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Optimal design of multi-energy systems with seasonal storage

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HIGHLIGHTS

- Novel MILP approaches to enable design of MES including seasonal energy storage.
- Good accuracy and much lower computational complexity compared to current approaches.
- Realistic Swiss case-study evaluated in terms of total annual cost and emissions.
- Extensive sensitivity analysis defining design guidelines for seasonal energy storage.

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ABSTRACT

Optimal design and operation of multi-energy systems involving seasonal energy storage are often hindered by the complexity of the optimization problem. Indeed, the description of seasonal cycles requires a year-long time horizon, while the system operation calls for hourly resolution; this turns into a large number of decision variables, including binary variables, when large systems are analyzed. This work presents novel mixed integer linear program methodologies that allow considering a year time horizon with hour resolution while significantly reducing the complexity of the optimization problem. First, the validity of the proposed techniques is tested by considering a simple system that can be solved in a reasonable computational time without resorting to design days. Findings show that the results of the proposed approaches are in good agreement with the full-scale optimization, thus allowing to correctly size the energy storage and to operate the system with a long-term policy, while significantly simplifying the optimization problem. Furthermore, the developed methodology is adopted to design a multi-energy system based on a neighborhood in Zurich, Switzerland, which is optimized in terms of total annual costs and carbon dioxide emissions. Finally the system behavior is revealed by performing a sensitivity analysis on different features of the energy system and by looking at the topology of the energy hub along the Pareto sets.

1. Introduction

Recently, the energy sector has been riding a wave of grand transformation: the necessity of decreasing the environmental impact has led to the deployment of conversion and storage technologies based on renewable energy sources [1]. In this context, multi-energy systems (MES) represent a new paradigm which exploits the interaction between various energy carriers (e.g. electricity and heat) at design and operation phase, allowing for improved technical, economic and environmental performance of the system [2]. Within this framework, seasonal storage systems have recently caught much attention due to their ability to compensate the seasonal intermittency of renewable energy sources [3]. However, compensating renewables fluctuations at the seasonal scale is particularly challenging: on the one hand, a few systems, such as hydrogen storage and large thermal storage, allow offsetting seasonal variations in renewable energy generation; on the other hand, the optimal design and operation is complicated by the large number of decision variables, due to the required length and resolution of the time horizon.

Several works provide comprehensive reviews of the model formulations and computer tools adopted for investigating MES and their integration with renewable energy sources and storage technologies. For instance, Alarcon-Rodriguez et al. focused on the multi-objective planning of distributed energy resources [4]; Connolly et al. presented a review of the computer tools implemented for analyzing the integration of renewable energy into various energy systems [5], whereas Keirstead

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Nomenclature

A	available area for solar installation (m^2)
a	binary variable for technology selection (–)
b	binary variable for technology selection (–)
D	number of design days (–)
d	design day index
E	stored energy (kWh)
e	annual CO_2 emission (ton_{CO_2}/yr)
F	input power (kW)
I	solar radiation (kWh/m^2)
i	technology index
J	annual cost (€/yr)
j	carrier index
K	length of the time horizon (hour of the day)
k	time index (hour of the day)
L	user demand (kW)
$\mathscr{M}$	set of available technologies
M	number of available technologies (–)
$\mathscr{N}$	set of available carriers
P	output power (kW)
Q	thermal output power (kW)
S	technology size (kW)
T	length of the time horizon (hour of the year)
t	time index (hour of the year)
U	import power (kW)
u	import price (€/kWh)
V	export power (kW)
v	export price (€/kWh)
w	binary variable for capital cost calculation (–)
x	binary variable for on/off status (–)
Y	length of the time horizon (day of the year)
y	time index (day of the year)

Greek letters

α	efficiency coefficient (–)
β	efficiency coefficient (–)
γ	efficiency coefficient (kW)
Δ	time variation (h)
δ	size coefficient (–)
ε	specific emission coefficient (ton_{CO_2}/kWh)
ζ	size coefficient (kW)
η	conversion or storage efficiency (–)
Θ	air temperature (°C)
θ	cost coefficient (–)
κ	size coefficient (–)
Λ	storage loss coefficient (h^{-1})
λ	cost coefficient (–)
μ	cost coefficient (€)
ν	size coefficient (kW)
Π	storage loss coefficient (–)
ρ	first principle-to-electrical efficiency ratio (–)
σ	sequence of design days along the year (–)
τ	storage charging/discharging time (h)

Subscripts

A	subset of technologies
B	subset of technologies
c	capital cost
e	electricity
g	natural gas
h	heat
m	maintenance cost
o	operation cost
S	subset of technologies

Superscripts

A	subset of decision variables
B	subset of decision variables
int	intermediate
max	maximum
min	minimum

Acronym

COP	coefficient of performance
CS	conventional scenario
edHP	electricity-driven heat pump
FC	fuel cell
FSO	full scale optimization
HS	hydrogen storage
HWTS	hot water sensible thermal storage
LiB	lithium battery
M0	method 0
M1	method 1
M2	method 2
MES	multi-energy system
MGT	micro gas turbine
MILP	mixed integer linear program
NG	natural gas
PEME	proton exchange membrane electrolyzer
PEMFC	proton exchange membrane fuel cell
PtG	power to gas
PV	photovoltaic
PWA	piecewise affine
SOFC	solid oxide fuel cell
TS	thermal solar

et al. [6] and Allegrini et al. [7] focused on urban energy system models; Mancarella provided an overview of concepts and models for the planning and analysis of multi-energy systems [2]. When storage technologies are available, the optimal design of MES is significantly complicated by the necessity to consider the system operation already at design phase to accurately make use of the storage systems. Although a few nonlinear approaches have been proposed, for instance by Elsido et al. [8], mixed-integer linear programming (MILP) has been particularly favored as optimization framework for MES design and operation since it catches well the features of the system with a reasonable computational complexity. The problem of optimal technology selection and unit commitment through MILP formulation has been extensively investigated in the past. For example, Marnay et al. presented the case of a commercial building micro-grid with heat and electrical storage [9]; Hawkes and Leach extended the study by considering a hospital and residential buildings [10]. Later, Angrisani et al. investigated the energy, economic, and environmental performance of micro tri-generation systems [11]. Fazlollahi et al. introduced methods for multi-objective design of complex energy systems [12], and Ahmadi et al. presented the thermodynamic modeling and multi-objective optimization of an energy system for the simultaneous generation of electricity, heating, cooling and hot water [13]. Whereas these works were mainly focused on small, yet centralized systems (i.e. one hub for different end users), a number of studies also investigated energy distribution among the different nodes of decentralized energy systems (i.e. multiple hubs for different end users). For example, Genon et al.