Layout Optimisation of Decentralised Energy Systems Under Uncertainty

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Abstract We present a modelling approach to support the layout optimisation of decentralised energy systems composed of photovoltaic (PV) panels and heat pumps with thermal storage capabilities. The approach integrates the simulation-based generation of model input on the basis of publicly available meteorological data and the subsequent optimisation. Selected results concerning the choice of an appropriate storage size are presented for an illustrative decentralised energy system.

1 Introduction

In the context of the ongoing transformation of the electricity generation system with an emphasis on renewables and low-carbon generation as well as the implementation of smart grid technologies, intelligent home energy management approaches making use of load flexibilities are discussed increasingly often. Especially, photovoltaic (PV) systems in combination with heat pumps and thermal storages have attracted attention in the recent past. The dimensioning of the individual components, such as the storage size, has an immediate impact on the system's economic performance. When modelling such systems using linear programming (LP) techniques, a variety of input data, subject to different sources of uncertainties, needs to be provided. Thus, we present an approach integrating modules for (a) simulating input data, such as solar irradiation or temperature profiles, by a stochastic process, (b) transforming these initial profiles to consistent sets of PV generation and heat demand profiles and (c) using the generated profiles in an optimisation.

This paper is structured as follows: The problem and its LP formulation are described in Sect. 2. In Sect. 3, we present our modelling approach focussing on

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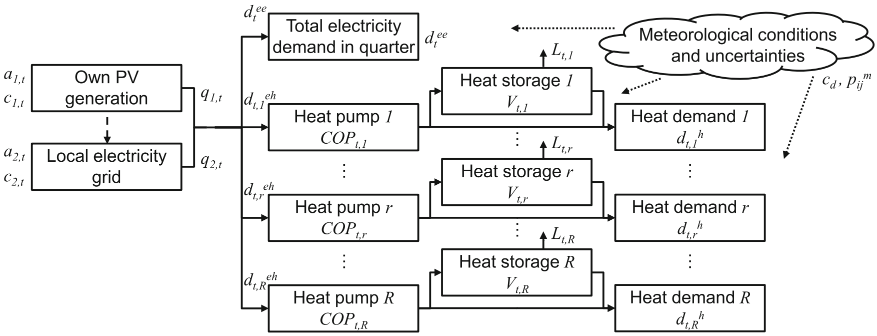

Fig. 1 Illustrative setup of the decentralised energy system

the stochastic simulation modules. Illustrative results are shown in Sect. 4. Finally, Sect. 5 summarises the main findings and indicates needs for further research.

2 Problem Description

Within decentralised energy systems, we focus on a residential quarter including several groups of multi-family or row houses. The setup is illustrated in Fig. 1. The energy is provided by own PV panels or the local grid. Fossil fuels are not used. Energy for room heating and hot water, represented by one heat demand profile per group of houses, is provided by heat pumps and storages for each group. The electricity demand beyond heating and hot water is considered as an aggregated profile for the whole quarter. If the PV generation exceeds the demand within the quarter, it can be fed into the grid. The quantities in Fig. 1 are explained in Table 1. As for (large) energy systems models, the system illustrated in Fig. 1 can be modelled as a classical LP problem. We define the target function as the minimisation of the total system expenses within each year, see (1). The storage size is not modelled as a continuous variable but varied exogenously on a discrete basis according to storages available on the market. Equations (2–5) represent the most important constraints. Equation (2) ensures that the used quantity $q_{f,t}$ of each electricity source does not exceed its availability $a_{f,t}$ at any time t. For the PV generation, $a_{f,t}$ is the fluctuating generation profile. Equation (3) guarantees that demand and supply are balanced at all times t. Subsequently, Eq. (4) represents the storage possibility of heat, i.e. the main flexibility in the system. Constraint (5) ensures that the storage volume can only vary within the given boundaries.

$$\min \sum_t \sum_f q_{f,t} \cdot c_{f,t} \tag{1}$$

Table 1 Nomenclature

Parameters		Variables		Indices	
d_t^{ee}	Electricity demand for electrical usage at time t	$V_{t,r}$	Volume of heat storage of building group r at time t	t	Time index indicating the hour $t \in \{1, \ldots, 8{,}760\}$ of the year
$d_{t,r}^h$	Heat demand of building group r at time t	$d_{t,r}^{eh}$	Used electricity for heating of building group r at time t	f	'Fuel' type index ($f = 1$: el. from PV; $f = 2$: el. from grid)
$a_{f,t}$	Availability of 'fuel' f at time t	$q_{f,t}$	Used quantity of 'fuel' f at time t	r	Index of the R building groups within the quarter: $r \in \{1, \ldots, R\}$
$c_{f,t}$	Costs of 'fuel' f at time t			m	Index $m \in 1, \ldots, 12$ indicating the month
$COP_{t,r}$	COP value of the heat pump of building group r at time t			d	Index indicating the day
$V_r^{\max}/V_r^{\min}$	max/min volume of heat storage of building group r				
$L_{t,r}$	Losses of heat storage of building group r at time t				
R	Amount of building groups within quarter				
Stochastic modelling quantities					
c_d	Random variable for the cloudiness on day d	p_{ij}^m	Transition probability: $p_{ij}^m = p(c_d = j \mid c_{d-1} = i)$		

subject to

$$0 \leq q_{f,t} \leq a_{f,t} \quad \forall t \, \forall f \tag{2}$$

$$\sum_f q_{f,t} = d_t^{ee} + \sum_r d_{t,r}^{eh} \quad \forall t \tag{3}$$

$$COP_{t,r} \cdot d_{t,r}^{eh} + V_{t-1,r} = d_{t,r}^{h} + V_{t,r} + L_{t,r} \quad \forall t \, \forall r \tag{4}$$

$$V_r^{\min} \leq V_{t,r} \leq V_r^{\max} \quad \forall t \, \forall r \tag{5}$$

3 The Developed Approach to Layout Optimisation

In order to solve the optimisation problem described by (1–5), manifold input data is needed. E.g., assumptions on the development of electricity prices ($c_{2,t}$) and profiles for the PV generation ($a_{1,t}$), the electricity (d_t^{ee}) and the heat ($d_{t,r}^{h}$) demand need to be available. However, this input data is subject to many different uncertainties which need to be addressed adequately in the layout planning process. To generate the necessary input data and to account for the associated uncertainties, we propose an integrated approach supporting the generation of consistent ensembles of load and solar PV profiles, i.e. it includes the fundamental relationships between weather and load as well as PV generation. These profiles are used in the subsequent optimisation. Hence, our approach includes three subsystems (see Fig. 2):

- The Weather Simulation Subsystem (WSS)
- The Demand and Supply Subsystem (DSS)
- The Economic Evaluation Subsystem (EES)

3.1 The Weather Simulation Subsystem

The main task of the WSS consists in the generation of solar irradiation and temperature profiles considering their stochastic nature. For the modelling of solar irradiation variations, several authors proposed Markov processes. Focussing on the long-term variations, Amato et al. [1] model daily solar irradiation using a Markov model. Focussing on the short-term variations in a high time resolution, Morf [4] proposes a Markov process aimed at simulating the dynamic behaviour of solar irradiation. However, the input data is often not available in the required granularity. Since our focus is on layout planning, our approach needs to take into account both, the short-term as well as the long-term variations, since both of these may affect the choice of the storage size. Hence, we suggest a two-step approach.

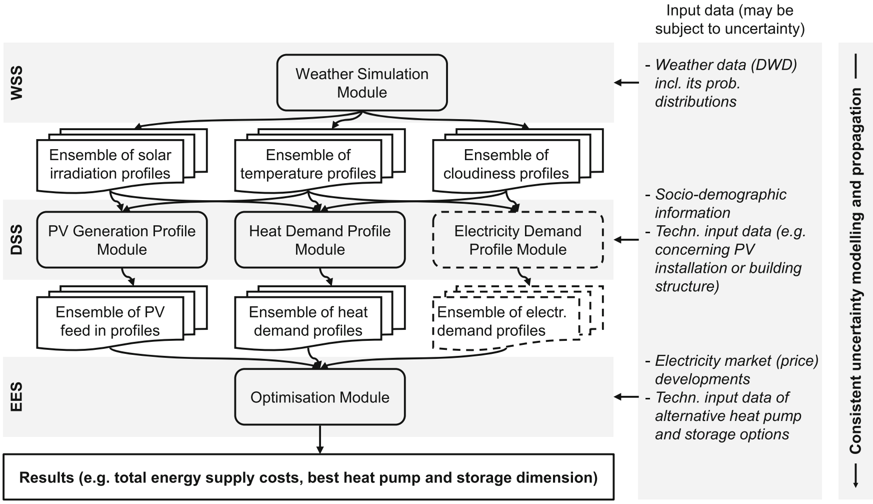

Fig. 2 Conceptual structure of the integrated modelling approach

In the *first step*, we model daily values in order to account for the long-term variations. Having an immediate impact on the heat demand as well as the efficieny of the solar PV panels, we need temperature profiles in addition to the solar irradiation profiles. We therefore go one step back and simulate daily meteorological conditions, particularly the cloudiness, on whose basis the values for daily solar irradiation and average daily temperature are derived under consideration of seasonality information (e.g. the months). In this sense, our approach goes beyond Ehnberg and Bollen [2] who simulate solar irradiation on the basis of cloud observations using a discrete Markov process. However, neither do they use the cloud observations for simulating consistently compatible temperature profiles nor do they introduce a monthly component in their markov process. Besides these differences, our approach is similar to the one proposed by [2]. The daily cloudiness $c_d \in \{0, \ldots, 8\}$ is considered in oktas in our Markov process, describing how many eighths of the sky are covered by clouds [3]. The transition probabilities p_{ij}^m for each month are derived on the basis of publicly available weather data from Germany's National Meteorological Service (DWD), which are available for a variety of locations across Germany for periods of often more than 50 years. Overall, a backtesting of the monthly Markov process shows good results, not only concerning the bandwidth and distribution of the average yearly cloudiness but also concerning the standard deviation of the daily cloudiness values.

In a *second step*, a stochastic process is used to generate hourly profiles on the basis of the daily simulation results of step 1. Besides the results of step 1, the process is based on hourly solar irradiation and temperature data, which was collected for Karlsruhe, Germany, over a period of 4 years. While 4 years would be a short period for understanding long-term variations, this period provides a valuable basis for modelling short-term fluctuations of solar irradiation and temperature.

3.2 The Demand and Supply Subsystem

The DSS's task is the transformation of the meteorological profiles into PV supply and heat demand profiles to be used in the subsequent optimisation. Theoretically, the DSS could also be used to generate electricity demand profiles but since we only consider the electricity demand on the quarter level, i.e. the total demand of approx. 70 households, we use the so-called 'standard load or H0 profile' as our analysis shows a strong convergence of the aggregate household load towards the H0 profile even for numbers of households much lower than 70. For the solar generation, a physical PV model has been developed on the basis of [5]. Concerning the heat load, a reference load profile approach is currently implemented in the DSS. The approach is based on the VDI4655 guideline [6] and uses the temperature profiles as an important input. In the long run, we envisage to replace the reference load approach by a physical model in order to achieve a higher accuracy.

3.3 The Economic Evaluation Subsystem

The ESS uses the profiles processed by the DSS as input and allows for carrying out economic optimisations on the basis of Eqs. (1–5). In the current state, PLEXOS for Power Systems®, a tool for power market modelling and simulation,[1] is used as optimisation module within the ESS. In the long run, we envisage to develop an own optimisation module tailored to the specific needs of our problem.

4 Illustrative Results

Figure 3 illustrates an example of the results, which can be produced by our approach. We applied our approach for meteorological data of Karlsruhe, Germany. The underlying demand and supply profiles correspond to an average meteorological year, the long-term variations are not yet considered. Moreover, a flat electricity tariff of 25 ct/kWh is assumed. It should be noted that already today, more attractive tariffs are available for heat pumps, especially, bearing in mind that not the individual households but the whole quarter of approx. 70 households can negotiate tariffs with the electricity supplier. The absolute IRR values should therefore not be overrated.

[1] See: http://www.energyexemplar.com. We thank Energy Exemplar for the provision of the software and their support.

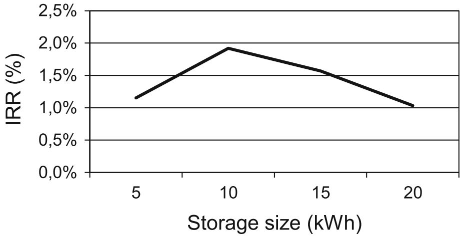

Fig. 3 Internal rate of return (IRR) for different storage sizes (Assumptions: 25 years technical lifetime; approx. 240 EUR additional invest per kWh additional storage capacity)

For a flat electricity tariff, however, a relative comparison shows a maximal IRR for a storage size of 10 kWh in our example.

5 Conclusions and Outlook

An approach to support the layout planning of decentralised energy systems has been presented. The approach has been applied to a residential quarter including approx. 70 households and allows for choosing an appropriate storage size. The approach now provides the basis for further analyses of the economic profitability of such systems as well as service related business models.

Possible enhancements of the approach include the implementation of a physical model to generate heat demand profiles, the development of a tailor-made optimisation module and the increase of the time resolution. Moreover, the uncertainties associated with the input data of the different modules and their impact on the results needs to be analysed and visualised in more detail.

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