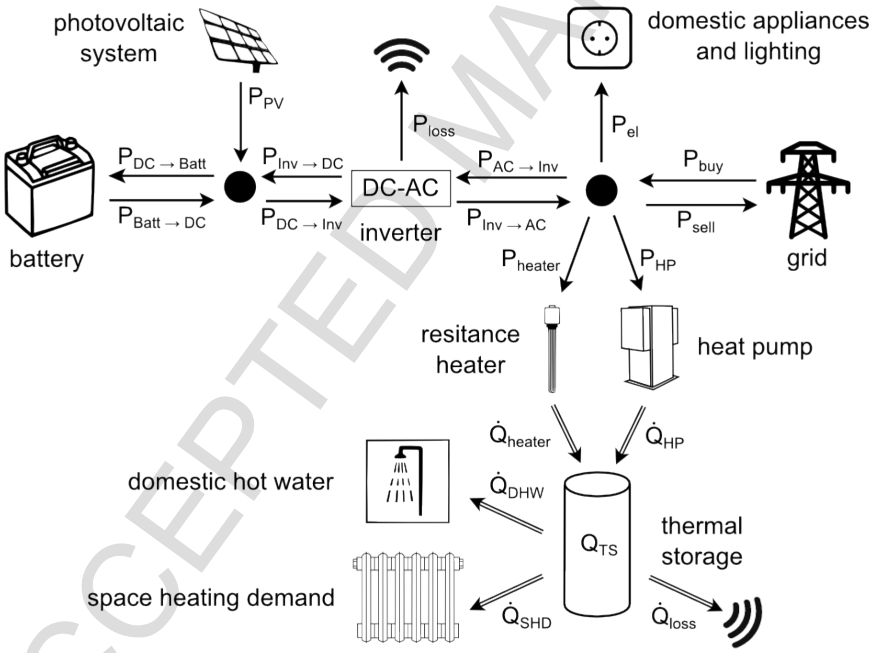


Fig. 9 - Energy system of the house model

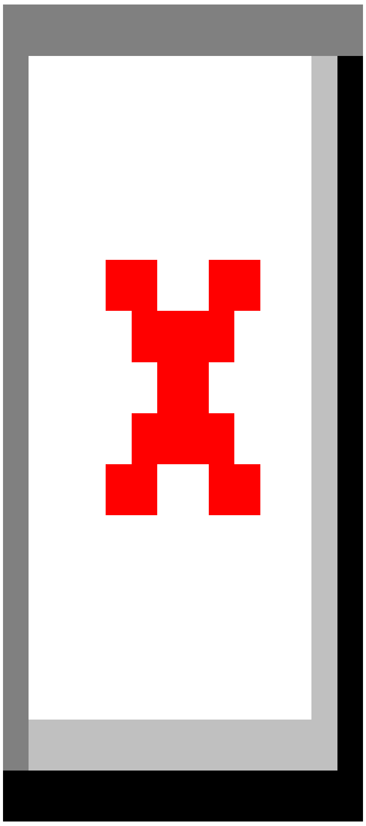


Fig. 10 – Flow chart of the optimization process

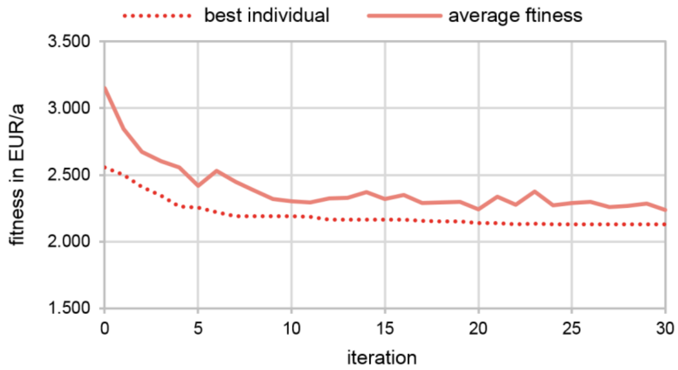


Fig. 11 – Convergence curve for the dynamic EOM scenario

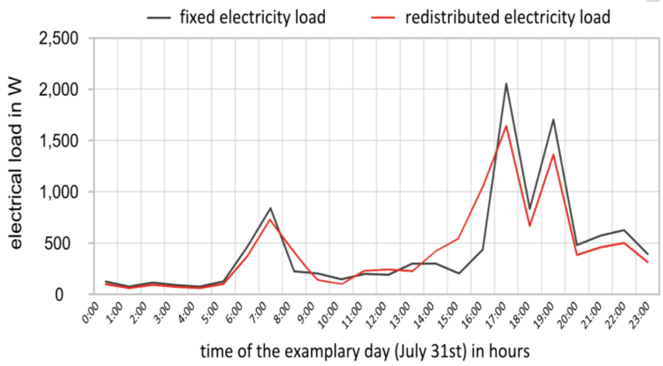


Fig. 12 – Daily distribution of electrical load with and without DSM

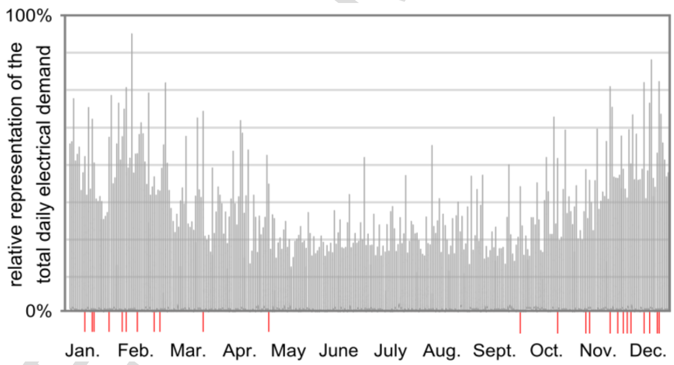


Fig. 13 – Distribution of wildcard hours (depicted by red vertical lines)

Highlights

Concerning the paper submitted to ENERGY Ref. No. EGY-D-16-04529

Cost optimal sizing of smart buildings' energy system components considering changing end-consumer electricity markets

Henryk Wolisz[a], Thomas Schütz[a], Tobias Blanke[a], Markus Hagenkamp[a], Markus Kohrn[a], Mark Wesseling[a], Dirk Müller[a]

[a] RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, 52074 Aachen, Germany, hwolisz@eonerc.rwth-aachen.de

- Impact analysis of different electricity markets on building supply system design
- Optimization of supply system sizing and operation by coupled heuristics and MILP
- High profitability of PV systems for self-consumption and feed-in
- Thermal energy storage allows for electricity load shifting and cost reductions
- Battery systems require a cost reduction of approximately 60% to become profitable