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Self-consumption through power-to-heat and storage for enhanced PV integration in decentralised energy systems

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Abstract

Many countries have adopted schemes to promote investments into renewable energy sources resulting, amongst others, in a high penetration of solar PV energy. The system integration of the increasing amount of variable electricity generation is therefore a highly important task. This paper focuses on a residential quarter with PV systems and explores how heat pumps and thermal and electrical storages can help to integrate the PV generation through self-consumption. However, self-consumption and PV integration are not only affected by technologies but also by pricing mechanisms. This paper therefore analyses the impact of different tariffs on the investment and operation decisions in a residential quarter and its interaction with the external grid. The considered tariffs include a standard fixed per-kilowatt-hour price, a dynamic pricing scheme and a capacity pricing scheme. To account for the inter-dependent uncertainties of energy supply, demand and electricity prices, we use a module-based framework including a Markov process and a two-stage stochastic mixed-integer program. Analysing a residential quarter in Southern Germany as a case study, we find that the integration of a PV system is economically advantageous for all considered tariffs. The self-consumption rate varies between $58-75\%$. The largest PV system is built when dynamic prices are applied. However, the peak load from the external grid increases by a factor of two under this tariff without any incentive for reduction. In contrast, capacity pricing results in a reduction of the peak load by up to 35%.

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1 Introduction

On 30 November 2016, the European Commission published its “Winter Package”, consisting of more than 40 planned measures, aimed at accomplishing climate targets on energy efficiency, greenhouse gases, and renewable energies (RE). One of the key objectives is to promote a better integration of electricity produced from renewable sources through market-based mechanisms. “The regulatory changes introduced by the current package and the shift from centralised conventional generation to decentralised, smart and interconnected markets will also make it easier for consumers to generate their own energy, store it, share it, consume it or sell it back to the market – directly or as energy cooperatives […] these changes will make it easier for households and businesses to become more involved in the energy system and respond to price signals.” (European Commission, 2016)

With regards to Germany, the transition towards a more decentralised energy system (DES) with emphasis on RE is pre-eminently driven by the regulatory framework. It defines the target of 80% RE covering German gross electricity consumption in 2050 (BRD (Bundesrepublik Deutschland) [Federal Republic of Germany], 2012). In line with this target, Germany has been the world’s top photovoltaic (PV) installer for several years (Rodrigues et al., 2016), outperformed only by China since 2015 (IEA, 2016). Particularly, the German Renewable Energy Sources Act (EEG) catalyses the expansion of decentralised renewable energy sources such as PV by guaranteeing a fixed feed-in tariff for the energy that is fed into the local grid. Since its introduction in 2000, electricity retail prices have risen about 5% per year on average until today. At the same time, the average costs of PV systems have decreased by an average of 9% per year (BSW (Bundesverband Solarwirtschaft) [German Solar Association], 2015). This cost decrease was accompanied by a continuous reduction of the PV feed-in tariff, which makes the self-consumption of electricity produced by PV more profitable and flexibilities to shift load (e.g., storages) more attractive. Fig. 1 shows the development of the household electricity price in comparison to the electricity production costs of PV systems for Germany, showing that the so-called grid parity has been achieved recently.

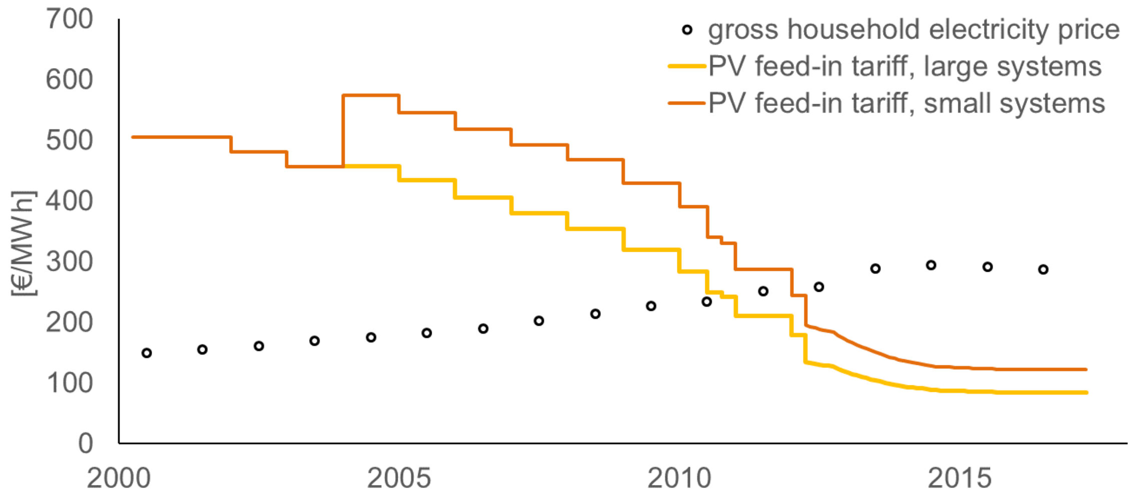

Fig. 1: Historical development of PV feed-in tariffs and end-user electricity price for households in Germany (Wirth, 2017).

In the light of these developments and the statements by the EU promoting self-consumption as a means to support RE integration, the question arises (from a consumer perspective) what flexibilities to shift load and increase self-consumption are most profitable and how to optimally combine different sources of flexibility in the presence of uncertainty. Some researchers, however, also hold critical views on self-consumption (Khalilpour and Vassallo, 2015; Simshauser, 2016; Bertsch et al., 2017). Their criticism is not directed at self-consumption and PV expansion as such, but mainly raises distributional concerns. In systems where consumers pay for costs to build and maintain the energy system infrastructure on a per-unit basis (e.g., network charges), those consumers that can afford investments into technologies increasing self-consumption contribute less to maintaining the system while still benefiting from the security of supply from being connected to the grid. As a consequence, a decreasing amount of consumers who cannot invest into self-consumption bear the costs of the system. Several approaches to overcome these concerns are discussed, including the introduction of capacity-based price components, also called demand tariffs in the literature (Kaschub et al., 2016; Simshauser, 2016). This gives rise to the question how such different retail tariffs (pricing mechanisms) impact the profitability of different flexibility sources such as power-to-heat applications or energy storages and their optimal combination. Also, the question emerges what levels of self-consumption can be expected and how these are influenced by different tariffs under RE uncertainty.

This paper therefore presents a two-stage stochastic program to analyse different pricing mechanisms for a residential quarter with the option of a PV system and electrical as well as thermal storages. The stochastic program is embedded in an integrated, module-based framework. The required input data (e.g., load profiles on the demand and supply side) are generated on the basis of Markov processes under consideration of their mutual dependencies. Our analysis focusses on the optimal investment decisions under different tariffs and on essential energy values such as total energy costs, the PV self-consumption rate and grid load under uncertain weather-related conditions.

The structure of the paper is as follows. Section 2 provides a brief overview of related literature. In the subsequent Section 3, the modelling framework is described including the generation of input data as well as the stochastic program. Section 4 introduces the case study of a real-world residential quarter. The results are presented in Section 5, followed by a discussion and acknowledgement of limitations in Section 6. A conclusion and an outlook finalise the paper in Section 7.

2 Related literature and work

In general, DES are considered as systems that provide a portion of the energy required to satisfy their demand on-site, within the boundaries of, or located nearby and directly connected to, a building, community or development (Wolfe, 2008). The literature on optimisation of DES is large and growing. Due to the fluctuating properties of some system elements, the majority is based on a high temporal resolution of 15min or 1h, considering a time horizon of less than a day up to 25 years. Prevalently, electrical demand and supply is simulated or optimised (McHenry, 2012; Erdinc, 2014; Komiyama and Fujii, 2014; Dufo-López and Bernal-Agustín, 2015; ElNozahy et al., 2015; Kaschub et al., 2016; Zebarjadi and Askarzadeh, 2016). Other research focusses on the heat management (Zhang et al., 2007; Wei et al., 2015; Bahria et al., 2016; Fischer et al., 2017). Several cases analyse both electricity and heat:

- Evins et al. (2014) formulate a general 'energy hub concept' that can methodologically represent the interactions of many energy conversion and storage technologies for applications such as power plants, industrial facilities and urban areas. While their modelling approach to aggregate and optimise energetic resources on a relatively small scale and with relatively high detail exhibits some similarity to the representation in our study, they focus less on the economic implications of the various system designs. However, they find a strong potential of system components such as heat pumps to reduce carbon emissions by up to 22%.
- Kanngießer (2014) considers scheduling optimisation of energy storages by trading load shifting potential and operating reserve on the electricity market for an exemplary compressed air reservoir and pumped-storage power plant.
- Shang et. al (2017) schedule storages with a combined heat and power (CHP) application. They apply a non-dominated sorting genetic algorithm as metaheuristic to an illustrative building and evaluate the potential for the reduction of fuel consumption through including electrical and thermal energy storage in the system. Jochem et al. (2015) and, similarly, Kia et al. (2017) optimise the day ahead scheduling of CHP units with electrical and thermal storage. While Jochem et al. (2015) focus on decentralised micro-CHP at the household level and find significant potential to self-consume the CHP's electricity output to more than 50%, Kia et al. (2017) evaluate the CHP's added value to avoid costs imposed by security constraints in two alternative IEEE electricity networks. Vögelin et al. (2017) analyse gas engine CHP plants for building and industry heat demand under varying price structures. Núñez-Reyes et al. (2017) optimise the scheduling of grid-connected PV plants with energy storage for integration in the electricity market.
- Lorenzi and Silva (2016) optimise the dimension of PV systems and the self-consumption with energy storages as well as Beck et al. (2017) do with a power-to-heat application. Similarly, but at the scale of an entire city, Salpakari et al. (2016) analyse how different

technologies, including power-to-heat, storage and load-shifting, can decrease surplus of variable renewable energy.

- Shirazi and Jadid (2017) have developed an energy management to optimise the household's energy operation cost by peak shaving through domestic load shifting and distributed energy resources with varying prices. Over the analysed 24h period they find significant potential to reduce the maximum amount of power needed to be imported to the household system from the electricity grid: Depending on the time of year, the optimisation algorithm active and the tariff scheme, the maximum imported power ranges from 1.7 kW to 17.2 kW.
- McKenna et al. (2017) model heat and electricity on the household level with a specific focus on self-consumption and energy autonomy. Their work goes beyond considering single households and they specifically look into the economies of scale when aggregating different numbers of households. However, they do not consider the impact of different pricing mechanisms at the retail level. Including micro-CHP, PV, gas boilers and thermal and electrical storage within their modelled energy systems, they find a range of 30% to nearly 100% of energy autonomy economically feasible, largely depending on the amount of aggregated households.

In these cases, however, deterministic programs are usually employed, in spite of the different uncertainties that influence the computational results. In line with this, uncertainties are often considered by using average values or by sensitivity or scenario analyses. However, such analyses can only provide an estimation of the impact on the optimisation results while the complex effect cannot be captured entirely. Stochastic modelling techniques enable an adequate consideration of the manifold uncertainties in the investment and operation planning processes of DES (see for example (Göbelt, 2001; Kelman et al., 2001; Wallace and Fleten, 2003; Möst and Keles, 2010)). Birge (1982) comprehensibly discusses the advantages and disadvantages of deterministic compared to stochastic programming.

The main contribution of this paper is the combined consideration of heat and electrical demand as well as supply of DES over a long time horizon and a high temporal resolution taking into account different tariffs and uncertain conditions in a stochastic program, which is novel to our knowledge. This study demonstrates the optimisation of a residential quarter modelled as a stochastic program with a temporal resolution of $15\ \mathrm{min}$ and a 20-year time horizon. The approach is related to Schwarz et al. (2017) and extended by endogenising investment decisions into PV, power-to-heat technology and electrical storage as well as the consideration of different tariffs including a dynamic electricity price generation module (see Section 3).

3 Methodology

The methodology relates to Schwarz et al. (2017) who describe a module-based model chain including stochastic programming to take into account weather-related uncertainties, e.g., PV supply, energy demand or electricity prices, and to endogenously determine optimal investment in the system's components. The model framework is explained in Section 3.1, the data generation and optimisation process are explained in detail in Section 3.2 and 3.3.

3.1 Model framework

This paper uses the comprehensive approach of Schwarz et al. (2017) that consistently models and propagates uncertainties through a model chain comprising three layers (see Fig. 2):

a) input layer,
b) transformation layer and
c) optimisation layer.

The approach accounts for the associated uncertainties by generating consistent ensembles of meteorological input parameter profiles at the input layer considering their probabilistic properties. These profiles are used at the transformation layer to provide energy supply and demand profiles or price profiles for the subsequent optimisation layer.

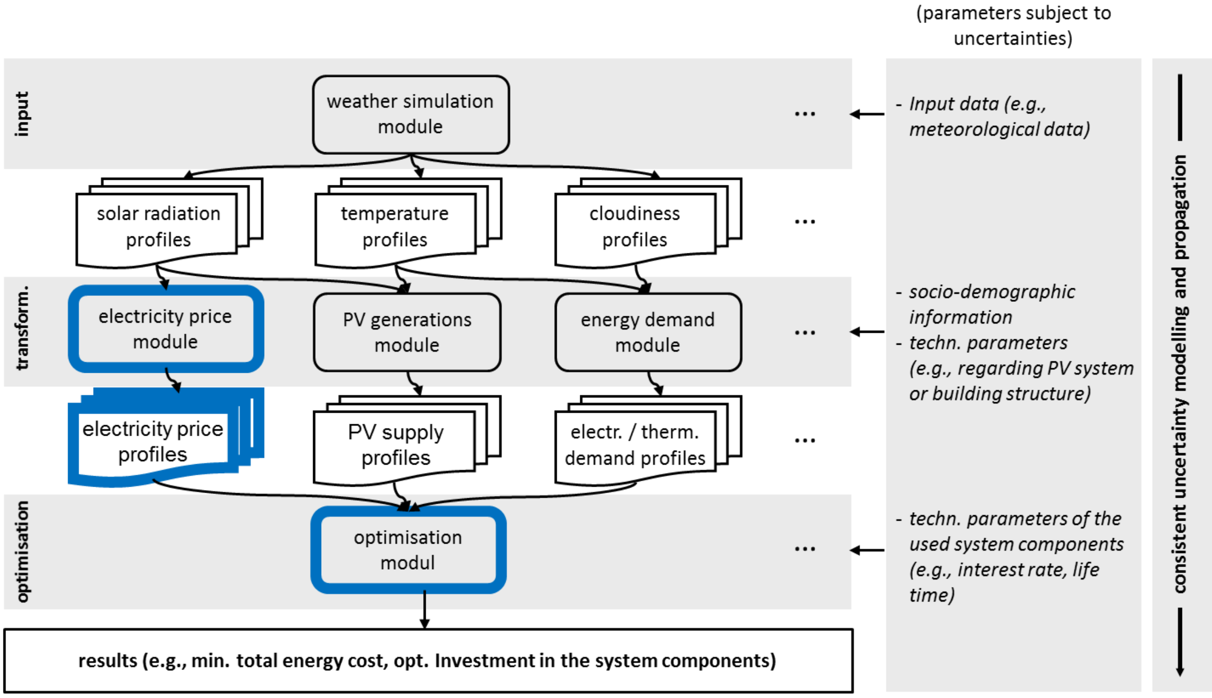

Fig. 2: Modell framework for DES taking into account uncertainties. The figure is obtained from Schwarz et al. (2017) and adapted to the focus of this study. Extensions and additions are explicitly marked by blue (bold) box-framing.

3.2 Data generation process

When simulating meteorological input parameter profiles, such as solar radiation and temperature, it is important to consider their fluctuating and stochastic nature as well as the interdependencies between them. Given the focus of the paper, which is investment and operational planning for PV integration under different tariffs and uncertainty, the simulation approach needs to take into account both: the short-term fluctuations and uncertainties of different load profiles as well as the long-term variations (e.g., ‘good’ and ‘bad’ solar years). Both have an impact on the choice of adequate dimensions for the energy system components and the short-term uncertainties also affect the operational planning. Moreover, since the considered energy system includes components on the demand and supply side, the approach needs to consider the interdependencies between profiles on both sides under consideration of meteorological conditions. This implies that the different profiles cannot be simulated independently.[1] Thus, our approach simulates meteorological conditions, such as the cloudiness, and its interdependencies with temperature and solar radiation.

Existing approaches for stochastic simulation of meteorological parameters can generally be divided into two groups. The first group includes regression models based on estimations of probability distribution functions of observations (see Diagne et al. (2013) for an overview). The second group includes Markov processes being based on a transition matrix representing the probabilities of future states depending on past realisations. For instance, Amato et al. (1986) focus on long-term variations of daily solar radiation using a Markov process, while Ehnberg and Bollen (2005) use cloud observations in three-hour intervals. Focussing on more short-term variations in a higher temporal resolution, Morf (1998) uses a Markov process to simulate the dynamic behaviour of solar radiation. An advantage of Markov processes is that they are well suited to consider interdependencies between cloudiness, temperature and solar radiation, which have been mentioned above as a central requirement.

We extend the Markov process used by Ehnberg and Bollen (2005) by including seasonal information. This is achieved by using transition probabilities that vary from month to month (see below). We also simulate temperature profiles, which are consistently compatible with the simulated solar radiation profiles. Aimed at considering long-term and short-term variations, we suggest a two-step approach.

First, to take the long-term variations into account, we use a Markov process to model the daily cloudiness index $\zeta \in \{0,\dots,8\}$ considered in Oktas. Oktas describe how many eighths of the sky are covered by clouds. $\zeta = 0$ indicates a completely clear sky while $\zeta = 8$ indicates a completely clouded sky (Jones, 1992). We define the transition matrix Θ_ζ^m (where m indicates the month) for this Markov process as follows:

$$\Theta_\zeta^m = \begin{pmatrix} \pi_{00}^{\zeta,m} & \dots & \pi_{08}^{\zeta,m} \\ \vdots & \ddots & \vdots \\ \pi_{80}^{\zeta,m} & \dots & \pi_{88}^{\zeta,m} \end{pmatrix}. \tag{1}$$

The transition probabilities $\pi_{ij}^{\zeta,m}$ in eq. (1) are derived from publicly available weather data provided by Germany's National Meteorological Service ('Deutscher Wetterdienst (DWD)'). These are available for a variety of locations in Germany for periods of usually five or more decades. The transition probability $\pi_{ij}^{\zeta,m}$ for month m denotes the conditional probability that the cloudiness ζ_δ on day δ equals j knowing that the cloudiness $\zeta_{\delta-1}$ on day $\delta - 1$ was i:

$$\pi_{ij}^{\zeta,m} = P(\zeta_\delta = j \mid \zeta_{\delta-1} = i); \; \sum_j \pi_{ij}^{\zeta,m} = 1 \;\; \forall m \, \forall i. \tag{2}$$

The Markov process for the cloudiness based on the transition probabilities in (2) then takes the form:

$$\zeta_\delta = f(\zeta_{\delta-1}, \Xi), \tag{3}$$

where Ξ is a uniformly distributed random variable in $[0,1]$. Let now ξ be a realisation of Ξ. ζ_δ can then be obtained as:

[1] For example, electricity generation from solar PV does not only depend on solar radiation but also on the temperature affecting the panels' efficiency. Likewise, heat demand depends on temperature and cloudiness.

$$\zeta_\delta = \begin{cases} 0\ if\ \xi \in \left[0, \pi^{\zeta,m}_{\zeta_{\delta-1}0}\right[, \\ 1\ if\ \xi \in \left[\pi^{\zeta,m}_{\zeta_{\delta-1}0}, \sum_{j=0}^{1} \pi^{\zeta,m}_{\zeta_{\delta-1}j}\right[, \\ \vdots \\ 8\ if\ \xi \in \left[\sum_{j=0}^{7} \pi^{\zeta,m}_{\zeta_{\delta-1}j}, 1\right]. \end{cases} \tag{4}$$

To simulate the daily solar radiation on the basis of the cloudiness, we use an additional Markov process. The transition probabilities of the corresponding transition matrix $\Theta^{m,\zeta}_{\rho}$ for the solar radiation ρ_δ on day δ can be expressed as a function of the month m, the cloudiness ζ_δ on day δ and the solar radiation $\rho_{\delta-1}$ on day $\delta-1$:

$$\pi^{\rho,m,j}_{kl} = P(\rho_\delta = l \mid \rho_{\delta-1} = k \cap \zeta_\delta = j); \sum_{l} \pi^{\rho,m,j}_{kl} = 1 \quad \forall m\, \forall j\, \forall k. \tag{5}$$

Similarly, values for average daily temperatures are derived. Overall, our analysis shows that deriving the transition probabilities on a monthly basis delivers more accurate results than using yearly transition probabilities.

Second, a separate stochastic process is used to generate profiles in 15min resolution on the basis of the daily simulation described above. This second step addresses the short-term variations. These short-term variations are simulated by an empirically determined, statistically varying term under the constraint that a given daily solar radiation is achieved. The Markov process generates time series of the required input parameters for the following subsystems and is applied to obtain a predefined number of scenarios. For further details, please see Bertsch et al. (2014) and Schwarz et al. (2017).

The transformation layer transforms the output of the input layer into data required for the subsequent optimisation. For the case study in Section 4, the meteorological data are transformed into electrical and thermal demand, PV supply and electricity price.

An energy demand module provides electricity demand profiles and heat demand profiles for space heating (SH) and domestic hot water (DHW). Therefore, a reference load approach is integrated that uses parameters such as weekday, season, temperature, cloudiness, insulation, location and occupancy. The generation of electricity demand profiles is based on the so-called ‘standard load’ or H0 profiles (Fünfgeld and Meier, 1999). To generate heat demand profiles for SH and DHW, the VDI guideline 4655 (VDI (Verein Deutscher Ingenieure) [Association of German Engineers], 2008) is used. Concerning PV supply profiles, a physical model on the basis of Ritzenhoff (2006) is used. It describes the dependencies of electrical yield primarily to incident light, solar module efficiency, orientation and capacity of the PV system. Thereby, the low-light performance and temperature dependency of the modules is taken into account. The global solar radiation profiles, coming from the input layer, are split into direct and diffuse solar radiation on the PV system on the basis of Liu and Jordan (1960). These radiation profiles are used in conjunction with ambient temperature to determine accurate electrical PV supply profiles for the optimisation layer.

A residential quarter will exchange electricity with the wider energy system by means of the electricity grid. Aside from electricity feed-in from generation units eligible to a feed-in tariff, any electricity exchange from or to the grid is assumed to cost or yield the wholesale market price plus a considerable amount of levies and taxes. While levies and taxes stay at a constant per-unit charge, aside from administrative adjustments from time to time, the wholesale market price for electricity is fluctuating. A major influence on the market price, amongst others, is the generation of renewable energy within the market area of interest. To harmonise the wholesale market prices we assume for our simulated scenarios, we derive electricity prices as a function of the same meteorological data which are utilised for the generation of irradiation profiles described above. This electricity price generation module constitutes a newly implemented component within the input layer and is explained in further detail in the following.

Firstly, we acquire historical data from the "PHELIX" day ahead spot market auction of the EPEX which represents the primal market place for power exchange in Germany (EPEX SPOT, 2017). We choose the price profiles from the four years 2012, 2013, 2014 and 2015 as data basis for the simulation.

Secondly, we aggregate global irradiation data over the same years 2012-2015 from a data set supplied by Anemos (2016) to daily irradiation. The original data is generated through downscaling of reanalysis data from the NASA program Modern-Era Retrospective Analysis for Research and Applications (MERRA) applying the mesoscale model MM5 (PSU/NCAR, 2003). It has a temporal resolution of 10min (spanning from 1990 to 2015) and a spatial resolution of $20\text{km} \times 20\text{km}$. We choose a location as close as possible to the measurement station that the above described generation of irradiation profiles is based on. We account for the systematic overestimation for global irradiation of the data set found by Schermeyer et al. (2015) through a correction factor.

Thirdly, given daily price profiles and corresponding daily irradiation, we cluster the price profiles by the following three dimensions:

- Daily irradiation [Wh/m²]: We partition the observations over the four years in five groups in such a way that the number of observations per group are equal (Fig. 3).

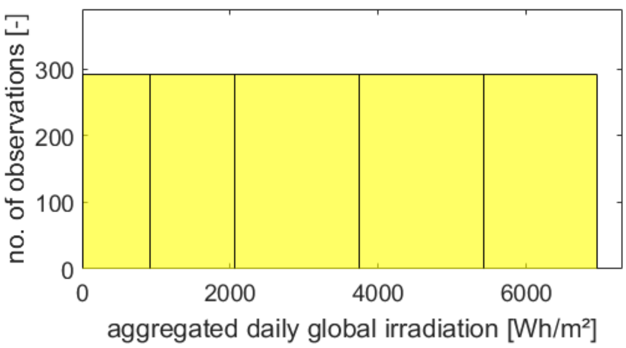

Fig. 3: Histogram of aggregated daily irradiation observations with bins sized such that every irradiation-class has an equal number of observations.

- Seasons: In order to account for seasonal influences on electricity prices (e.g. changing electricity demand driven by temperature or daylight length) we separate the observed price profiles by the four seasons.
- Day type: We also differentiate the observed price profiles by the day types weekday, Saturday or Sunday in order to account for systematic difference in electricity demand influencing electricity prices.

Altogether, we separate the observed daily price profiles into $5 \cdot 4 \cdot 3 = 60$ groups. For the final generation of price scenarios matching the generated weather scenarios, we classify each daily profile of the generated weather scenarios to belong to one of the 60 price groups. Then, we draw one of the daily price profiles assigned to this price group by a uniformly distributed random variable. Fig. 4 shows the results of the price simulation of four randomly selected years as a duration curve compared to the duration curve of the historic prices in 2012 – 2015.

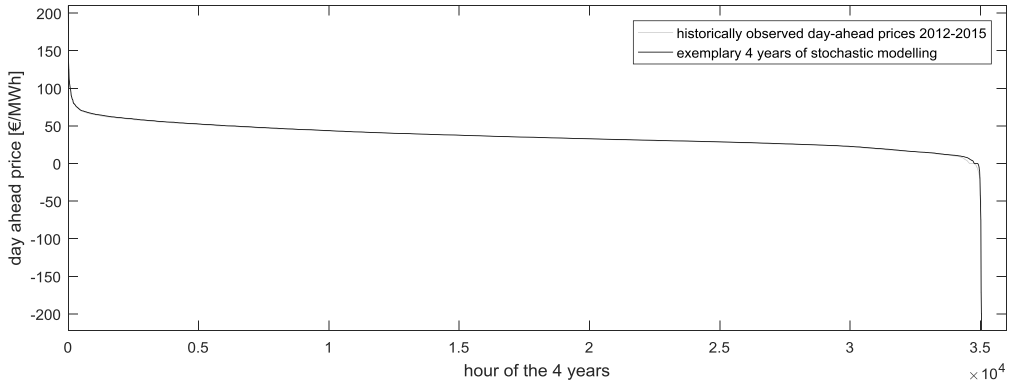

Fig. 4: Price duration curve of historically observed and modelled day-ahead market prices over the hourly time steps of 4 years.

Additionally, Tab. 1 compares some key figures of the generated price scenarios with the historical price realisations.

Tab. 1: Basic statistics comparing the observed historical prices to the modelled prices.

	Historic prices (2012-2015) in $€/\mathrm{MWh_{el}}$	Modelled prices (100 scenarios) in $€/\mathrm{MWh_{el}}$
Quantiles		
0.1 quantile	18.47	18.29
0.4 quantile	31.96	31.92
0.7 quantile	42.84	42.54
0.9 quantile	55.97	55.54
Mean	36.21	36.39
Max	210.00	210.00
Min	−222.99	−222.99
Standard deviation	15.95	16.23
Volatility	44%	44%

3.3 Optimisation process

In order to determine minimal total energy costs and optimal investment in the system's components under uncertain conditions, the residential quarter is modelled as a two-stage stochastic program in the optimisation layer.[2] As mentioned above, the stochastic program is based on Schwarz et al. (2017). The main investment variable of the original model was the heat storage size while the PV capacity was given exogenously and electrical storage was

[2] For a compact introduction in two-stage stochastic programming, see Ahmed (2010).

not considered. The objective function of the original program therefore took the following form:

$$costs^* = \min_{c_{g,i}, e^{gridin}_{\omega,t}, e^{PVfi}_{\omega,t}} \sum_{i}^{I} ANF_i\left(cost_i^{\text{fix}} + cost_i^{\text{var}} \cdot c_i\right) + \frac{1}{N}\left(\sum_{\omega=1}^{N}\sum_{t=1}^{T}\left(p^{gridin}_{\omega,t} \cdot e^{gridin}_{\omega,t} - p^{PVfi}_{\omega,t} \cdot e^{PVfi}_{\omega,t}\right)\right). \tag{6}$$

At the first stage, the capital costs of each investment $i \in I$ are converted into an equivalent series of uniform amounts per period, where I is the set of all possible investment options (e.g., PV system, heat pump, el. storage etc.) including all possible combinations. The lifetime LT_i of the investment and an alternative investment possibility at a certain interest rate r of the fixed capital is taken into account by the annuity factor.

At the second stage, energy costs of each scenario $\omega = \{1, \dots, N\}$ result from the electricity obtained from the external grid $e^{gridin}_{\omega,t}$at price $p^{gridin}_{\omega,t}$ minus the PV energy fed into the grid $e^{PVfi}_{\omega,t}$ at compensation rate $p^{PVfi}_{\omega,t}$ at each time step $t = \{1, \dots, T\}$. In total, the energy costs are minimised by finding the unique investment at the first stage that is optimal for N equi-probable scenarios at the second stage.

An essential constraint of the system is that the electrical and thermal demand and supply are balanced at any time. Furthermore, the electrical or thermal supply in the system can be limited by technological or other restrictions. Storage units in the system connect the states of time step t and $t + 1$ and lead to a complex stochastic linear program (SLP) or stochastic mixed-integer linear program (SMILP) depending on the used component technologies. See Schwarz et al. (2017) for further information about the stochastic program.This paper extends the stochastic program as outlined in equation (7) in order to analyse different pricing mechanisms.

$$costs^* = \min_{c_{g,i}, e^{gridin,max}_{\omega}, e^{gridin}_{\omega,t}, e^{gridout}_{\omega,t}, e^{fi}_{\omega,t}} \sum_{i=1}^{I}(ANF_i + MF_i)\left(cost_i^{\text{fix}} + \frac{cost_i^{\text{var}}}{(1 - DF_i)} \cdot c_i\right) + \frac{1}{N}\left(\sum_{\omega=1}^{N} CP \cdot e^{gridin,max}_{\omega} + \sum_{t=1}^{T}\left(p^{gridin}_{\omega,t} \cdot e^{gridin}_{\omega,t} - p^{gridout}_{\omega,t} \cdot e^{gridout}_{\omega,t} - p^{PVfi}_{\omega,t} \cdot e^{PVfi}_{\omega,t}\right)\right). \tag{7}$$

We additionally integrate maintenance costs by a maintenance factor MF_i multiplied by the investment of component i that complies with Kaschub et al. (2016). Due to the possible aging of a component i, we also adjust each investment by a degradation factor DF_i. It takes into account the reduction of the initial capacity by the end of the life time. At the second stage, we add the possibility to feed electricity into the external grid $e^{gridout}_{\omega,t}$ at price $p^{gridout}_{\omega,t}$. Also, a capacity price of the external grid CP multiplied by the maximal obtained electricity (peak load) $e^{gridin,max}_{\omega}$ is implemented.

In particular for the electrical storage, the capacity $c_{i=es}$ needs to be extended to:

$$c_{i=es} = c'_{i=es} + \frac{0.3}{T} \cdot \sum_{t=1}^{T} s^{es}_{\omega,t}, \tag{8}$$

to include a reduced calendar lifetime for high states of charge (SoC) according to Lunz et al. (2012) and Kaschub et al. (2016). This simplified linear relationship suggests that a storage that is always fully charged reduces its whole life time by about one third. In this context, the life time reduction is considered by a partial replacement investment. In analogy to the thermal storage, the SoC has to be smaller than the capacity $s_{\omega,t}^{es} \leq c'_{i=es}$. Additionally, the charging power cannot exceed a certain limit $\Delta s_{\omega,t} \leq \Delta s_{\omega,t}^{es,max}$.

Practically, the charging is connected with a loss that depends on the charging efficiency η^{es} of the storage. Therefore, positive auxiliary variables are used to differentiate between charging and discharging:

$$s_{\omega,t+1}^{es} - s_{\omega,t}^{es} = pos_{\omega,t}^{es} - neg_{\omega,t}^{es} \ \forall \omega, t. \tag{9}$$

The energy losses for charging and discharging are incorporated into the balancing constraint for electrical demand and supply by the negative terms $(1 - \eta^{es}) \cdot pos_{\omega,g,u,t}^{es}$ and $(1 - \eta^{es}) \cdot neg_{\omega,g,u,t}^{es}$. Furthermore, a self-discharging over time in dependency of the storage level is taken into account by an additional negative term $l^{es} \cdot s_{\omega,t}^{es}$.

In addition, the charging power is limited for high SoC with respect to Kaschub et al. (2016) and Kaschub et al. (2013):

$$\Delta s_{\omega,t}^{es,max,red} \geq C \cdot \left(4 s_{\omega,t}^{es} - 3 c'_{i=es}\right) \ \forall \omega, t, \tag{10}$$

$$\Delta s_{\omega,t}^{es,max} = C^{rate} \cdot c'_{i=es} - \Delta s_{\omega,t}^{es,max,red} \ \forall \omega, t. \tag{11}$$

The maximum possible charging power $\Delta s_{\omega,t}^{es,max}$ is generally limited by the battery capacity $c'_{i=es}$ and the C-rate C^{rate}. This charging power $\Delta s_{\omega,t}^{es,max}$ is linearly reduced by $\Delta s_{\omega,t}^{es,max,red}$ for a SoC above 75% depending on the charged energy $s_{\omega,t}^{es}$, the battery capacity $c'_{i=es}$ and the C-rate. Thus, the charging power $\Delta s_{\omega,t}^{es,max}$ is not reduced below a SoC of 75% and it amounts to zero at a SoC of 100% (when $C^{rate} \cdot c'_{i=es}$ equals $\Delta s_{\omega,t}^{es,max,red}$). The discharging minimum limit is implemented correspondingly.

Computationally, the stochastic program is feasible by decoupling in combination with distributed optimisation on high-performance computing (HPC) systems. Therefore, intra- and inter-scenario connections are explicitly given such as the different investment in the quarter's components among the scenarios or storage levels over time steps within the scenario. Then the program is decoupled in many subprograms that are optimised by CPLEX, a commercial LP and MILP solver, on several computing nodes. Subsequently, the subprograms are coupled to compute the minimal costs of the fixed variables. The optimisation of these fixed variables is performed by an outer derivative-free optimisation (DFO): a steepest-ascent hill-climbing approach (Taborda and Zdravkovic, 2012). Note that the used hill-climbing approach is a local search approach that can only guarantee local optimality. It can be replaced by any other DFO algorithmic, even by a global search approach, if enough computational power is available. We have deliberately chosen a hill-climbing algorithm in this paper, because it requires only a few iterations of the very expensive evaluations to find an optimal solution. Also important is its reliable and robust solution process, especially a high tolerance to inaccuracy of the solutions of the subprograms. That allows using lower relative gaps for the subprograms to considerably reduce the computing time (more accuracy of the subprograms is needed to get closer to the optimum).

4 Case study and data assumptions

In our case study, a residential quarter as DES pools 29 residential units in row and multi-family houses into a living and energy community. Its demand of electricity, DHW and SH is covered by a PV system, heat pumps, heating elements and an external energy supplier. The option of flexible electrical and thermal storage units enables an increased self-consumption and solar PV integration. Fig. 5 illustrates the energy setup of the quarter.

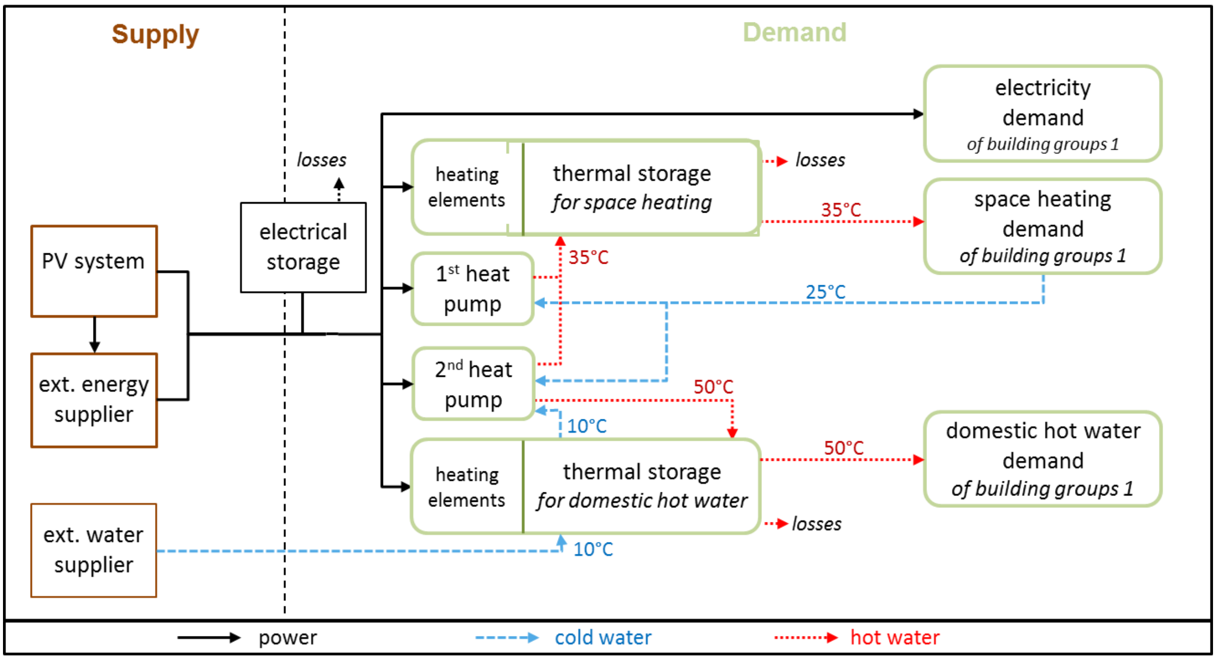

Fig. 5: Energy setup of the residential quarter.

The PV system of the quarter is east-west orientated with regards to a higher self-consumption in the morning and evening hours. In addition, through the lower tilt of 15° and a lower shadowing, it allows a higher installable capacity on the roof in comparison to usually mounted, south-orientated systems with a tilt of about 40°. The maximal system capacity is restricted by the available roof area. The average net costs for PV systems up to $100\mathrm{kW_p}$ amounts to $1300€/\mathrm{kW_p}$ in 2015 (BSW (Bundesverband Solarwirtschaft) [German Solar Association], 2015). This includes all PV system parts and installation costs, whereas the solar modules have a share of about 50%. The initial capacity is reduced by a degradation factor of $DF_{i=pv} = 16\%$ meaning that the usable capacity at the end of the life time is 84%. Annual maintenance costs are considered as 1.5% of the investment in the PV system. When the local electrical demand of the households and the heating system exceeds the supply of the PV system and the possible electrical storage, electricity can be obtained from the external grid. Otherwise, PV surplus can be fed into the external grid or buffered in the electrical storage (depending on the corresponding investment decision).

For the electrical storage, a generic Li-Ion based battery is used in the model. This paper assumes a price of $600€/\mathrm{kWh_{el}}$, which includes all system components, such as battery cell packs, with management system or inverter based on Kaschub et al. (2016) and Tesla (2015). A calendar lifetime of 20 years with degradation of $DF_{i=es} = 20\%$ is assumed according to Schmiegel and Kleine (2014) and Weniger et al. (2014). The C-rate[3] is set to 1, the charging efficiency η^{es} equals 94% and a self-discharging of 2% per month is considered as in Quaschning (2015). Maintenance costs are set to 1% of the investment in correspondence with Kaschub et al. (2016).

The heating system is separated into two cycles, each with its own water tank storage in combination with a power-to heat technology: Air-water heat pumps provide heat up to $120\mathrm{kW_{th}}$ depending on the ambient air temperature. For the DHW cycle, fresh water is obtained from an external water supplier and heated by heat pumps in an open loop from about $10°\mathrm{C}$ to $50°\mathrm{C}$. The closed cycle for SH runs at a lower temperature of $35°\mathrm{C}$ resulting in a higher coefficient of performance (COP) of the other heat pumps and lower heat losses of the storage. This target temperature can drop by approximately $10\mathrm{K}$ which results in smaller energy content at the same volume compared to storages for DHW. In case of very cold ambient temperatures and high SH demand, heat pumps of both cycles can be used for keeping the target temperature. Additional heating elements in both storage types secure the thermal coverage in times of peak demand and the disinfection function in the DHW storage. While the heating elements can modulate their heat output on a continuous scale, the heat pumps can only run stepwise at idle, half or full load leading to a mixed-integer linear stochastic program. This paper uses a maintenance factor of $MF = 1.5\%$ for all elements of the heating system.

In Germany, the current feed-in tariff for PV is approx. $0.11€/\mathrm{kWh_{el}}$ (Wirth, 2017). Typically, electricity is obtained from the external energy supplier by a fixed per-unit price and a small basic charge in the household sector. This average electricity price for households was at $0.29€/\mathrm{kWh_{el}}$ in 2015 (BNetzA (Bundesnetzagentur) [Federal Network Agency for Electricity, Gas, Telecommunications, Post and Railway], 2015). In the future, dynamic prices for households may be introduced along with a smart meter rollout. Besides, capacity-based price components are in discussion to charge the actual power load of the grid (e.g., (Kaschub et al., 2016; Simshauser, 2016)). This would be a new tariff component for German household customers, whereas such a demand charge is already used for industrial customers.

With the different pricing mechanisms and under weather-related uncertainties, this paper endogenously dimensions the energy system components of an exemplary residential quarter in Southern Germany (Karlsruhe). The optimisation task includes investment and operational decisions. In terms of the investment optimisation, the task consists in determining the optimal sizes of the different system's components. In terms of optimising the operational decisions, energy demand for SH and DHW can be shifted to times when a PV surplus is available by using heat pumps in combination with heat storage units. The electrical storage can also be used to shift PV surplus to times when it is needed within the quarter. Besides, the electrical storage can be used to trade electricity with the external energy supplier. In addition, minimisation of storage losses as well as ramp-up losses of the heat pumps and avoiding the use of the inefficient heating elements will lower the energy costs. Both electrical and thermal demand is subject to weather-related uncertainties. Furthermore, PV and heat pump supply depend on uncertain meteorological parameters such as temperature and solar radiation. The paper generates 100 different scenarios to take into account these uncertainties. The following Tab. 2 lists all model assumptions for the components of the residential quarter.

[3] The C-rate gives rate of charging/discharging in relation to its maximum capacity. A C-rate of one means that a $1\mathrm{kWh_{el}}$ battery can be charged/discharged in one hour,

Tab. 2: Model assumption for the components of the residential quarter.

	PV system	heat pump	SH storage	DHW storage	electr. storage
$cost_i$ (net)					
fix	$1000€$	$0€$	$436€$	$610€$	$0€$
variable	$1300€/kW_p$	$25500€/pc.$	$91.8€/kWh_{th}$	$70.7€/kWh_{th}$	$600€/kWh_{el}$
Maintenance factor MF_i	1.5%	1.5%	1.5%	1.5%	1%
Degredation factor DF_i	16%	0%	0%	0%	20%
Life time LT_i	20 years	20 years	20 years	20 years	20 years
Losses	6% of PV yield*	5% of load change when ramp up	0.3% of storage level per 15min	0.6% of storage level per 15min	0.0007% of storage level per 15min 6% when (dis)charg.
Restrictions	capacity≤ $70kW_p$	heat supply≤ temp.-depending max. power	storage level ≤ max. capacity	storage level ≤ max. capacity	storage level ≤ max. capacity (dis)charg. ≤ max. (dis)charg. power

* This loss is already subtracted from the PV yield in the PV generation module of the transformation layer

In terms of the tariff options, this paper considers three different cases:

- Reference (REF) case: In this case, the paper assumes an electricity price of the external energy supplier of $0.29€/kWh_{el}$, and the option of selling electricity at the dynamic wholesale market price that excludes the value added tax of 19%, other governments' taxes and levies and the distribution provision of the energy supplier and is $0.036€/kWh_{el}$ on average.
- Dynamic Pricing (DP) case: This case uses dynamic retail electricity prices that are $0.29€/kWh_{el}$ on average and dynamic wholesale market electricity prices that are $0.036€/kWh_{el}$ on average. Both time series are generated as described in Section 3.2 but scaled to the differently.
- Capacity Pricing (CP) case: This case excludes network charges of $0.07€/kWh_{el}$ from the per-unit price and considers this part as demand charge of the electricity tariff by charging the maximum peak load during one year with $18€/kW_{el}$ based on Kaschub et al. (2016). The dynamic wholesale market electricity price is assumed to remain unaffected at $0.036€/kWh_{el}$ on average. The capacity price of $18€/kW_{el}$ represents the network charges of $204€$ per year. This is the average amount that each household with a mean peak load of about $11.5kW_{el}$ pays by the retail electricity prices.[4]

In addition, each case is computed deterministically with the expected values of the 100 scenarios.

5 Computational results

Fig. 6 shows the optimal investment in the residential quarter's components for the three different tariffs considered. The optimal number of heat pumps is two in all three cases and

[4] The cost of $204€$ per household results from 40 million German household with a mean consumption of $3200kWh_{el}$ multiplied by the network charges of $0.065€/kWh_{el}$ in 2014.

also in the deterministically considered reference case, one used for SH and one mainly for DHW. This result is therefore not included in the figure.

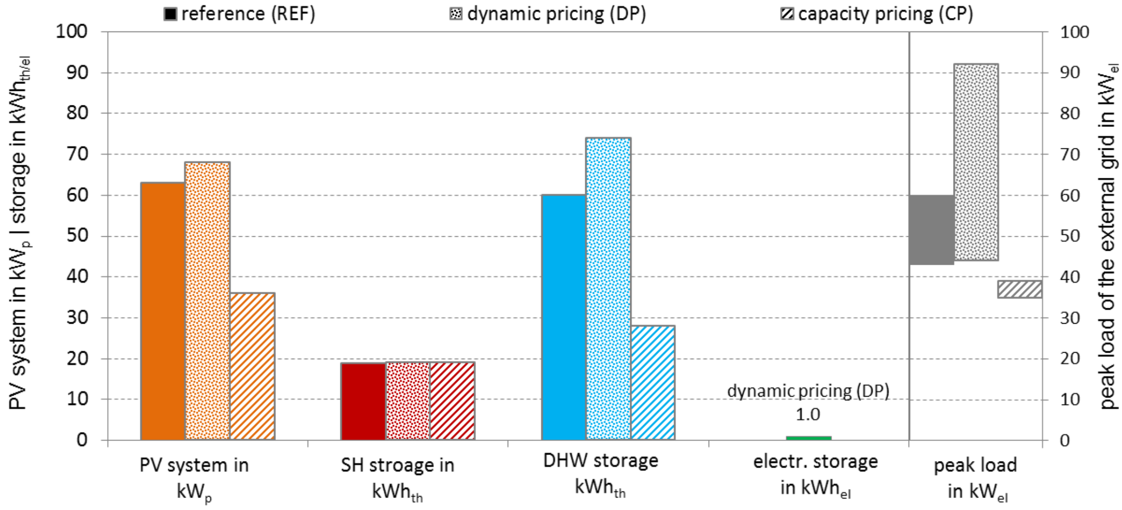

Fig. 6: Optimal investment in the energy system components of the residential quarter for the reference (REF), dynamic pricing (DP) and capacity pricing (CP) cases. In addition, the maximum obtained electricity energy from the external grid (peak load) for each case is plotted and assigned to the right ordinate.

The optimal stochastic solution for the PV system capacity is $63\mathrm{kW_p}$ in the REF case. It is 10% larger in case of DP and reaches almost the maximal possible installation capacity of $70\mathrm{kW_p}$ (resulting from rooftop area limitations). When CP is applied, the optimal PV system is 40% smaller, which can be mainly explained by the reduced retail electricity price of $0.22€/\mathrm{kWh_{el}}$.

However, the stochastically optimal investment in SH storage is the same in all three cases with a size of $19\mathrm{kWh_{th}}$. The reason for this is the need of heat in very cold winter scenarios to cover peak demand and compensate the low heat supply provided by the heat pumps at cold ambient temperatures. Another reason for negligible changes in SH size between the different tariffs is the negative seasonal correlation between SH demand and PV supply. This also leads to a strongly limited suitability of SH storage for PV integration which makes this flexibility option less attractive compared to other sources of flexibility.

On the contrary, the DHW storage increases by 23% in the DP case in comparison to the REF case ($60\mathrm{kWh_{th}}$) and decreases by around 50% in the CP case, i.e. its size changes along with the size of the PV system.

An investment into an electrical storage is not optimal in the REF or CP case. Only in the DP case, the stochastically optimal size is $1\mathrm{kWh_{el}}$.

Regarding the peak load from the external grid, this amounts to a maximum of $60\mathrm{kW_{el}}$ in the REF case, up to $90\mathrm{kW_{el}}$ in the DP case and only up to $39\mathrm{kW_{el}}$ in the CP case.

The various computational results for the different tariff options are also listed in Tab. 3. The deterministic solutions using expected values of the uncertain parameters are listed in parentheses for each case.

Tab. 3: Various computational results of the case study for 100 scenarios (deterministic solutions in parentheses).

	reference (REF)	dynamic pricing (DP)	capacity pricing (CP)
Retail electricity price			
capacity (fix)	$0€/\mathrm{kW_p}$	$0€/\mathrm{kW_p}$	$18€/\mathrm{kW_p}$
per unit (variable)	$0.29€/\mathrm{kWh_{el}}$	$Ø\ 0.29€/\mathrm{kWh_{el}}$	$0.22€/\mathrm{kWh_{el}}$

Wholesale market electricity price	Ø $0.036€/\mathrm{kWh_{el}}$	Ø $0.036€/\mathrm{kWh_{el}}$	Ø $0.036€/\mathrm{kWh_{el}}$
Interest rate	5%	5%	5%
Investment in			
PV system	$63\mathrm{kW_p}$ ($66\mathrm{kW_p}$)	$68\mathrm{kW_p}$ ($73\mathrm{kW_p}$)	$36\mathrm{kW_p}$ ($40\mathrm{kW_p}$)
heat pumps	2pc (2pc)	2pc (2pc)	2pc (2pc)
SH storage	$19\mathrm{kWh_{th}}$ ($16\mathrm{kWh_{th}}$)	$19\mathrm{kWh_{th}}$ ($17\mathrm{kWh_{th}}$)	$19\mathrm{kWh_{th}}$ ($14\mathrm{kWh_{th}}$)
DHW storage	$60\mathrm{kWh_{th}}$ ($65\mathrm{kWh_{th}}$)	$74\mathrm{kWh_{th}}$ ($56\mathrm{kWh_{th}}$)	$28\mathrm{kWh_{th}}$ ($19\mathrm{kWh_{th}}$)
electr. storage	$0\mathrm{kWh_{el}}$ ($1\mathrm{kWh_{el}}$)	$1\mathrm{kWh_{el}}$ ($1\mathrm{kWh_{el}}$)	$0\mathrm{kWh_{el}}$ ($0\mathrm{kWh_{el}}$)
PV supply	$43\,784 - 50\,286\mathrm{kWh_{el}}$ ($49\,515\mathrm{kWh_{el}}$)	$47\,241 - 54\,256\mathrm{kWh_{el}}$ ($54\,467\mathrm{kWh_{el}}$)	$25\,349 - 29\,113\mathrm{kWh_{el}}$ ($29\,709\mathrm{kWh_{el}}$)
PV self-cons. rate[5]	$58.9 - 65.2\%$ (65.4%)	$58.3 - 64.9\%$ (62.2%)	$72.0 - 78.1\%$ (73.7%)
Self-sufficiency rate[6]	$29.3 - 33.9\%$ (35.0%)	$31.3 - 36.2\%$ (36.5%)	$20.5 - 23.7\%$ (23.7%)
Peak load (ext. grid)	$43 - 60\mathrm{kW_{el}}$ ($45\mathrm{kW_{el}}$)	$44 - 92\mathrm{kW_{el}}$ ($45\mathrm{kW_{el}}$)	$35 - 39\mathrm{kW_{el}}$ ($37\mathrm{kW_{el}}$)
Min. total costs	29 978€ (29 548€)	30 453€ (29 718€)	25 607€ (25 397€)

6 Discussion and limitations

In general, the PV system is economically advantageous for residential quarters in both deterministic and stochastic variants. This result holds under all considered pricing mechanisms. The PV self-consumption rate of $58 - 75\%$ coupled with the self-sufficiency rate of $21 - 36\%$ primarily varies with the size of the PV system. In the REF case, the optimal size does not reach the maximal possible expansion on the roof area as it would be the case in previous years. High feed-in compensation rates had guaranteed a secure financial return. This had incentivised a complete utilisation of the available roof area. Nevertheless, PV systems remain attractive in the household sector with the current compensation and electricity prices. They become more attractive when dynamic pricing is applied and utilise almost the complete roof area. The main reason is that the electricity price is negatively correlated with the PV supply and positively correlated with the residual demand of the quarter. This results in higher costs for electricity at the retail level on average and, hence, a higher value of the PV system for the quarter.

In contrast, the PV system is smaller in the CP case. In this case, the network charges are priced by the peak load of the residential quarter and not included in the per-unit prices. The reduced per-unit price makes the consumption of energy from the external grid more attractive. In general, DES such as residential quarters benefit from capacity pricing of network charges. The load peaks of the living units are strongly balanced within the quarter because of a diversity effect of occurrence. The result is a low peak load per living unit and reduced energy costs.

Thermal storage units are clearly preferred over electrical storage units. The main reason is that the specific investment costs are only $10 - 15\%$ of those for electrical storages. Moreover, an expected higher value of shifting $1\mathrm{kWh_{el}}$ instead of $1\mathrm{kWh_{th}}$ is not competitive

[5] The self-consumption rate is calculated as relation of the PV generation that is consumed within the quarter to the total PV generation over the entire period.
[6] The self-sufficiency rate is calculated as relation of the total PV self-consumption to the total electrical demand of the quarter over the entire period.

with the thermal storage units in combination with heat pumps that provide heat of $3.0 - 3.7\mathrm{kWh_{th}}$ on average while demanding electricity of $1\mathrm{kWh_{el}}$ (Ø $COP_{SH} = 3.7$ and Ø $COP_{DHW} = 3.0$).

The DHW storage size is larger than the SH storage size, because the energy demand for DHW is more or less constant over the year. Consequently, the load flexibility provided by DHW storage units is also distributed more constantly over the year than the flexibility of SH storage units, i.e. DHW storage units provide a noteworthy load flexibility also in times of high PV supply. Hence, larger DHW storage units enable a more cost-efficient opportunity for self-consumption of the PV system and can help enhance PV integration. That is also why the DHW storage units increase when the PV system increases and vice versa. As discussed above, the value of the SH storage units is less in load shifting: Beyond reducing the number of ramp ups, they cover peak demands in winter, when the air-water heat pumps may supply low heat due to cold ambient air temperatures. This requires SH storage units of at least $19\mathrm{kWh_{th}}$ in all cases caused by scenarios with very cold winters.

Electrical storage units only play a minor part in the residential quarter under current (cost) assumptions. Even for the CP case, the annualised capital costs for electrical storage of about $60€/\mathrm{kWh_{el}}$ versus a capacity price of $18€/\mathrm{kW_{el}}$ are still too high. This holds also for a high assumed C-rate of 1. The load flexibility to reduce the peak load comes already from the heat pumps. Moreover, bearing in mind that this paper considers a residential quarter rather than individual households, balancing between the individual households' loads occurs 'automatically' increasing the self-consumption and PV integration.

Furthermore, our results show that for the optimal combinations of flexibility options, the PV self-consumption rate varies between 58% (lower limit of REF/DP) and 75% (upper limit of CP). The self-sufficiency rate varies between 21% (lower limit of CP) and 36% (upper limit of DP). Concerning the levels of self-consumption, our results suggest that power-to-heat with heat storages can make a significant contribution to solar PV integration. The highest levels of self-consumption are achieved under the CP case. The main reason for this finding is obviously the lower PV capacity. However, one could also argue that the CP tariff incentivises investments into PV systems whose generation can be largely self-consumed and thus help avoid stress on the grid. This finding also applies to the consumption of electricity from the grid where the CP case leads to the lowest peak demand among all considered tariffs. Looking at the self-sufficiency levels, this paper finds that consumers in residential quarters as considered in our paper will only need between 64% and 79% of their electricity from the grid. Since our analysis assumes current market prices and conditions, this finding does not describe a future scenario but is an imminent development. While the EU generally supports this development (European Commission, 2016), it is important to understand that it brings about changes and challenges for both electricity retail companies and policy makers. For retail companies, this development means that the volumes that they supplied in the past are expected to decrease which can seriously affect their business. For policy makers, the main challenge is that a decreasing amount of electricity consumption and electricity consumers will need to come up for the costs of the energy system infrastructure, particularly in systems where consumers pay for these costs on a per-unit basis. Consequently, one can expect that the per-unit system charges will increase over time as less and less electricity is extracted from the grid and contributes to paying the same overall pot. This may soon result in a spiral where incentives for self-sufficiency and per-unit charges increase continuously (Bertsch et al., 2017). This brings about distributional implications but is also worrying because of the overall system (in)efficiency. If self-sufficiency of residential quarters is incentivised, this implies that potential efficiency gains from balancing supply and demand over areas of different sizes (using the existing grid infrastructure) are lost.

Capacity-based price components are discussed, among other approaches, to overcome the distributional implications. While this paper finds that the maximum grid load is the lowest for the CP case (reduction of the external grid load by up to 35% in comparison to the REF case) and PV integration is highest, capacity pricing is also criticised for its distributional implications in its own right. This criticism usually points out that small households that have a low overall consumption but may have some demand peaks at few occasions in a year would be affected negatively by capacity pricing. On the other hand, consumers such as those in a residential quarter as considered in this paper would definitively benefit from such a tariff. The load peaks of the individual living units within the quarter can be expected to be well balanced resulting in a low peak load per living unit and reduced energy costs which our findings support.

To set our results into perspective, we compare selected findings to those of the studies referred to in section 2. In general, this proves difficult since each study has a different focus and none of the studies we are aware of are exactly comparable. In particular, literature on interactions between technologies (such as heat pumps and different storage technologies) and retail tariffs (including dynamic pricing and capacity pricing) is rare. Nevertheless, the comparison of some high-level findings is interesting. In terms of the rates of self-consumption of around 27%-74% reported by Jochem et al. (2015), these are in a similar range for the self-consumption in our model despite the source of electricity being PV. With regard to the maximum demand from the electricity grid, this paper finds less variation than Shirazi and Jadid (2017). Across the scenarios, the maximum amount of imported electricity from the grid changes by not more than a factor of 2, while Shirazi and Jadid (2017) find much larger differences between their scenarios. However, it should be noted that their scenarios differ from ours. While the overall framework of McKenna et al. (2017) is also quite different from our study (they specifically look into energy autonomy with regard to the heat and power), it seems worth mentioning that they conclude higher levels of electrical self-sufficiency to be economically feasible: 80% when at least 100 households are aggregated and 65% for 29 households which corresponds with the size of our case study. However, the somewhat higher levels of self-sufficiency can mainly be explained by their consideration of micro-CHP. Hence, the levels of self-sufficiency are not entirely comparable as the micro-CHP plants require a (usually conventional) fuel to produce electricity and heat, which needs to be imported in to the home, quarter or district, which is fundamentally different from electricity produced by PV modules.

Limitations of the model in this paper include that it does not consider the lifetime of the heat pumps which is sometimes additionally restricted by the cycles of ramp-ups. The achieved cycles in our computations of less than $70\,000$ cycles never hit the limitation of $100\,000$ up to $150\,000$ cycles according to the manufacturer information. The same applies to the electrical storage restricted by the cycles of charging and discharging as in Kaschub et al. (2016). They assume $7\,000$ equivalent full cycles with a lifetime of 20 years[7]. Because this limit is not achieved on average, this paper does not implement this constraint in the computations as this would increase the computational effort enormously. Further, this paper considers a temporal consideration of $15\mathrm{min}$ steps. With respect to CP for instance, this could already reduce some peak loads within this time step or the need for load shifting and therefore lead to an underestimation of the storage value. Moreover, although the electricity price module represents the historical spot market prices accurately, changes in the energy market that may affect these prices are not considered such as expansion of RE or phasing-

[7] The equivalent full cycles are based on the specification of 5000 full cycles and are higher, because more cycles can be achieved when the battery is only partially charged and discharged.

out of nuclear power in Germany until 2022. Finally, the employed hill climbing approach as DFO of the investment variables can only guarantee local optimality. However, it reliably, robustly and efficiently proceeds to this optimum within few iterations.

7 Conclusions und outlook

This paper endogenously determines the optimal investment and operation of the energy system components for a residential quarter in Southern Germany. This investment and operation planning is subject to manifold uncertainties with mutual dependences. Therefore, the paper uses a comprehensive module-based framework to consistently model and propagate these uncertainties and their inter-dependencies through the model chain. The paper starts with the generation of meteorological input data scenarios. These are used in a subsequent transformation process to provide the required data for the optimisation module. Finally, a two-stage stochastic mixed-integer linear program evaluates and optimises the energy system components of the quarter, including PV systems, power-to-heat and thermal as well as electrical storages.

In conclusion, PV systems in such residential quarters under the considered tariffs are economically advantageous. The PV self-consumption and self-sufficiency rates primarily vary with the size of the PV system. In terms of the demand side flexibility options for enhanced PV integration, this paper finds that thermal storage units in combination with a power-to-heat application are more beneficial than electrical storage units in such a system. Especially, storage units for domestic hot water are profitable and beneficial because of their low investment needs and an utilisation throughout the year. Storage units for space heating serve more to reduce the risk of not covering the heat demand in cold winters.

In relation to the usage of stochastic programming, this study finds that it reduces the risk of insufficient or even infeasible investments under uncertain future conditions. When optimising the problem deterministically, the PV system tends to be over-dimensioned by about 10%. However, the thermal storage units rather tend to be too small compared to the stochastic solution which results in the possibility of not being able to cover thermal peak demands in cold winters. The minimal costs are always lower in the deterministic program, because the investment is specifically optimal for one scenario of the uncertain parameter. In contrast, the stochastic solution is not optimal for a single scenario but expected to be optimal for all scenarios.

With respect to the aims of the Winter Package of the European Comission, a higher penetration of renewable energies (such as PV) can be achieved by dynamic prices instead of a fixed per-unit price. The main reason is that the energy costs of the quarter under dynamic prices are slightly higher because the market prices at those times where the quarter needs electricity from the grid are higher than the average prices. Times where market prices are below average are often correlated with high PV supply both on the market and in the quarter. Consequently, there is a low or no demand from the quarter to buy electricity at these times of low prices. Moreover, this paper shows that dynamic pricing can strongly increase the peak load without any incentive for reduction whereas capacity pricing reduces the peak load up to 35%. Energy communities such as residential quarters would profit from such a tariff option. In contrast, single households with high peak loads in relation to low energy consumption would be worse off. Also, the expansion of renewable energies (such as PV) might be moderated under capacity pricing, at least with the current electricity retail prices for households.

Future research should focus on analysing more tariff options for decentralised energy systems. In this context, the impact of an increasing self-sufficiency on the grid and on the other participants in the entire energy system should be considered. Especially with regards to the Winter Package and our results, there is a high need for research in distributional fairness in the future and how tariffs might be designed to perform best in terms of social, ecological and economic restrictions and aims.

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