Energy 156 (2018) 73–83

Contents lists available at ScienceDirect

Energy

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

A new combined clustering method to Analyse the potential of district heating networks at large-scale

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ARTICLE INFO

Article history:
Available online 7 May 2018

Keywords:
Combined clustering
Energy hubs
Distributed energy systems
Genetic algorithm
MILP energy optimisation

ABSTRACT

For effective integration of large amounts of renewables and high-efficiency energy technologies, their benefits have to be quantified. Network-level energy optimisation approaches can determine the optimal location of generation technologies within a region and the optimal layout of energy distribution networks to link them. Mixed-integer linear programming (MILP) formulations are generally employed and this is often a burden for large scale models as the computational time drastically increases with the problem size.

Most methods used to reduce the complexity of MILP problems focus on the temporal scale or use aggregated demand profiles for the spatial dimension. There is a lack of a method addressing the spatial complexity to assess the potential of interlinked energy networks at large scale. Therefore, this paper introduces a new combined clustering schema enabling quantification of the potential of district heating networks based on results from building scale energy optimisation problems and taking into account building characteristics.

A city-scale case is divided into multiple districts based on the output of a density based clustering algorithm. The parameters taken into account by the clustering method are the cluster density, homogeneity index and load magnitude. The analysis of the clustering map along with building characteristics of each cluster reveals the required characteristics for the installation of a district heating network or distributed energy systems.

1. Introduction

The COP21 conference in Paris 2015 aimed to maintain below 2 °C the rise of global temperature above pre-industrial levels, fixing a target of 1.5 °C [1]. This is ensured by the ratification of "Paris Agreement" protocol by 55 Parties responsible for at least an estimated 55% of global greenhouse gas emissions (GHG) [2]. Mitigating climate change by lowering GHG emissions from energy systems while still providing a desired level of services is possible when considering the vast range of renewable and highly efficient energy technologies available today [3]. However, the transition towards low carbon energy systems needs to be effective. This can be achieved by quantifying the needs for the creation, expansion or modification of energy networks in order to adequately integrate renewables and high-efficiency energy converters.

This paper first presents the challenge researchers face when dealing with large scale optimisation of distributed energy systems (DES) and the solution obtained by using clustering techniques in order to reduce the problem complexity. The methodology employed in Ref. [4] to facilitate large scale modelling of DES in a bottom-up approach is presented in the next section, followed by a section introducing a new combined clustering method based on building characteristics. The clustering method developed is employed with the bottom-up framework in an iterative process involving an evolutionary approach to converge toward an optimal solution. An application to a case study assesses the computational benefits of the developed framework in handling a large-scale

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https://doi.org/10.1016/j.energy.2018.05.027
0360-5442/

Nomenclature

CHP	combined heat and power
COP	conference of the parties
CRF	capital recovery factor, calculated with a discount rate of 3% [−]
DB	Davies-Bouldin index
DES	distributed energy systems
DHN	district heating network
EAC	equivalent annual cost
ELDC	error in the load duration curve
LP	linear programming problem
MILP	mixed integer linear programming problem
MST	minimum spanning tree algorithm
NPV	net present value
OPTICS	ordering points to identify the clustering structure
PV	photovoltaic solar panel
REH	receding horizon
RH	rolling horizon
TS	thermal storage
TSP	travelling salesman problem

Greek symbols

α	weight coefficient multiplying normalised density index
β	weight coefficient multiplying normalised and reversed homogeneity index
γ	weight coefficient multiplying normalised load magnitude index
δ	binary variable
η	efficiency technology
Θ_{m}	efficiency matrix coupling energy supply and energy demand of an energy hub, [−]

Roman symbols

A	storage system charging (−) or discharging (+) efficiency, [−]
B	big M constraint to reduce computational time, B is an arbitrary large number, [−]
C^{supply}	cost of energy resources used per technology, [CHF/kW]
C^{linear}	linear cost per technology, [CHF/kW]
$Carb^{em}$	linear carbon emissions per energy stream, [kgCO_2/kW]
CRF	Capital Recovery Factor, calculated with a discount rate of 3% [−]
E	energy storage term, [kWh]
HL	heat losses proportional to the distance and heat transfer between two energy hubs, [%]
I_{tech}	investment cost per technology, [CHF]
L	energy hub loads, [kW]
N	energy dissipation, self-losses of an energy storage system, [−]
OC_{tech}	operating costs per technology, [CHF]
P^{max}_{tech}	design variable on size of a given technology, [kW]
Q	energy exchange between two energy hubs [kWh]
$M_j^{cl_x}$	j-th member of cluster x, [−]
N_{cl_x}	number of members within cluster x, [−]
N_e	number of energy hub e, [−]

Subscripts

$+$	discharging storage
$-$	charging storage
cl_x	cluster x
e	energy hub e
j	j-th member of cluster x
t	time step [hour]
$tech$	technology available

optimisation problem while conserving a building level of detail on the energy model.

Finally, the parameters intrinsic to the clustering algorithm are highlighted and their importance is quantified. The case study reveals that the density, qualifying how distant buildings are from each other, and the heterogeneity in the scheduling of the energy consumption, are both important parameters which have to be considered. Conversely the loads magnitude indicator, representing how large a consumer is, appears to be of relatively minor significance for the design of district heating networks (DHN). An extension of this work will apply the method to multiple case studies to deduce the characteristics driving the requirements for the deployment of DHN.

1.1. Distributed energy systems optimisation

Evaluating the potential savings available by combining multiple energy sources and carriers is an energy optimisation problem, assessing the trade-off between centralised and/or distributed energy system infrastructures for the supply of energy at different scales. Such problems dealing with the design and/or operations scheduling of single or multiple energy systems are often formulated as Linear Programming (LP) [5–8] or Mixed-Integer Linear Programming (MILP) in the literature [6,9–20]. Researchers are today moving from the single plant optimisation problem [7,21], (current practice of centralised energy system for energy supply) towards the distributed energy systems (DES) optimisation problem where multiple energy converters and carriers can be installed and operated together. In this new context of multi-energy systems, finding the optimal design and operating strategy to increase the overall energy efficiency of a system is not straightforward. The benefit of decentralised energy systems (increase of overall efficiency, decrease of transport losses and risk minimisation [22,23]) versus the benefits of centralised systems (economies of scale already existing networks) has to be carefully evaluated [24].

Tools incorporating large scale optimisation problems have been developed in the past, MARKAL [5], TIMES [25], and more recently Calliope [26]; however aggregation schemas are often employed at the spatial and temporal scale to reduce the computational burden. While the first two tools only consider LP problem, Calliope allows MILP problems by enabling technology specific constraints, as purchase costs for technologies (represented as global integer variables) or on/off constraints (adding binary variables at every time step) employed with a Big-M formulation [27].

1.2. Clustering methods enabling large scale energy optimisation

Considering multiple energy systems in a MILP problem becomes computationally demanding in terms of solving time when increasing the problem space by augmenting the number of integer variables (exponential increases of the solving time [9]). This is often the case when adding specific constraints on technologies (minimum part-loads, banded efficiencies and/or costs), or when