Sustainable Cities and Society 23 (2016) 16–22

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Investment planning of residential energy supply systems using dual dynamic programming

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ARTICLE INFO

Article history:
Received 30 November 2015
Received in revised form 16 February 2016
Accepted 18 February 2016
Available online 22 February 2016

Keywords:
Multi-carrier energy systems
Distributed energy systems
Generation planning
Dual dynamic programming
Benders' Decomposition

ABSTRACT

The residential sector contributes significantly to primary energy consumption. Energy efficiency measures in this sector consequently play a key role in the transformation towards a more sustainable energy system. There are a multitude of options available to increase the energy efficiency, e.g. the installation of various electricity and heat supply systems or retrofitting of the building stock. Due to the availability of all these options, the investment planning decision for residential energy supply systems is very complex and requires the support of mathematical optimization methods. However, existing works in this field often use simplifications with regard to the considered portfolio of measures or the considered time resolution in order to maintain computational feasibility. These simplifications lead to sub-optimal or incomplete decisions for residential energy system investments. In this paper, a novel optimization model for the integrated investment and operation planning decision for residential energy supply systems is presented. Instead of using simplifications, the presented model uses a dual dynamic programming approach to reduce computational complexity. Due to this efficient solution strategy, additional decision variables can be integrated into the optimization without meeting computational limits. The functionality and mathematical structure of the decomposition approach are presented and compared to a general mixed-integer linear programming model. An exemplary case study is conducted for both a single family and an apartment building.

1. Introduction

In the structural change of energy supply systems towards more sustainability and higher shares of renewables, the residential sector has to play a key role as it contributes significantly to energy consumption. In the EU-27 countries, it accounts for almost 27% of total energy consumption, which is second to only the transportation sector (Bertoldi, Labanca, & Hirl, 2012). In order to enhance energy efficiency in the residential sector, different measures are available from a technical point of view. These include both retrofitting of the building envelope to reduce heat losses and the application of efficient electricity and heat supply systems. The latter comprises the investment in various microgeneration units (such as combined heat and power (CHP) systems, heat pumps, solar heat or photovoltaic systems) as well as heat and electricity storages. Due to the variety of available energy efficiency measures and the multitude of possible combinations, the task of optimally allocating these measures is very complex (Mancarella, 2014; Allegrini et al., 2015). In order to support decision-making, a model is required which allows to determine the optimal expansion planning.

1.1. Modeling of distributed energy systems

In this context, a number of models for the expansion planning of distributed energy systems have already been developed. Multiple approaches examine the optimal system design of CHP plants, peak load boilers and heat or electricity storage units (e.g. Bracco, Dentici, & Siri, 2013; Alishahi, Hosseini, Maskani, & Shabanian, 2012). Mehleri, Sarimveis, Markatos, and Papageorgiou (2013) presented an optimization model for the design and operation of an energy system in a Greek neighborhood, including PV and CHP units, auxiliary boilers, thermal storage tanks and district heating networks. The concept is continued by Wouters et al., who developed an optimization model for the design and operation of residential distributed energy systems. This model takes a wider range of generation units, storage systems and district heating networks into account (Wouters, Frage, & James, 2014). Similar approaches for the optimal design of distributed energy systems

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http://dx.doi.org/10.1016/j.scs.2016.02.014

Nomenclature

af	annuity factor
c	cost coefficient in EUR/kWh
C^{CAPEX}	capital costs in EUR
C^{OPEX}	operating costs in EUR
C_x	specific costs in EUR/kW or EUR/kWh
C_y	specific costs in EUR/unit
d^{el}	electricity demand in kW
d^{th}	heat demand in kW
E	emissions in t of CO_2 equivalents
r	feed-in-compensation payments in EUR/kWh
t	time
$x^{\mathrm{el,fi}}$	electricity feed-in in kW
$x^{\mathrm{el,sc}}$	electricity self-consumption in kW
x^{el}	electrical power in kW
x^{soc}	state of charge in kWh
x^{th}	thermal power in kW
X	nominal capacity in kW or kWh
Y	Boolean investment variable
T	technology matrix
α	size ratio in m^2/kW
θ	approximation of operating costs in EUR
σ	power to heat ratio
ψ	dissipation factor in %
η	efficiency factor in %
λ	optimal solution of the dual subproblem
γ	weighting factor of different objectives

Subscripts

b	building
i	generation unit/storage system
j	iteration step of Benders' Decomposition
r	retrofitting measure
t	time
pv	photovoltaic
sh	solar heat
grid	electrical grid
els	electrical storage
ths	thermal storage

were previously presented in Weber and Shah (2011), Ren and Gao (2010) and Rieder, Christidis, and Tsatsaronis (2014).

Voll, Klaffke, Hennen, and Bardow (2013) and Voll (2013) promoted an optimization framework for the operation and sizing of distributed energy supply systems based on superstructure-based solution methods. At an urban scale, Jennings, Fisk, and Shah (2014) described the tool RESCOM for the optimization of residential energy systems, incorporating both distributed and centralized generation and demand side technologies. With regard to single buildings, Ashouri, Fux, Benz, and Guzzella (2013) developed an optimization model for the selection and sizing of a smart building system. It includes thermal and electrical storages, various heating and cooling systems as well as different renewable energy sources. In Penna, Prada, Cappelletti, and Gasparella (2015), a model for the optimization of retrofit solutions was proposed, which concentrates on the heat supply. Fabrizio, Corrado, and Filippi (2010) promoted a model for the design and optimization of multi-energy systems for single buildings that uses the energy hub concept as proposed in Geidl (2007). Relying on the same concept, Orehounig, Mavromatidis, Evins, Dorer, and Carmeliet (2014) and Orehounig, Evins, and Dorer (2015) performed an analysis of different energy systems for a neighborhood, including centralized and decentralized renewable sources as well as retrofitting of the building stock.

In Benam, Madani, Alavi, and Ehsan (2015), a stochastic optimization approach was presented in order to determine the number and size of combined heat and power system components, taking into account uncertainties like load forecasting inaccuracies and random outages of the CHP system. Fleten, Maribu, and Wangensteen (2007) considered uncertainties regarding energy prices in the evaluation of investment strategies in distributed energy systems. Zhou et al. (2013) focused on demand and supply uncertainties in a model for the optimal design of distributed energy systems, which was applied to a hotel in Beijing.

The models for the expansion planning of energy systems presented above are typically set up as integrated investment and operation problems, since investment and operation are mutually dependent. A common solution method for these problems is the use of mixed-integer linear programming (MILP) (e.g. Mehleri et al., 2013; Wouters et al., 2014; Weber & Shah, 2011; Ren & Gao, 2010; Rieder et al., 2014; Voll et al., 2013; Voll, 2013). The mathematical formulation induces large problem sizes, as the operation planning requires the definition of individual decision variables for each time step and each potential conversion technology. Furthermore, Boolean variables are necessary in order to represent investment decisions or to linearize non-linear relationships (e.g. investment cost curves).

Due to the resulting mathematical complexity, previous models addressing this topic often use simplifications. A common approach is to reduce the selection of considered generation units. For example, in Bracco et al. (2013), Alishahi et al. (2012) and Voll (2013) the focus is set on CHP plants, peak load boilers and heat or electricity storage. Other approaches include further technologies, e.g. photovoltaic units, conventional furnaces, heat pumps or the application of district heating networks, but neglect thermal insulation measures as an alternative (Mehleri et al., 2013; Wouters et al., 2014; Weber & Shah, 2011; Ren & Gao, 2010; Voll et al., 2013; Voll, 2013).

Another common approach to reduce the computational complexity is to shorten the time period under consideration by using representative time periods or low temporal resolution. Representative periods are specified by a selection of sample days with typical meteorological patterns (Mehleri et al., 2013; Wouters et al., 2014; Weber & Shah, 2011). In this context, Fazlollahi, Bungener, Mandel, Becker, and Maréchal (2014) proposed the use of a *k*-means clustering algorithm to reduce the data set to a limited number of sample periods. However, by applying representative sample periods, time-coupling constraints can only be included within the respective periods. Potential flexibilities between different sample periods cannot be considered. Furthermore, volatilities in demand and feed-in of renewable energies are underestimated, because only a reduced segment of the relevant observation period is taken into account (Mavrotas, Diakoulaki, Florios, & Georgiou, 2008). If an entire year is considered, the temporal resolution is reduced to multiple hours per time step (Rieder et al., 2014). Due to the highly fluctuating feed-in of renewable sources, a high temporal resolution is however necessary in order to correctly determine – inter alia – self-consumption rates of photovoltaic systems.

As an alternative or additional measure to meet the challenges of computational complexity, the overall problem can be decomposed into multiple subproblems. In each subproblem, only a part of the decision variables and constraints is considered. In order to find solutions for the overall problem, an iterative coordination between the subproblems is required. One decomposition approach is the use of metaheuristic optimization algorithms, e.g. evolutionary algorithms as in Penna et al. (2015), Zhou et al. (2013) and Menon, Paolone, and Maréchal (2013). But, particularly for complex problems, such algorithms have the drawbacks of slow convergence and the risk of converging to local optima. Finding the optimal solution is not guaranteed. Therefore, alternative decomposition approaches must be applied.