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A Time-series-based approach for robust design of multi-energy systems with energy storage

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Abstract

This work proposes a mixed-integer linear program approach to consider the uncertainty of input data in the optimal design of distributed multi-energy systems involving both conventional and renewable-based conversion technologies, as well as storage units. The design procedure determines the minimum-cost combination of technology selection, size and operation. Traditionally, distributed multi-energy systems are designed using deterministic optimization methods, implying that the input data are known when the system optimization is performed. However, such input data are commonly affected by significant uncertainty, making the deterministic solution possibly suboptimal or even unfeasible. Recently, both robust and stochastic optimization have been applied to the optimal design of multi-energy systems. Nevertheless, when including energy storage in the analysis, the traditional techniques are complicated by the short- and long-term evolution of the input data of the underlying optimization problem, as well as their complex interactions. Moreover, the analysis of the uncertainties characterizing such input data for the optimal design of multi-energy systems, as well as the evaluation of their impact on the system design, have been investigated in little details. The approach proposed in this work is based on the analysis of the historical time-series representing the input data of the mixed-integer linear program for different years. First, the most important input data in terms of optimality and robustness of the system design are identified. Moreover, the most relevant features of the corresponding time-series are determined and assessed. Then, this information is used to build a custom set of input data which translates into a system design able to guarantee both security of supply and cost optimality.

Keywords: Multi-energy systems, time-series analysis, MILP, stochastic optimization, energy storage

1. Introduction

The necessity of reducing the environmental impact of the current energy system has led to the development and deployment of conversion technologies based on renewable energy sources, storage systems to compensate for the resulting intermittent generation, as well as novel paradigms to design the future energy system, International Energy Agency (2016). Within this framework, distributed multi-energy systems (MES) integrating multiple energy carriers (e.g. electricity, heat, natural gas, hydrogen) with high fractions of renewable energy and storage technologies, are promising options to cope with this challenge, Mancarella (2014). Within the analysis and optimization of MES, mixed integer linear program (MILP) has been particularly favored as optimization framework since it well catches the features of such systems with a reasonable computational complexity, Allegrini et al. (2015).

Traditional MILP approaches for the design of distributed multi-energy systems use deterministic optimization, implying that the boundary conditions of the optimization problem, i.e. weather conditions, energy prices and demands, are known with certainty when the optimization is performed, e.g. Weber and Shah (2011); Gabrielli et al. (2017a). However, the aforementioned input data are commonly affected by considerable uncertainty, making the deterministic solution possibly suboptimal or even infeasible, Ben-Tal et al. (2009). Recently, robust and stochastic MILP methods have been proposed to tackle the data uncertainty so as to guarantee the feasibility of the solution, which translates into security of energy supply under different operating conditions. In fact, both approaches have been investigated in literature. During his thesis, Mavromatidis (2017) investigated the optimal design of distributed urban energy systems under uncertainty. He compared a stochastic formulation, the traditional robust formulation by Soyster (1973), the robust optimization with uncertainty budget proposed by Bertsimas and Sim (2004), and the affinely adjustable robust optimization introduced by Ben-Tal et al. (2004). Another approach was proposed by Majewski et al. (2017), who proposed a two-stage robust optimization considering at the same time the average and the worst-case scenarios and applied it to the optimal design of an industrial park. They found that robustness and optimality are not mutually exclusive, as the the robust design itself is not more expensive, but the cost of the system increases only when worst-case operation occurs. Furthermore, Billionnet et al. (2016) have considered the design of a stand-alone energy system under uncertainty pertaining to both energy demands and solar and wind generation, whereas Zatti et al. (2017) proposed a three-stage stochastic integer programming model accounting for the uncertainty in the short-term forecast, the day-ahead electricity bidding, the day-ahead scheduling of large power plants and the possibility of real-time scheduling adjustment of flexible energy systems (through integer recourse). Despite these previous works, the analysis of the uncertainties characterizing the boundary conditions for the optimal design of distributed multi-energy systems, as well as the evaluation of their impact on the system design, have been investigated in little details. Moreover, when considering energy storage, traditional robust and stochastic optimization techniques are further complicated by the short- and long-term evolution of the input data, as well as their interactions. Indeed, large optimization problems can result from stochastic optimization due to the creation of a large number of scenarios, or from robust optimization due to the adoption of large uncertainty sets. Here, a three-stage procedure is developed based on the analysis of the historical time-series of the input data of a MILP problem aimed at determining the optimal combination of technology selection, size and operation in terms of total annual cost of the system. First, the optimal deterministic system design is determined for several sets of input data from different years. Next, each of the resulting designs, corresponding to a given year, is tested by operating it for all the other years. Within this phase, every design is evaluated in terms of cost optimality and robustness. Finally, the most relevant inputs, as well the most important features of the time-series, are identified and assessed to build a custom year which ensures both cost optimality and robustness. A Swiss case-study is considered.

2. Problem formulation and system description

The multi-energy system (MES) considered in this study has the primary scope of supplying electricity and heat to a defined user. The MES is connected to the electrical grid and is composed of a set of conversion and storage technologies. A deterministic MILP is formulated to determine the optimal system design. It can be written in the general form as

$$
\begin{aligned}
&\min_{\mathbf{x},\mathbf{y}} \left(\mathbf{c}^T\mathbf{x}+\mathbf{d}^T\mathbf{y}\right)\\
&\text{s.t.}\\
&\mathbf{A}\mathbf{x}+\mathbf{B}\mathbf{y}=\mathbf{b}\\
&\mathbf{x}\geq\mathbf{0}\in\mathbb{R}^{N_x},\mathbf{y}\in\{0,1\}^{N_y}.
\end{aligned}
\tag{1}
$$

Inputs to the optimization problem are the (i) electricity price, (ii) end-users energy demands, (iii) weather conditions (ambient temperature and solar radiation), and (iv) set of available technologies with the corresponding performance and cost coefficients. Outputs of the optimization problem are the design and operation strategy which yield to the minimum total annual cost. In particular, the following decision variables are returned: (i) the size of the installed technologies, (ii) the scheduling (on/off) status of the conversion units, (iii) the input/output energy of both conversion and storage technologies, (iv) the amount of energy in the storage units, (v) the imported/exported energy from/to the electricity grid. The objective function of the optimization problem is the total annual cost of the system, given by the sum of capital, operation and maintenance contributions. The constraints of the optimization problem include the (i) energy balances within the multi-energy system, and (ii) performance of conversion and storage technologies. The former require that the sum of imported and generated power equals the sum of exported and used power for all the involved energy carriers. The latter describe the behavior of the conversion and storage units. Affine and piecewise affine descriptions of conversion and storage technologies are implemented to correlate the output power to the input power and to the unit size, as indicated in Gabrielli et al. (2018). The optimization framework implements the time-series aggregation method M2 introduced by Gabrielli et al. (2017b) to consider the entire year with hour resolution as the time horizon at reduced computation complexity. Overall, a detailed description of the optimization framework can be found in Gabrielli et al. (2017b).

2.1. Modeling the uncertainty

The input data (i)-(iii) are time-dependent profiles for one year with hourly resolution, based on historical realizations for a neighborhood in Zurich, Switzerland. Such input data are calculated and discussed by Murray et al. (2017). The proposed design approach is based on the following three-stage procedure:

- First, the MILP discussed above, given by Eq. 1, is applied to obtain the optimal deterministic design for the aforementioned multi-energy system for different sets of input data describing different years.
- Next, each of the resulting designs is tested by operating it on all the other years. At this stage, every design is evaluated in terms of cost optimality and robustness. In specific, an optimality index O is introduced for every year i:

  $$O_i = \frac{1}{N}\left(\sum_{j=1}^{N}\frac{c_{jj}}{c_{ij}}\right) \tag{2}$$

  where N is the number of considered years and $c_{i,j}$ the total annual cost (in /yr) obtained by operating on year j the design determined with year i. Similarly, a robustness index R is introduced for every year i:

  $$R_i = 1-\frac{1}{v_{\max}N}\left(\sum_{j=1}^{N}v_{ij}\right) \tag{3}$$

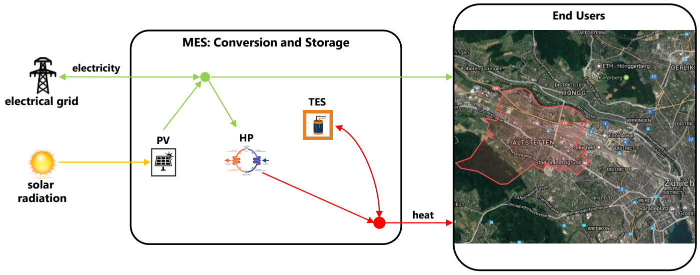

Figure 1: Schematic representation of the investigated multi-energy system.

where v_{ij} is the thermal demand not delivered (in kWh/yr) when operating on year j the design determined by using year i and $v_{\max}$ is the maximum registered violation. Note that the decision of defining the robustness index based on the thermal demand (instead of the electrical or the total demand) stems from the consideration that, in this work, the electrical demand can always be satisfied by purchasing electricity from the grid.

- Finally, the most relevant inputs, as well the most important features of the time-series, are identified and assessed to build custom years ensuring both cost optimality and robustness at design level.

2.2. Case study

The proposed methodology is applied to the simple multi-energy system illustrated in Fig. 1, composed of photovoltaic (PV) panels, electricity-driven heat pump (HP), and hot water sensible thermal storage (TES). The system is connected to the electricity grid and provides electricity and heat to a neighborhood requiring a peak electrical and thermal demands of 0.42 MW and 2.01 MW, respectively. Here, we consider a single energy hub that satisfies the heat and electricity demands; therefore, the energy is converted and stored in a central node and then delivered to the buildings (see Gabrielli et al. (2017b)). Moreover, a constraint of 260 ton/yr is imposed on the maximum amount of CO_2 emissions. Such constraint corresponds to a 50% emission reduction with respect to the worst possible value for all the years. Such a limit is imposed to force the installation of PV panels, so to account for the solar radiation within the analysis.

3. Results

Some preliminary results are presented in this section, by using four different years including extreme high weather conditions (ambient temperature and solar radiation), extreme low weather conditions, and average weather conditions for two different years. Figure 2 shows the robustness-optimality Pareto front for the investigated years, where the color code indicates either the total electrical and thermal annual demand (left-hand side) or the 5-day peak thermal demand (right-hand side). The 5-day peak thermal demand is the largest thermal demand during a sequence of five days for all the considered years (integral value). For the considered pool of years, the analysis suggests that this is a good indicator of the robustness of the system design. Similarly, the total electrical and thermal annual demand is found to be a good indicator of the system optimality. Indeed, the left-hand side of Fig. 2 shows that an increase in optimality is observed when decreasing the total annual demand. Thus, the year 1 is the most optimal year, but the least robust one. Moreover, the right-hand side of the figure shows that an increase in robustness is observed when increasing the 5-day peak thermal demand. Therefore, the year 4 is the most robust year, but the

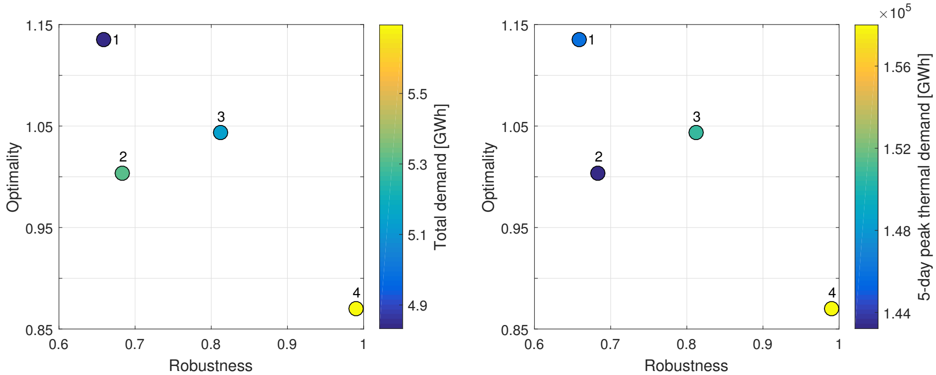

Figure 2: Robustness-optimality Pareto front for the four considered years. The color code indicates the total electrical and thermal annual demand (left) and the 5-day peak thermal demand (right).

least optimal one. The years 2 and 3 are located in the middle of the robustness-optimality plane, with year 2 being dominated by year 3.

Following these considerations, a custom year is built by replacing the five days of year 4 where the peak thermal demand occurs within the year 1, characterized by the lowest total demand. Such a custom year is reported on the robustness-optimality Pareto front in Fig. 3. One can note that the custom year improves the optimality by about 15% while reducing the robustness of only 0.7%. This suggests that starting from favorable conditions and adding an extreme event translates into an optimal and robust system design. Note that, in addition to providing a method to increase optimality and robustness at the same time, a quantitative evaluation of indicative extreme events can provide relevant insights (i) from a robust optimization perspective, e.g. indications for choosing suitable uncertainty sets; (ii) in terms of most suited clustering features for modeling the time horizon. Indeed, the investigated application highlights the necessity of detecting sequences of day, in this case a five-day sequence of high thermal demand, when applying clustering techniques

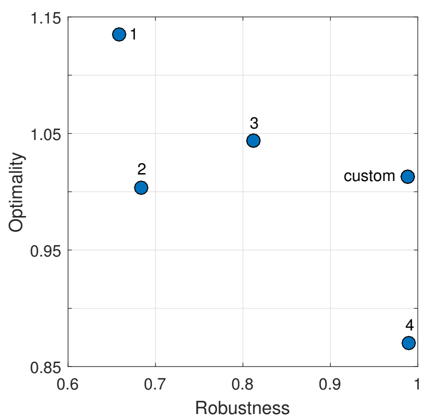

Figure 3: Robustness-optimality Pareto front for the four considered years and the custom year built by combining the total demand of year 1 and the 5-day peak thermal demand of year 4.

on the time horizon.

4. Conclusions

This work proposes a MILP approach to consider the uncertainty of the input data in the optimal design of distributed multi-energy systems involving both conventional and renewable-based conversion technologies, as well as storage units. A three-stage procedure is developed, based on the analysis of the historical time-series of the input data characterizing the underlying optimization problem. First, the optimal deterministic system design is determined for several sets of input data describing different years. Next, each of the resulting designs, corresponding to a given year, is tested by operating it on all the other years. Within this phase, every design is evaluated in terms of cost optimality and robustness. Finally, the most relevant inputs, as well the most important features of the time-series, are identified and assessed to build a custom year ensuring both cost optimality and robustness of the design. Findings show that the total electrical and thermal annual demand is an important indicator of the system optimality, whereas a five-day sequence of peak thermal demand is found to be a good indicator of the system robustness. A custom year built by accounting for both these features is found to ensure optimality and robustness at the same time.

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