ARTICLE IN PRESS

Applied Energy xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

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

A holarchic approach for multi-scale distributed energy system optimisation

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HIGHLIGHTS

- Comparison of MILP formulations for optimal system design and operating strategy.
- Environomic multi-scale distributed energy system optimisation.
- Aggregation schema to enable optimisation of urban energy systems at large scale.
- New modelling formulations reducing computational time while preserving accuracy.
- District heating networks allow a decrease of system's costs and environmental impact.

ARTICLE INFO

Keywords:
Urban energy system
Density-based clustering
Multi-scale modelling
Aggregation method
Energy hub
Multi-objective optimisation

ABSTRACT

The benefits of decentralised energy systems can be realised through the optimal siting of distributed energy systems and the design of highly interlinked district heating networks within existing electrical and gas networks. The problem is often formulated as a Mixed Integer Linear Programming (MILP) problem. MILP formulations are efficient and reliable, however the computational burden increases drastically with the number of integer variables, making detailed optimisation infeasible at large urban scales. To tackle complex problems at large scale the development of an efficient and robust simplification method is required. This paper presents an aggregation schema to facilitate the optimisation of urban energy systems at city scale.

Currently, spatial and/or temporal aggregation are commonly employed when modelling energy systems at spatio-temporal resolutions from plant scheduling up to national scenarios. This paper argues for solving different scales separately using a bottom-up approach, while keeping track of the error made by reducing the resolution when moving from building to urban scale. Novel modelling formulations and optimisation techniques are presented. They enable drastic reduction of the computational time (by up to a factor of 100) required to find an optimal solution in reasonable time without sacrificing the quality of the results (no more than 1% loss in accuracy).

A density-based clustering algorithm enables intelligent division of a large city-scale problem into sub-optimisation problems by creating clusters of different density. In each cluster, the trade-off between centralised and decentralised energy systems and the associated district heating network design is evaluated. A solution is selected based on a local optimisation of the network costs. Demand profiles of each building are assigned appropriately, then at an upper level the energy optimisation problem is solved considering the network losses at lower levels. This method enables large-scale modelling of urban energy systems while taking into account building-scale levels of detail. The clustering method enables assessment of the potential of district heating networks on city scale based on building characteristics and available urban energy systems.

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http://dx.doi.org/10.1016/j.apenergy.2017.09.057
Received 16 May 2017; Received in revised form 15 August 2017; Accepted 10 September 2017
0306-2619/

Please cite this article as: Marquant, J.F., Applied Energy (2017), http://dx.doi.org/10.1016/j.apenergy.2017.09.057

Nomenclature

CHP	combined heat and power
CRF	Capital Recovery Factor
DB	Davies-Bouldin index
DES	distributed energy systems
DH	district heating
DHN	district heating network
EAC	equivalent annual cost
ELDC	error load duration curve
LP	linear programming problem
MILP	Mixed Integer Linear Programming problem
MOO	multi-objective optimisation
MST	Minimal Spanning Tree algorithm
NPV	net present value
OPTICS	Ordering Points To Identify the Clustering Structure
PV	photovoltaic solar panel
PVF	present value factor
RH	rolling horizon
TS	thermal storage
TSP	Travelling Salesman Problem

Greek symbols

δ	binary variable
η	efficiency technology
Θ	coupling matrix with efficiency per technology

Roman symbols

A	storage efficiency
C_{supply}	energy resource cost [CHF/kW]
$Carb_{em}$	carbon dioxide emissions per resource [kg/kWh]
$Corr$	correlation
E	state of charge of storage [kWh]
e	energy hub entity
	homogeneity index
HL	heat losses
HP	heat to power ratio
I	investment cost [CHF]
k	number of typical days
L	loads or energy demand [kWh]
LC	linear investment cost [CHF/kW]
M	sufficiently large value
N_e	number of hubs
n_s	storage energy dissipation
N_{cl_i}	number of buildings within a cluster
O	order of each hub
OC	operating cost [CHF]
P^{max}	capacity technology [kW]
$P_{tech,t}$	output of technology *tech* at timestep *t* [kWh]
Q	heat flux [kWh]
xi	density drop

Subscripts

$+$	discharging storage
$-$	charging storage
cl_i	clusters
i,j	buildings, hubs
j,k	members of a cluster
t	timestep [h]
$tech$	technologies available

1. Introduction

1.1. Towards an energy transition

Renewable energy and energy efficiency are two out of the four main routes (energy efficiency, renewable energy, nuclear energy, and carbon capture and storage) set by the European Commission in its 2011 Energy Roadmap, in General Secretariat of the Council [1], for a more sustainable and energy secure future [2,3]. Following Paris COP21, the Lima-Paris Action Agenda, LPAA [4], attempts to ensure that actions will be taken to mitigate global warming and remain on a 2 degree pathway. The LPAA promotes the deployment of renewable energy and more efficient generation systems using a wide variety of different technologies to decarbonise supply.

With recent increases in the share of renewable energy and the proliferation of small-scale systems (ranging from less than 1 kW to tens of MW, Ren and Gao [5]), there is a shift from centralised to more distributed energy systems structures [6]. Combined with a smart grid approach, where consumers become prosumers, the benefits of distributed energy systems include an increase in overall energy efficiency through more optimal system operation, a decrease in transport losses through avoidance of system installations in remote locations, and minimisation of investor risk through greater modularity [7–10]. However, it is not always clear where distributed energy systems prevail over centralised energy systems, which can benefit from economies of scale and pre-existing networks, as highlighted in Bouffard and Kirschen [7].

In the context of an increasing number of interconnected networks and technology combinations, urban planners and decisions makers will have to assess the potential of many interlinked technologies. In order to evaluate the benefits of integrating more efficient and low carbon systems and quantify the need for expansion and/or modification of the current energy networks, it is important to analyse the trade-off between centralised and decentralised energy systems under different conditions. This is only possible if enough detail is retained (e.g. on energy loads and supply technologies, in particular their temporal and spatial distribution) in the formulation of the optimisation problem. Thus, it is of prime importance to enable large-scale optimisation of urban energy systems while preserving a high level of resolution at the building level. The goal of this paper is to present a methodology which enables efficient and effective identification of the trade-off between centralised or decentralised energy systems, as well as analysis of the parameters driving the design solution in terms of key environmental and economic metrics.

1.2. Research in energy optimisation

The focus here is primarily on energy supply options, where models generally determine supply-side parameters related to design and operation to satisfy defined loads. Researchers dealing with the optimisation of supply systems use a range of techniques, as reviewed by Keirstead et al. [11]. The most common are Linear Programming (LP) beginning with the MARKAL model in Fishbone and Abilock [12] and continued in multiple publications, e.g. Kong et al. [13], Makkonen and Lahdelma [14], Ren et al. [15] and Mixed Integer Linear Programming (MILP) e.g. Dimitriadis et al. [16], Gustafsson [17], Yokoyama et al. [18], Hiremath et al. [19], Sugihara et al. [20], Chinese [21], Lozano et al. [22], Casisi et al. [23], Li et al. [24], Keirstead et al. [25], Mehleri et al. [26], Fazlollahi and Marchal [27], Pruitt et al. [28], Omu et al. [29], Uhlemair et al. [30], Pantaleo et al. [31], Bischi et al. [32], Marquant et al. [33], Moreno et al. [34], Silvente et al. [35], Morvaj et al. [36]. Recently numerous holistic methods have been developed to