

A holarchic approach for multi-scale distributed energy system optimisation

Journal Article**Author(s):**

Marquant, Julien F.; Evins, Ralph; Bollinger, L. Andrew; Carmeliet, Jan

Publication date:

2017-12-15

Permanent link:

<https://doi.org/10.3929/ethz-b-000237821>

Rights / license:

In Copyright - Non-Commercial Use Permitted

Originally published in:

Applied Energy 208, <https://doi.org/10.1016/j.apenergy.2017.09.057>

A holarchic approach for multi-scale distributed energy system optimisation

Julien F. Marquant^{a,b,*}, Ralph Evins^{a,c}, L. Andrew Bollinger^a, Jan Carmeliet^{b,d}

^aLaboratory for Urban Energy Systems, Swiss Federal Laboratories for Materials Science and Technology, EMPA, Dübendorf, Switzerland

^bChair of Building Physics, Swiss Federal Institute of Technology, ETH Zürich, Switzerland

^cDepartment of Civil Engineering, University of Victoria, 3800 Finnerty Road, Victoria, BC, Canada

^dLaboratory for Multiscale Studies in Building Physics, Swiss Federal Laboratories for Materials Science and Technology, EMPA, Dübendorf, Switzerland

Abstract

The benefits of decentralized 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 centralized and decentralized 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.

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

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 (2011), for a more sustainable and energy secure future (da Graça Carvalho (2012) and General Secretariat of the Council (2014)). Following Paris COP21, the Lima-Paris Action Agenda, LPAA (Kerr

*Corresponding author

Email addresses: Marquant@arch.ethz.ch (Julien F. Marquant), Ralph.Evins@empa.ch (Ralph Evins), Andrew.Bollinger@empa.ch (L. Andrew Bollinger), Jan.Carmeliet@empa.ch (Jan Carmeliet)

Nomenclature

Acronyms

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	
HI	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_{cli}	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	

(2016)), 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 (2010)), there is a shift from centralised to more distributed energy systems structures (Wolfe (2008)). 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 (Bouffard and Kirschen (2008); Jones (2008); Kok et al. (2009); Li et al. (2010a)). 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 (2008).

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. (2012a). The most common are Linear Programming, (LP) beginning with the MARKAL model in Fishbone and Abilock (1981) and continued in multiple publications, e.g. Kong et al. (2005); Makkonen and Lahdelma (2006); Ren et al. (2010) and Mixed Integer Linear Programming, (MILP) e.g. Dimitriadis et al. (1997); Gustafsson (1998); Yokoyama et al. (2002); Hiremath et al. (2007); Sugihara et al. (2008); Chinese (2008); Lozano et al. (2009); Casisi et al. (2009); Li et al. (2010b); Keirstead et al. (2012b); Mehleri et al. (2012a); Fazlollahi and Marchal (2013); Pruitt et al. (2013); Omu et al. (2013a); Uhlemair et al. (2014); Pantaleo et al. (2014); Bischi et al. (2014); Marquant et al. (2015b); Moreno et al. (2015); Silvente et al. (2015); Morvaj et al. (2016b). Recently numerous holistic methods have been developed to tackle the complex problem of the design and operation of multiple energy systems at different scales. Gerber et al. (2013) presents a systematic methodology for sustainable system design using multi-objective optimisation methods combined with a MILP formulation. Geidl et al. (2007) developed the energy hub concept to represent the interactions between multiple energy systems and carriers with a coupling matrix representing technology efficiencies.

The energy hub concept is employed as a MILP formulation in this work. Although MILP formulations are reliable and efficient, the computation time dramatically increases with the number of variables when solving large scale models of urban energy systems, as demonstrated in Marquant et al. (2015b). This makes the optimisation non-trivial when considering multiple energy hubs. In order to deal with these limitations, multiple methods to decrease the computational time have been developed in the literature. They are mostly of two sorts: (1) spatial aggregation methods and (2) time aggregation methods. Both of these can reduce the dimensionality of the problem, as shown in Table 1. For example, Omu et al. (2013b) cluster buildings as a function of their yearly heating demand in order to optimise distributed energy resources. Weber and Shah (2011) optimise a district energy system for an eco-town in the UK and cluster buildings into single-type nodes (e.g. residential buildings, offices, schools) where the demand profiles are aggregated. Keirstead et al. (2012b) also aggregate demand profiles in zones based on building locations in order to evaluate biomass energy strategies for the same eco-town. Pirouti et al. (2013) use a set of manually selected clusters in which the demand profiles are aggregated.

In the past, spatial aggregation has been done in a more manual manner following rules of thumb or based on administrative boundaries. More recently, however, clustering methods have been used to insure the quality of these aggregation methods. Fazlollahi et al. (2014b) use a k-means algorithm to represent an urban area as a set of zones, based on energy distribution network costs and spatial clustering quality parameters. Fonseca and Schlueter (2015) identify clusters based on building location using the intensity of clustering and its probability of occurrence. In this work, the clusters are computed using a k-means algorithm available in the ArcGIS® software. Outliers are detected and removed manually based on high energy demand profiles. Lately, Jafari-Marandi et al. (2016) investigated possibilities of clustering based on load profiles considering the heterogeneity index of a set of buildings.

Regarding the temporal domain, solving MILP problems at hourly resolution over a whole year is difficult to accomplish in a reasonable amount of time. Common approaches select "typical days" to overcome this issue. Domínguez-Muñoz et al. (2011) select a user-chosen number of typical days optimally selected using a k-medoids clustering algorithm. Based on a k-means clustering algorithm assisted by an ϵ constraint optimisation technique, Fazlollahi et al. (2014a) use typical periods selected from multiple demand profiles, minimising the number of typical periods while accounting for extreme demand peaks. To compute the optimal design of a distributed energy systems for a neighbourhood of 10 buildings, Mehleri et al. (2012b) divide a year into 18 different time periods (6 periods per day, for summer, mid-season and winter). Morvaj et al. (2015a), when selecting the optimal distributed energy resources for an urban district, used 12 typical days, selected as average values per month. Carvalho et al. (2012) used 24 representative days (one working day and one holiday/weekend day for each month) in an optimisation of a trigeneration system.

Other approaches involving decomposition methods as Bender, Lagrangian, bi-level or rolling horizon decompositions can be used to reduce the computational time of problems with numerous variables, as described in Grossmann (2012). Rolling horizon (RH) approach allows to solve a large size problem by breaking it down in multiple smaller ones solved iteratively Dimitriadis et al. (1997). For example, it has been applied to determine the optimal operation strategy of an integrated solid-oxide fuel cell and compressed air energy storage plant model in Nease and Adams (2014), and for the operation scheduling of an energy hub model in a study evaluating the benefits of RH approach in Marquant et al. (2015b). However, the rolling horizon approach can not be applied directly for determining the design. Indeed, design is a one time decision which can not be dynamically changed within different planning intervals. As a result, clustering techniques have to be used to reduce computational complexity of optimisation models that determines both operation and design.

Whether for spatial or temporal aggregation, techniques are often selected without looking at the possible errors made by reducing model resolution. To address this challenge of resolution in time and space, our goal is to establish a connection between small and large scale modelling. Pfenninger et al. (2014) presents three stylised scales relevant for energy systems based on uncertainty level and spatio-temporal resolution from plant scheduling to national scenarios. We argue for the separate optimisation of different scales using a bottom-up approach, while keeping track of the error made by reductions in resolution in moving from smaller to larger scales (from building to district as illustrated in Figure 1).

1.3. A novel approach to energy optimisation

This paper introduces a multi-scale framework to handle large scale urban energy system design and operation while keeping track of lower level resolution. The term "holarchy" describes the framework, referring to the holonic nature of the energy hub approach used in a hierarchical context. Indeed, the term "holon" is introduced in Koestler (1972), describing something which is at the same time a whole and a part. A holon is then self organised, but also nested within another holon, thus making it independent, and at the same time part of a larger structure when organised in a hierarchical approach, referred as holarchic. An energy hub in the developed multi-scale approach can represent a building, a neighbourhood or a district based on its level of organisation, it is then considered in this context as a holon. Figure 1 illustrates the hierarchical framework developed. At the building level, a clustering method is employed, combined with a schema for interconnecting buildings in the same cluster with a district heating network (DHN). The optimal solution for different clusters at neighbourhood scale is retained and constraints on energy system sizing are passed to the higher level problem (district-scale) for the design of larger scale networks. A re-evaluation of the operating costs for the entire city with larger distribution grids is then computed. This differs from current practice in which buildings, districts or cities are modelled as single loads, considering centralized distribution, as is still mostly the case in our cities. The developed framework overcomes a key weakness of single level approaches, in which all buildings or nodes (aggregated buildings) are considered within the context of a single optimisation problem, which fail for a large number of nodes (e.g. more than 50 nodes for the energy hub model presented in section 4.1).

The main novelty of the framework resides in the possibility to preserve a relatively high level of detail concerning building characteristics while increasing computational speed. This enables solution of large, urban-scale optimisation problems with high levels of accuracy, advancing research on strategies for the design and operation of distributed energy systems. The framework, by retaining details on building characteristics, allows further analysis on the interactions of different energy systems and carriers with, for examples, the built environment, user behaviours, and building typologies.

	Grouping approach				Optimisation	
	Spatial clustering		Temporal clustering	Structure	Design and operation	Objective function(s)
	# Buildings	# Clusters				
<i>Neighborhood scale</i>						
Morvaj et al. (2016a)	12	None	12 average days (1/month)	single scale	YES	MOO Cost-CO ₂
Omu et al. (2013b)	6	None	4 typical days (1/season)	single scale	YES	Cost scenarios
Mehleri et al. (2012a)	10 - 20	None	18 time periods	single scale	YES	MOO Cost-CO ₂
<i>District scale</i>						
Pirouti et al. (2013)	527	7 clusters selected aggregation	12 representative days (1/month)	single scale	design cases	Operating cost OR energy
Yang et al. (2015)	4	3 buildings 1 cluster aggregation	3 typical days bi-hourly mid-season winter/summer	single scale	YES	Cost
<i>City and regional scale</i>						
Fazlollahi et al. (2014a)	475 zones 500'000 inhabitants	13 clusters k-means aggregation	7 segmented typical periods	single scale	YES	MOO Cost-CO ₂ Efficiency
Keirstead et al. (2012b)	3132 households	39 clusters aggregation	2 average days winter/summer	single scale	YES	Cost scenarios
<i>Multi-scale model</i>						
Our approach	2316 households 221 buildings	14 clusters OPTICS	12 typical days (greedy algo)	multi scale	YES	MOO Cost-CO ₂

Table 1: Comparison between modelling approaches from small to large scale distributed urban energy studies

This paper is organised as follows. In the first section, a new methodology for modelling and optimising district heating networks at neighbourhood scale is presented, which enables significant improvements in computational efficiency. Inspired by *rolling horizon* techniques (temporal clustering), the technique is termed the “rolling hub” approach (spatial clustering). It is compared with the usual approach to distributed energy systems (DES) optimisation described in Allegrini et al. (2015) where problems are solved in a single optimisation. Based on the techniques highlighted in the first section, a framework is presented in section 2.4. The following section assesses the computational benefits of the methodology, and compares relative errors with a reference model for multiple cases at neighbourhood scale. Finally, application of the framework to a city-scale case study is presented in the last section, which allows for analysis of the trade-offs between centralised and DES at large scale. In this study, available energy systems (ranging from small to large scale) include combined heat and power engines (CHP), boilers, photovoltaic panels and heat storage devices; district heating networks were also included. The conclusions (section 6) highlight the benefits and drawbacks of the modelling techniques and framework, and discuss possibilities for future research to increase the robustness of the clustering methods employed in the framework.

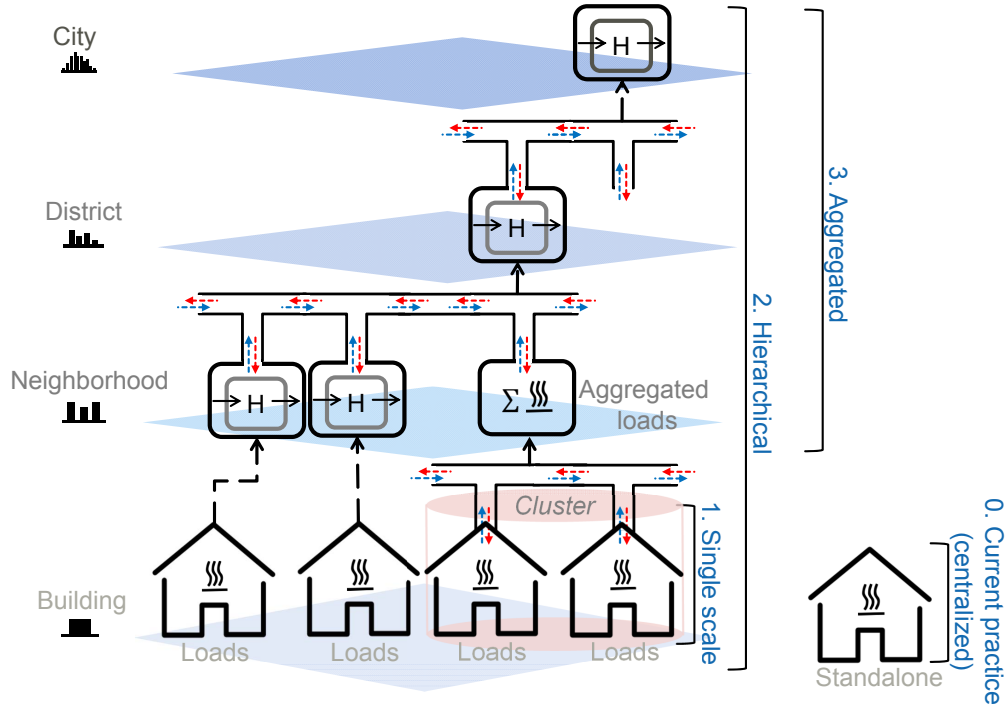


Figure 1: Multi-scale hierarchical approach to DES optimisation:

0- is the centralized approach, considered as current practice: a central energy system supplies the total energy demand of a city seen as one aggregated node. 1- is the single scale approach currently used at neighbourhood scale where all building energy demand profiles are considered in the DES optimisation problem. 2- is a hierarchical nested approach where multiple scales are considered in the optimisation problem. 3- adds aggregation of loads within the same district heating (DH) network while solving the optimisation problem using a bottom-up approach.

2. Methodology

The objective of the optimisation problem considered here is to find which energy systems combined with which network configuration should be installed, and how this should be operated for every time step of the problem horizon in order to minimise the cost function. The principal criteria for optimal design of energy systems are the costs and environmental impact. The cost is chosen to assess the methodology as the carbon minimisation has to be considered along with a cost minimisation or energy efficiency minimisation to not get an oversized solution. However, a carbon minimisation is also presented in the case study results section 4. The cost function is calculated as the equivalent annual costs (EAC) for design and operation of multiple urban energy systems including networks to provide the energy demand of a given set of buildings. It is then an optimisation problem taking into account the design and respective operating strategy at a neighbourhood scale. The focus here is on a district heating network considering multiple urban energy systems. In presenting the methodology, various neighbourhood scale models are used which are extracted from the large case study presented in section 4.1. The urban energy systems competing here are combined heat and power (CHP) engines, natural gas boilers, thermal storage and photovoltaic panels (PV), with systems ranging from small size (2kW) to large size (5MW). The choice of technologies in this paper is not exhaustive. However, as the aim of the paper is mainly to illustrate the methodological framework rather than to perform a complete comparative analysis, a limited set of technologies is selected. Additional renewable technologies are not included due to their low popularity in the Swiss context (solar thermal panels) or due to their low suitability for urban environments (biomass boilers). Additionally, electrical storage in the form of batteries is not included due to the currently high costs associated with these technologies.

2.1. New modelling formulations at neighbourhood scale

In conventional MILP-based approaches from Table 1 at neighbourhood scale (with buildings represented individually) or at district level (with groups of buildings aggregated), the optimisation problem constitutes a set of equations describing the system in its totality, which is passed to the solver to determine the optimal solution. This often consists of a large number of constraints and variables, including integers, covering all timesteps and locations. Such optimisation problems become intractable when considering additional constraints such as minimum loads, step functions (to represent technology efficiencies depending on loads), or economies of scale (prices of technology depending on size).

Instead of solving the full optimisation problem at once, a new approach is developed; termed the “rolling hub” approach. This is based on a decomposition method similar to the rolling horizon method, a temporal decomposition method. Instead of applying the method to the temporal dimension, it is applied here to the spatial dimension. The large problem is divided into multiple smaller problems, solved iteratively. The computational benefit comes from the fact that, for MILP problems, the solving time grows exponentially with the number of variables (Marquant et al. (2015b)). To overcome this, the rolling hub approach divides the problem into multiple independent optimisation problems representing different network configurations and anchor points. The network generation process and optimisation models described here are illustrated in Figure 2.

1. Select an anchor building based on the building with the highest annual heating demand in the current cluster (marked with a red square in Figure 2).
2. Increase the district heating network size (represented with a red line in Figure 2) via radius-based incrementation (from 1 to N buildings included in the network), by adding the nearest buildings from the anchor building. The shortest distance, often referred as ‘green solution’, is employed to calculate the network distance. This assumption¹ enables the use of the Minimum Spanning Tree (MST) algorithm to compute the cost of the network which can be solved in a polynomial time. This allows a faster computation compared with the use of the Steiner algorithm, NP-hard problem, which has to be employed for solving a road following optimisation problem.
3. Generate all possible network configurations using the Minimum Spanning Tree algorithm from multiple anchor points, from highest to lowest energy demanding buildings. The minimum spanning tree from graph theory algorithm computes the minimum possible path to connect all vertices (buildings) with an undirected graph and without creating any cycles.
4. Roll optimisation problems for each generated cases considering aggregated (aggregation of the building loads included in the network) and disaggregated building demand profiles, based on the network shape. Each optimisation problem corresponds to an energy hub problem.

The aim of the rolling hub method is to facilitate the optimisation of large-scale energy systems. To do so, loads of the different buildings within a cluster are aggregated and the heating network lengths and costs for the cluster are calculated in a simplified manner, using the minimum spanning tree (MST) algorithm, in an iterative process as shown in Figure 2. In the iterative generation step, buildings attached to the district heating network are aggregated (demand profiles) and heating losses are calculated considering the anchor load as an energy centre and buildings situated at equidistant from the anchor load. Outlier buildings are not connected to the district heating network and are considered as standalone buildings.

2.2. Optimisation problem description and assumptions

The energy hub formulation (Geidl et al. (2007)) is used to solve the optimisation problem within each entity considered as an independent energy hub. The process of generating multiple sub-problems is iterative. However, all sub-problems can then be solved separately and in parallel. The equations solved for each energy hub are given below.

¹This assumption makes sense in our case study representative of a more rural area, where a greenfield approach can be looked at.

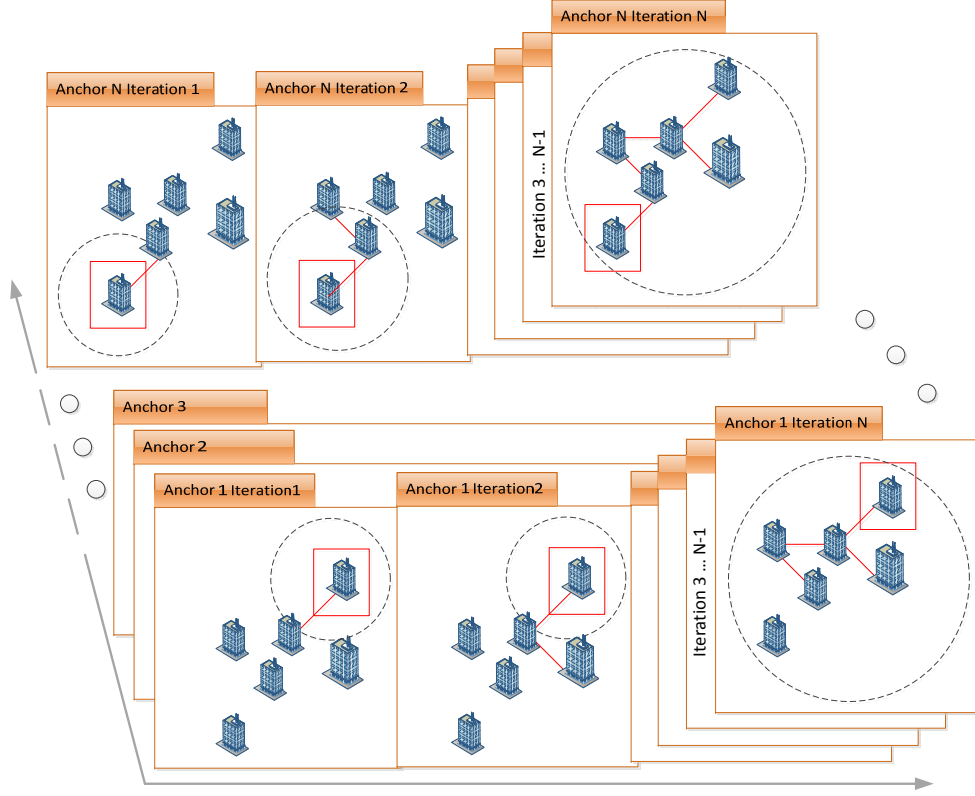


Figure 2: Dividing a neighbourhood scale optimisation problem in multiple sub-problems run in parallel

Objective The objective is to minimise the total costs of an energy hub e . These costs consist of the equivalent annual costs (EAC) of the purchased technologies I_{tech} , and the operating costs $OC_{tech,t}$ for running them, subject to multiple constraints formulated below. An example with minimising CO_2 emissions is presented in the results section 4.

$$\min \sum_{e=1}^{n_e} (I_{tech} \times CRF + OC_{tech,t}) \quad (1)$$

The Capital Recovery Factor (CRF) is the inverse of the present value factor (PVF) used in the calculation of the net present value (NPV); a discount rate of 3% which corresponds to a social discount rate for sustainability policy Jakob et al. (2014), was used with a 20 years lifespan for the technologies and 40 years lifespan for the network pipelines. The investment costs (Equation 2) represent costs of each technology installed taking into account economies of scale (see table 4) where the price per kW of each technology depends on its size band. A detailed formulation explaining the linearisation of the multiplication between integer and binary variables, to consider the economy of scale formulation, can be found in Marquant et al. (2015a).

$$I_{tech} = \sum_{tech=1}^{n_{tech}} \delta_{tech} \times LC \times P_{tech}^{max} \quad (2)$$

where δ_{tech} assures that the term in Equation 2 is zero if the technology is not installed. LC is the linear relation determining the technology price depending on the size band P_{tech}^{max} . P_{tech}^{max} is the optimally installed capacity per technology which is subject to integer lower and upper bound constraints.

The operational costs (Equation 3) sum up the cost of electricity imported from the grid, the gas used by the boiler

and CHP engine, (minus the electricity produced and sold to the grid). The operating costs are calculated over a one year period.

$$OC_{tech,t} = \sum_{t=1}^{n_t} P_{tech,t} \times C_{supply} \quad (3)$$

where $P_{tech,t}$ corresponds to the power consumed or generated by a technology at each time step and C_{supply} the cost of the energy resource use by the technology. The carbon emissions related to the consumption of energy are calculated annually. It corresponds only to the emissions produced in operation and does not consider the life cycle emissions of the technologies.

$$Carb_{tech,t} = \sum_{t=1}^{n_t} P_{tech,t} \times Carb_{em} \quad (4)$$

where $P_{tech,t}$ corresponds to the power consumed or generated by a technology at each time step and $Carb_{em}$ the carbon emissions attributed to the energy resource use by the technology.

Energy demand constraints General constraints ensure that electricity and heating demand will be met for each building at each time step $L(t)$. This is summarised by an efficiency matrix Θ of the different technologies coupling the demand to be met and the available supply from the different energy resources, taking into account the storage flux Q . As for the cost of each technology, the efficiency factor depends upon the system size and account for economies of scale (see table 4).

$$L(t) = \Theta \times P(t) + A_- Q_-(t) - A_+ Q_+(t) \quad (5)$$

where $P(t)$ represent the decision variables for the energy resources consumed or produced at each time steps t . The storage flux Q is subject to charging A_- and discharging A_+ efficiency. The storage continuity is modelled by Equation 6.

$$E(t+1) = n_s \cdot E(t) + Q_+(t) - Q_-(t) \quad (6)$$

where n_s is the energy dissipation between two time steps (self losses), Q_+ and Q_- the maximum charge or discharge at every time step.

Minimum part load constraints Additional constraints are added in order to take into account the operating characteristics of technologies in multi-energy systems, such as part-load constraints for CHP engines. As in Morvaj et al. (2016a) the minimum part load constraint is set at 50% to guaranty that CHP engines are not operating at lower efficiency (CHP engines operate poorly at low part load Moniz et al. (2011)). Minimum part-load constraint is recommended in order to be able to approximate by a constant efficiency term CHP engines in MILP models.

$$\eta_{CHP} \cdot P_{CHP}(t) \leq M \cdot \delta_{CHP}^{ON}(t) \quad \forall t \quad (7)$$

$$0.5 \cdot P_{CHP}^{max} \leq \eta_{CHP} \cdot P_{CHP}(t) + M \cdot (1 - \delta_{CHP}^{ON}(t)) \quad \forall t \quad (8)$$

where η_{CHP} is the CHP efficiency, P_{CHP} represents the gas input to the CHP system and $\eta_{CHP} \cdot P_{CHP}$ the power output of the CHP engine. δ_{CHP}^{ON} is a binary variable equal to 1 if the installed CHP engine is on or 0 otherwise at every time step. M is an arbitrary large number ('Big-M' method of formulating binary constraints for linear programming Dasika et al. (2003)).

District heating network Here we describe the reference model, which involves passing the full optimisation problem, without aggregation, to the solver where each entity is able to install its individual energy system. Heat can be produced and transferred from one entity to another through the district-heating network whose structure is determined during the solving of the MILP problem. This formulation – based on Morvaj et al. (2016c) – allows an exchange of energy between individual buildings $Q_{ji}(t)$ and $Q_{ij}(t)$, considering the heat losses HL_{ij} . Equation 5 is transformed to take into account the possible transfer of heat from or to another building. There is no loop of heat loss possible, using the constraint formulation of Mehleri et al. (2012a) – motivated by the Travelling Salesman Problem (TSP, e.g. Liu et al. (2008)) – Equation 11. This allows to avoid directed loops which could generate heat waste and heat circulation.

$$L(t) = \Theta \times P(t) + A_- Q_-(t) - A_+ Q_+(t) + \sum Q_{ji}(t) \times HL_{ij} - \sum Q_{ij}(t) \quad (9)$$

$$Q_{ij}(t) \leq \delta_{ij} \times M \quad \delta_{ij} + \delta_{ji} \leq 1 \quad (10)$$

Heat loss constraints Heat losses HL_{ij} are proportional to the distance between two buildings, as stated in Mehleri et al. (2012a) for distances of the order of hundreds of meters, with losses of 4% per kilometre.

$$O_j \geq O_i + 1 - N_e \cdot (1 - \delta_{ij}) \quad \forall \quad i, j \quad \text{where} \quad i \neq j \quad (11)$$

Typical days approach To decrease the computational burden a method is applied to extract k-medoids typical days D_k to represent at best a full year of data at hourly resolution. The method employed in Marquant et al. (2015a) is based on the approach of Domínguez-Muñoz et al. (2011) where the number k of typical days is selected in order to minimise two clustering quality indicators: the error in the load duration curve (ELDC) and the Davies-Bouldin index (ratio of the intra-cluster scatter to the inter-cluster separation, lower is the value better is the cluster).

A cyclic constraint allows to consider the daily specificity of the short term storage. This constraint is added to Equation 6 to consider in the first hour of the day the level of storage during the last hour of the day. This is done in a similar way as described in Morvaj et al. (2017), in which the initial state of the stored energy is not optimized, but the initial and final state of charge are optimised.

$$E(t) = n_s \cdot E(t + 23) + Q_+(t) - Q_-(t) \quad \text{for} \quad t = 1 \quad (12)$$

2.3. Bi-stage optimisation

Our methodology employs bi-stage optimisation to improve computational efficiency. The optimality gap is the difference between the integer solution of the MILP problem and the fully-relaxed problem (LP), expressed as a percentage of the fully-relaxed problem (LP). Figure 3 describes the bi-stage optimisation processed used to run each energy hub model. First, the MILP problem is run until 2% optimality gap with design and operating variables, then in a second stage the optimality gap is run to 0% considering the design as fixed. This is possible because operating costs are much higher than investment costs. In our formulation, investment costs are expressed in terms of equivalent annual costs taking into account the technology lifespans (in our case study 20 years for energy systems and 40 years for the network (Wagner et al. (2015))). Benefits of the multi-stage approach for optimisation are described in the computational benefits section 3.1. The optimal selected value of the optimality gap in the first stage depends on the problem. The value should be low enough to provide an accurate result which can be accepted. The objective of a two stage solution process is to reduce the computational time; the lower value should allow reducing drastically the solving time. This can be done by choosing an inflection point of the curve representing the optimality gap evolution with the solving time. For this specific problem the time for solving a problem from 2% to 0% optimality gap was important compared to the time to solve the problem from 100% to 2%. The same patterns often occur in MILP solving. In the previous literature, the optimality gap is often chosen higher than few percent to limit the computational time (for example the optimality gap limit is fixed at 10% in Keirstead et al. (2012c)).

2.4. Framework: multi-scale approach

Based on findings and modelling assumptions of the previous sections, a framework enabling optimisation of multiple distributed energy sources and carriers at larger scale is presented in figure 4.

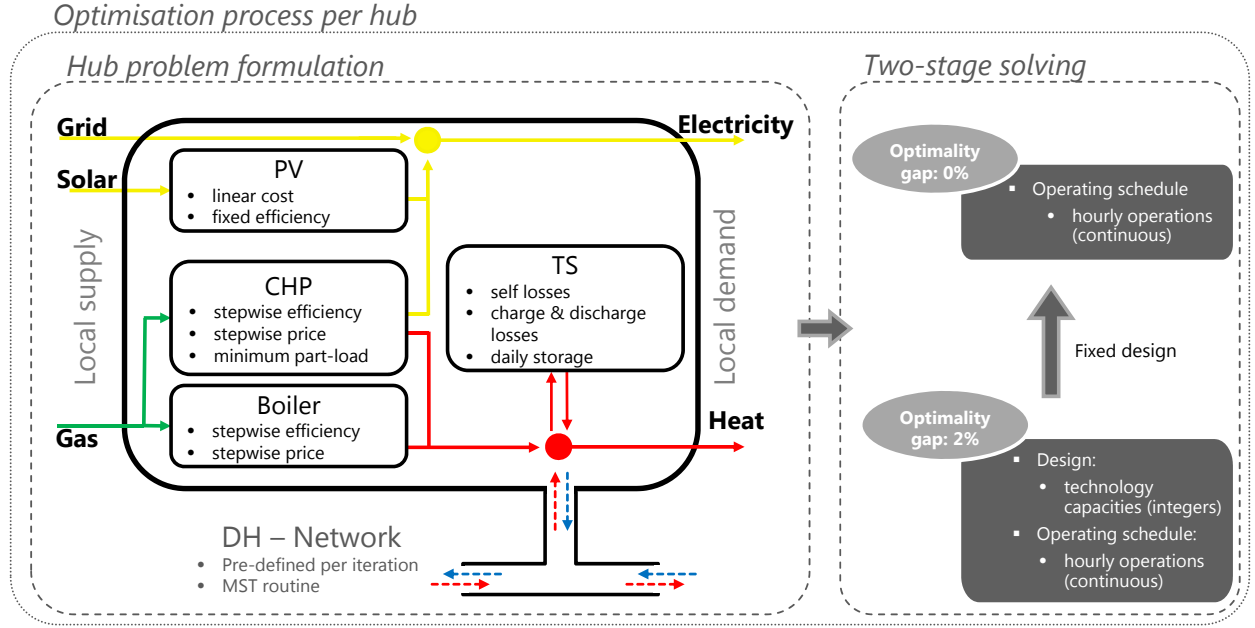


Figure 3: Optimisation problem assumptions in a multi-stage optimisation framework

Overview The presented methodology is a bottom up approach enabling assessment of the potential of distributed energy systems at large scale while considering high resolution at lower scale. A benefit of the defined framework is its ability to assess loss of accuracy when changing the resolution of the optimisation problem across scales. The framework enables solving large optimisation problems dealing with the design and operating strategy of multiple interconnected energy systems and networks. It is highly adaptable to different model set-ups and configurations.

The framework is divided into three different parts, visible in figure 4: clustering, optimisation per cluster and inter-cluster network optimisation. A first density-based clustering method divides the problem into multiple sub-problems giving as output a clustering map representing all sub-problems. For each cluster, the rolling hub model is employed to locally find an optimal solution to the objective function. Once the optimal solution of each sub-problem or a selected combination of solutions is determined (optimisation per cluster), then this solution is used as input in the next step considering the entire problem (inter-cluster optimisation). Section 4 gives an overview of the optimisation results for assessing the trade-off between environmentally and economically optimal solutions of the design and operating strategy of multiple interconnected energy systems at a city scale.

Clustering In a previous work, Marquant et al. (2015a), a radius-based clustering method was employed to assess the potential of a district heating network in a 103 building case study. This work has been expanded to include spatial density-based methods. A density-based and hierarchical algorithm is employed, called OPTICS_{xi} (Ordering Points To identify the Clustering Structure). Density based algorithms evaluate for each object of a cluster that their is a minimum number of objects *MinPts* in a maximal neighbourhood distance *EpsDist*. *xi* parameter is a contrast parameter defining the relative drop in density. More details on OPTICS algorithm can be find in Ankerst et al. (1999). For the distance matrix, the Minkowski Euclidean distance function is chosen as it best represents a measure of the distance between two objects. OPTICS is chosen as it is a density-based algorithm which does not require entering the number of clusters. It requires only the minimum number of points to form a cluster, the maximal reachability distance and the data to cluster.

Optimisation within each cluster Within each cluster the rolling hub model is run and results give a palette of solutions representing the trade-off between economically vs. environmentally advantageous solutions.

Optimisation between clusters Once the optimisation problem has been solved for each cluster, an inter-cluster optimisation problem is solved in a bi-level approach with constraints imposed by the sub-level optimisation problems. The inter-cluster network optimisation model is a large-scale network model which enables identification of an optimal district heating network connecting optimal energy hubs (model A from section 2.2).

2.5. Software

As can be seen in Figure 4, data on building shapes, areas and loads are stored in a shapefile and manipulated in ArcGIS® software. The framework is built in Matlab and the clustering algorithm in ELKI open software. The energy modelling part is executed in AIMMS using IBM CPLEX as the solver of the mathematical model.

3. Computational benefits versus models accuracy

The model described in section 2.2 explores all possible network using a binary variable for each possible connection accounting for the flow direction. However as the MILP problem time grows exponentially with the number of variables, it becomes intractable to use this model at large scale. In this section, the computational benefits of the rolling hub approach are analyzed. To evaluate the effectiveness of the methodology, the rolling hub-based solution is compared with the solution achieved with a reference model (section 2.2). The different assumptions and simplifications made to enable large-scale optimisation are tested in this section, starting with the network and aggregation errors and finally the clustering decomposition and its limitations. The different model formulations compared in this section are as follows, (with their inheritance specified in Table 2 along with their position in term of solving time):

	A	B	C	D
Rolling hub	✗	✓	✓	✓
Anchors	✗	Multiple	1	Multiple
Two stage	✗	✗	✓	✓

Table 2: Inheritance relationship between model formulations variations

- (A) **MILP optimisation of the district heating network:** The full model described in the previous section, where the district heating network is fully optimised. This model serves as reference case.
- (B) **Single level optimisation:** In this model formulation, only one optimisation problem is run per network generation with an optimality gap fixed at 0% for the design and operating strategy. Design and operation are optimised simultaneously and not in two stages as presented in figure 3.
- (C) **Single anchor aggregation:** In this model formulation, only the building with the highest energy demand is considered for the network generation, which limits the number of network shapes. Only networks including the highest consuming building are taking into account.
- (D) **Multiple anchor aggregation and bi-stage rolling hub optimisation:** In this model formulation (from section 2.1) buildings are aggregated by iteration around an anchor building and considered as part of a district heating network; outlier buildings are considered as being independent from the district heating network.

Model formulations A serves as reference model as widely employed in the literature (Morvaj et al. (2015a), Mehleri et al. (2012a)). Model D applies the rolling hub approach and bi-stage optimisation. Models B and C are variants of model D. Model C only considers networks from a single anchor node. Model B is a single-stage optimisation allowing to find the global optimal solution, fixing the optimality gap at 0%. Comparing models B and D highlights the benefits of two stage optimisation in terms of solving time and problem complexity.

Computational set-up For model formulations comparison and to assess the computational benefits for large-scale simulation, all optimisation problems have been computed on the same system – an Intel Xeon machine with 3.1 GHz CPU, 8 cores and 64 GB of RAM. The energy modelling part is executed in AIMMS and the MILP problem solved using CPLEX 12.6 in deterministic mode to allow comparison (no heuristic cuts while computing branch and bound algorithm).

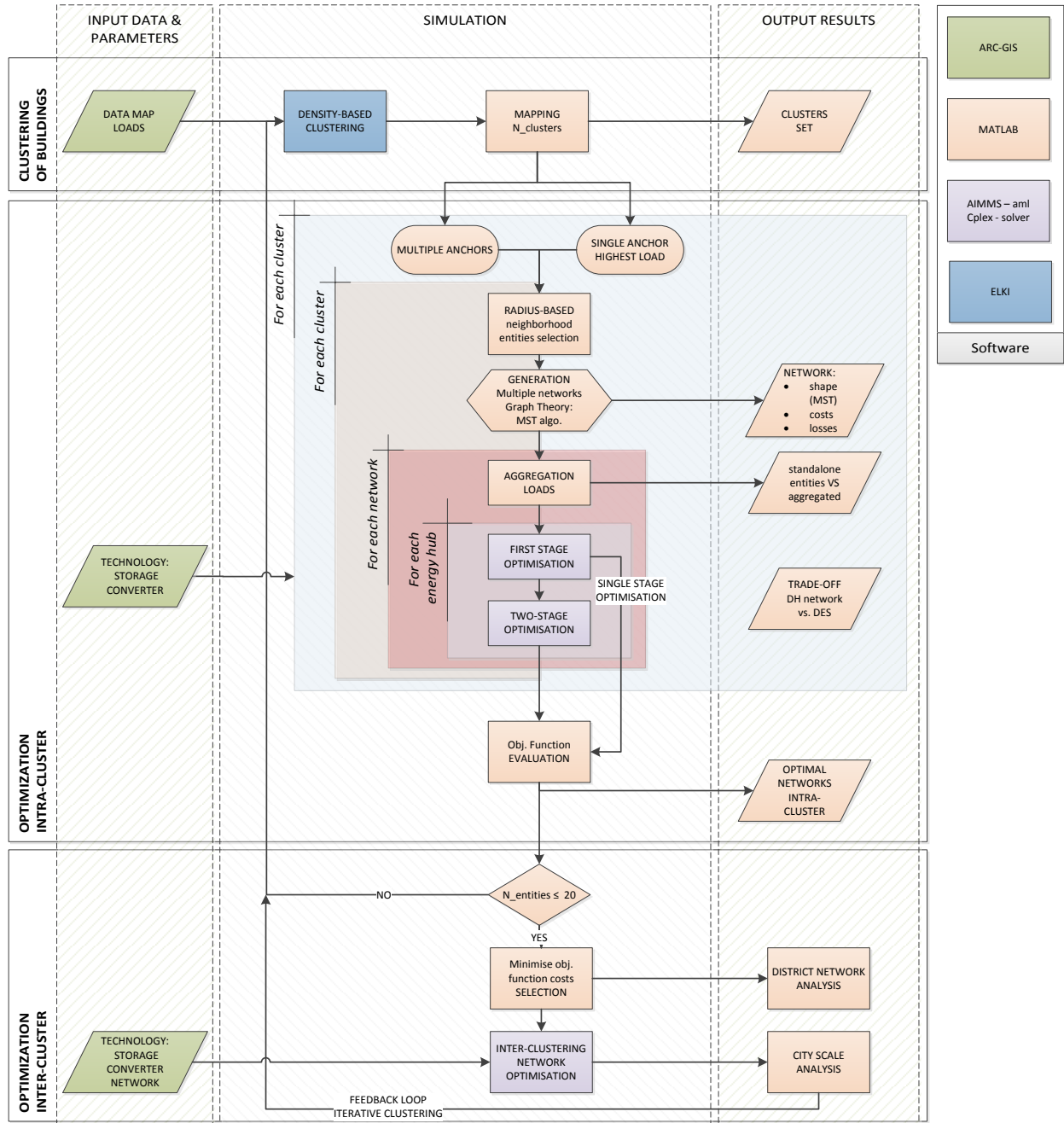


Figure 4: Multi-scale optimisation framework

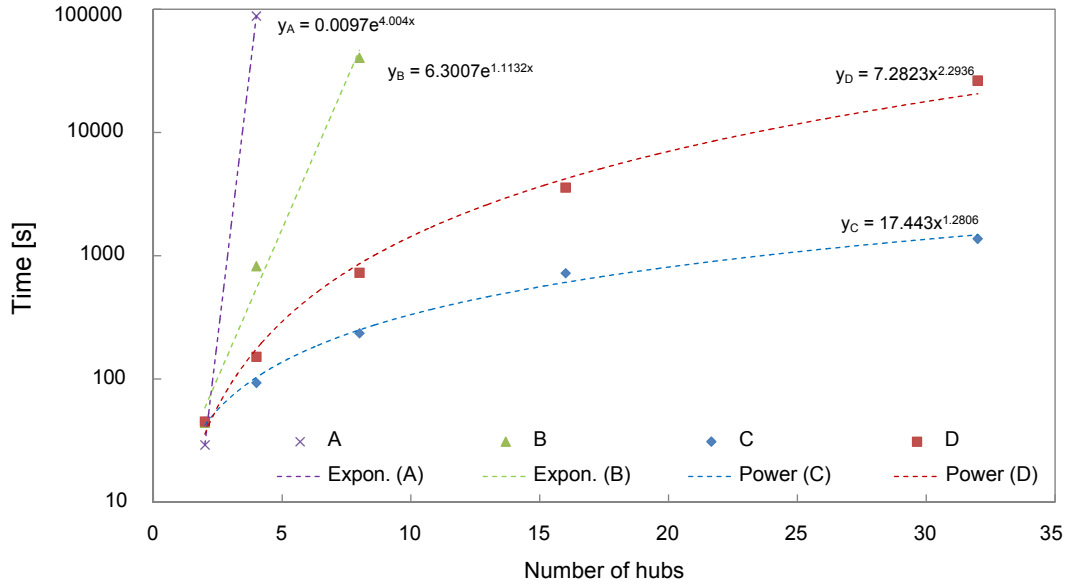


Figure 5: Solving time comparison with log scale

3.1. Clustering

A clustering method can divide a large-scale problem into solvable sub-problems. This is accomplished by grouping buildings together based on their spatial locations. Based on a density function of a district, buildings are grouped together to form clusters. In this section, it is assumed that clusters are already formed and given as input data for the optimisation problem. The goal is to study the evolution of the computational time and optimisation accuracy in relation to the number of clusters and their sizes. First, the model formulations listed above are compared with different problem sizes (different numbers of clusters). Then, the same problem is solved considering an increasing number of sub-divisions in these clusters.

3.1.1. Number of hubs

Figure 5 shows a comparison of the total time to find the optimal solution for formulations A, B, C and D. Evaluation has been done on a selected area of the case study (Figure 10b) with 2 to 32 buildings, doubling for each case the number of buildings. Total time is an aggregation of the solving time necessary to find the optimal solution in CPLEX and the pre-solving time to build CPLEX readable code from a mathematical formulation in AIMMS. In model A, the full problem is passed to the solver at once and solved. In each of the other cases, it is divided into multiple sub-problems according to the rolling hub approach. Each sub-problem is solved independently, thus creating multiple iterations between AIMMS and the solver CPLEX. There is then a trade off between the problem size (number of integer variables) and solving time. For the smallest problem with 2 hubs, there are 10^4 432 variables with 606 integers. In this case it is faster to find a solution with A (30 seconds) than with B, C or D (around 45 seconds for each). From 4 hubs – when the number of integers is doubled for A and quadrupled for the other models per sub-problem – using the modelling techniques of D represent an important advantage (about 500 times faster than A for 4 hubs and 50 times faster than B for 8 hubs). This advantage is further enhanced with the problem size.

The fitting curve on the graph highlights the tendency of MILP problems to grow exponentially with the number of variables (curve A), and the benefit of dividing a large problem into sub-problems. The error from the assumptions employed in model D are always lower than 1%. In some cases, there is no difference between the solution of models A and D, where the district heating network is not a choice retained in the optimal solution and each building has its own energy systems.

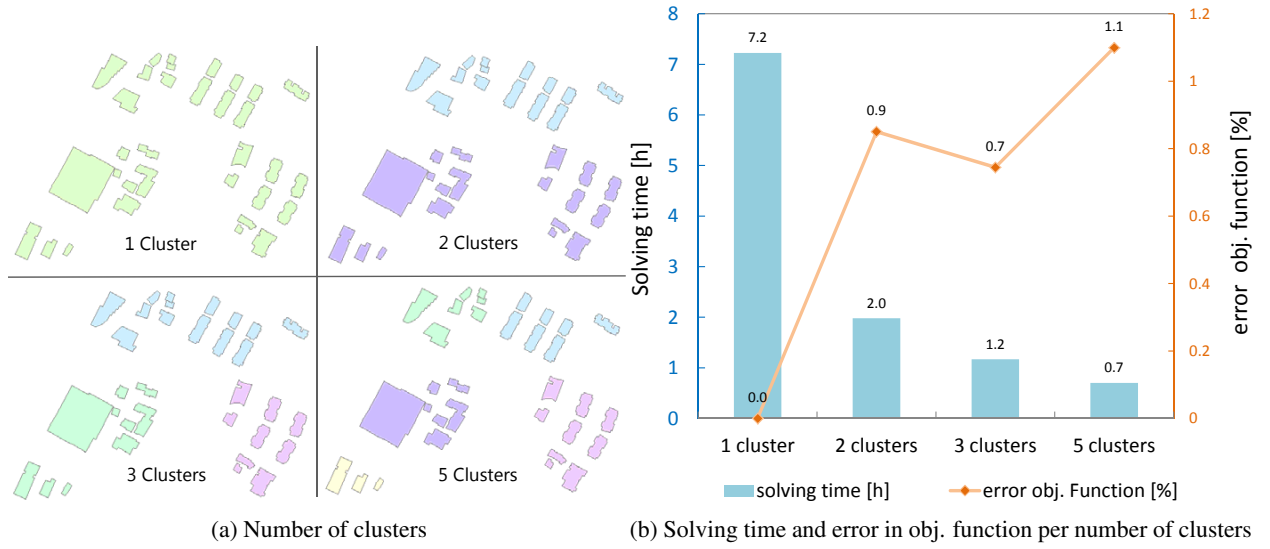


Figure 6: Clustering computing time and error

3.1.2. Number of clusters

Using the 32 hub case from the last section, an analysis has been run on the consequences of sub-dividing the problem in terms of time and optimal results. The 32 hub case has been divided into up to 5 clusters. For all the cases model D was used. Figure 6a illustrates the four different clustering cases and Figure 6b shows the results in term of total solving time for the full problem based on the number of clusters into which the original problem has been divided. The deviation from the optimal results obtained by solving the full problem (1 cluster) is also shown. It is possible to reduce up to 10 times the total time to solution when sub-dividing the problem into 5 clusters without sacrificing the optimal result by more than 1.1%. The congruence of the system's design and operating strategy according to the clustering division is examined in 3.3.

3.2. Examination of the results within each cluster

In this section, the assumptions made about the network optimisation problem and the aggregation method are considered, and the results are compared to the reference case (model A, with MILP optimisation of the district heating network). This has been done for two cases (fixed cluster of 4 buildings) of different density: a sparse case where the buildings are farther apart (average distance of 130 meters) and a dense case in which closer to each other (average of 30 meters). The sparse case is shown on the left in Figure 7 and the dense case on the right. Figure 7a shows the results for model A, and Figure 7b shows the results for model D. The sizes and types of energy systems installed for each hub are illustrated. In the sparse case there is no DH network; the solution is the same for both models with no difference in energy systems or objective function result. This is due to the fact that when there is no energy exchanged by the network the two models are identical. In the dense case, however, the optimal solution contained a district heating network which leads to minimal differences in the cost of the optimal solution (0.71%, seen in Table 3). The sum of the technologies installed in a decentralised manner in (a) is equivalent to the technologies installed in (b). The network shape is also the same. These examples highlight the efficiency and effectiveness of the proposed approach to identify optimal DH networks under different conditions. The objective of the framework is to look at the trade offs of having a DH network, depending on district characteristics. Therefore, the specific sizes per building taken by the design variables within each cluster are not critical, as long as the general trends are correct. This is illustrated in Figure 7a, showing the difference between model A and model D formulations in terms of detailed results. Model A gives a knowledge on the heat exchanged direction and in which building precisely is it optimal to place the energy systems. Whereas model D shows that a DH network is worst to be considered interconnecting buildings in a certain manner, and gives the optimal total size of the energy systems to be installed. Model D is then used by decision makers and planners at large scale to get an idea of where considering the installation of DH network

combined with which systems, whereas model A would be used to compute the optimal positioning of the energy systems within a restricted area. These results have been replicated for 12 different neighbourhoods of 4 buildings extracted from the case study, with a mixed of sparse and dense cases. The average difference in the objective function for the 12 cases is 0.11 % relative error (between model A and D) with a maximum relative error of 1.1%.

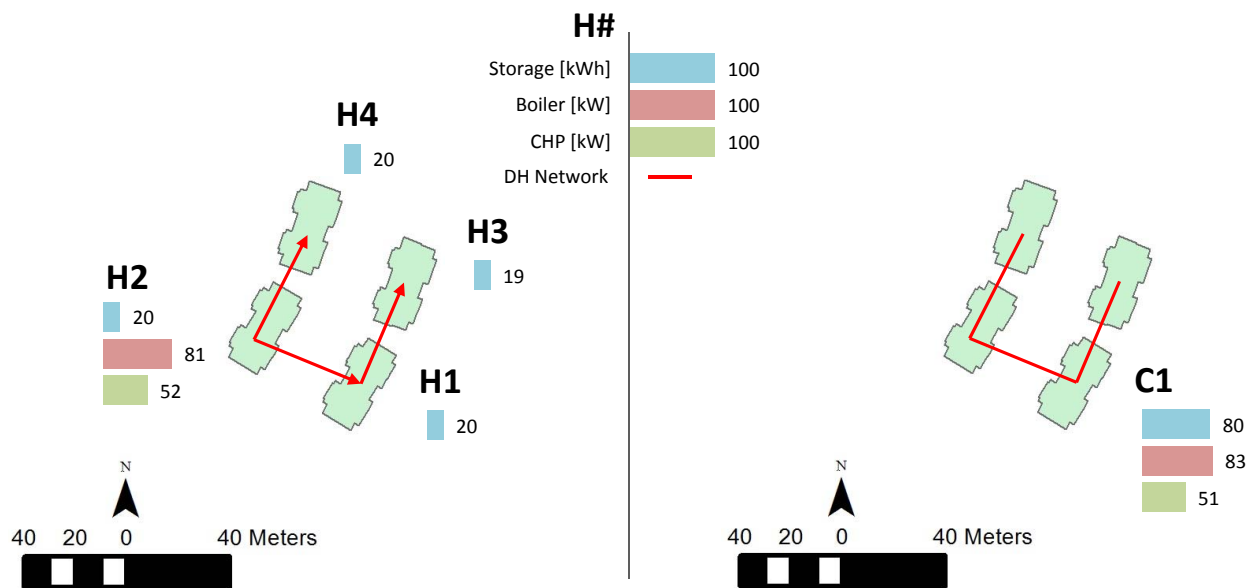
Case		Sparse	Dense	Case		Sparse	Dense
Time [s]	Model (A)	102'565.6	434'742.8	Difference [%]	Model (A)	-	-
Solving	Model (D)	148.3	314.5	Obj. Function	Model (D)	0.00%	-0.71%

Table 3: Sparse and dense case: time and error comparison model (A) vs (D)

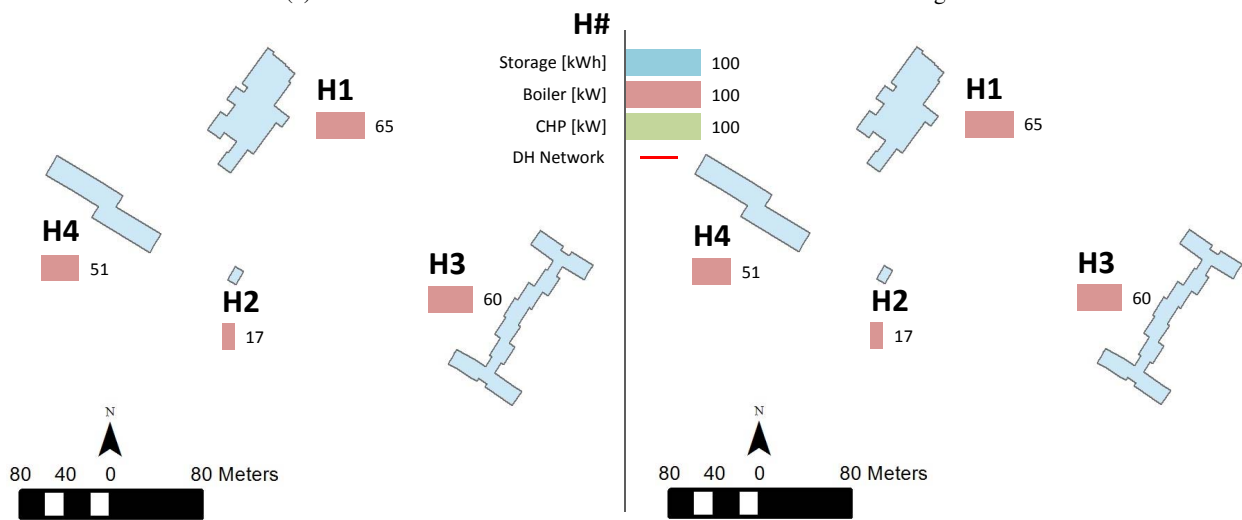
3.3. Inter-cluster optimisation

In this part, the results of applying a nested approach with different cluster decompositions for the same problem are analysed. The goal is to understand the limitations of the decomposition per cluster and the influence on the final results in terms of different clustering parameters (distances, load profiles). The same case study as the one used above in Figure 6a is employed with 3 different (randomly selected) cluster decomposition possibilities, into 2, 3 or 5 clusters. Via this analysis, the limitations of the multi-scale framework (presented in the next section 2.4) are tested from intra- to inter-clustering optimisation.

The results are shown in figure 9. The colours in Figure 8 enable differentiating the composition of the clusters. The gray color indicates the anchor building per cluster. The dashed lines on figures 8b and 8d indicate a district heating network connection between two clusters, as determined by the inter-clustering optimisation problem. The solid lines indicate the optimal network shape as determined by the intra-cluster optimisation. Based on the number of clusters and cluster shape selected at the beginning, the map of the network differs. In this case, the overall optimal solution is achieved for the 3 clusters case 8c with a 5.5% difference to the case where the problem has not been divided (single cluster, Figure 8a). In the respectively 3 and 5 clusters cases, the overall operating costs are lower compared to the single cluster case used as reference case. This is achieved by increasing the size of energy systems (better efficiency of CHP engines), which reduces technology investment costs and leads to a better deployment of the district heating network. In all cases, dense buildings (distance-based) seem to be connected, for example buildings from cluster four (C4) in figure 8d are also connected in other clustering maps. However, buildings from (C5), also in figure 8d are not connected, even if they are close to each other. This is due to the demand profiles of those buildings which are more similar (residential buildings only) than for buildings in cluster 4 (mixed-types buildings), reducing the economy of scale gain possible when interconnecting buildings with shifted loads. This shows that there are other indicators of the buildings which could help in identifying in which cluster they may best fit in order to achieve to the optimal overall solution (C3). Summing up all technologies installed within each clustering schema when dividing the case study into 1, 2, 3 or 5 clusters gives similar results, especially clusters are relatively small (C3) and (C5), as can be seen in Figure 9, due to the inter-cluster (upper scale optimisation formulation) allowing more network connectivity options when a larger number of clusters is considered.



(a) Dense case results for model A on the left and model D on the right



(b) Sparse case results for model A on the left and model D on the right

Figure 7: System's design and network shapes comparison between formulation employed for model A and model D for a dense (a) and a sparse (b) case.

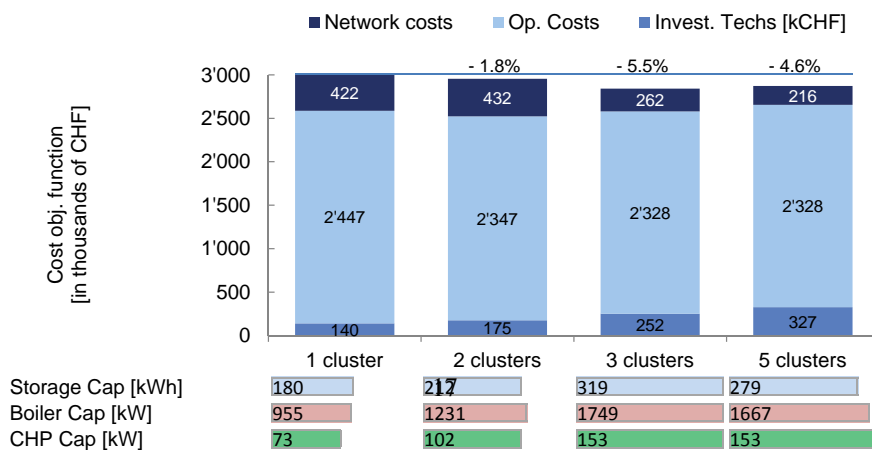


Figure 9: Technology's design and objective function, results between different clustering schema, from 1 to 5 clusters.

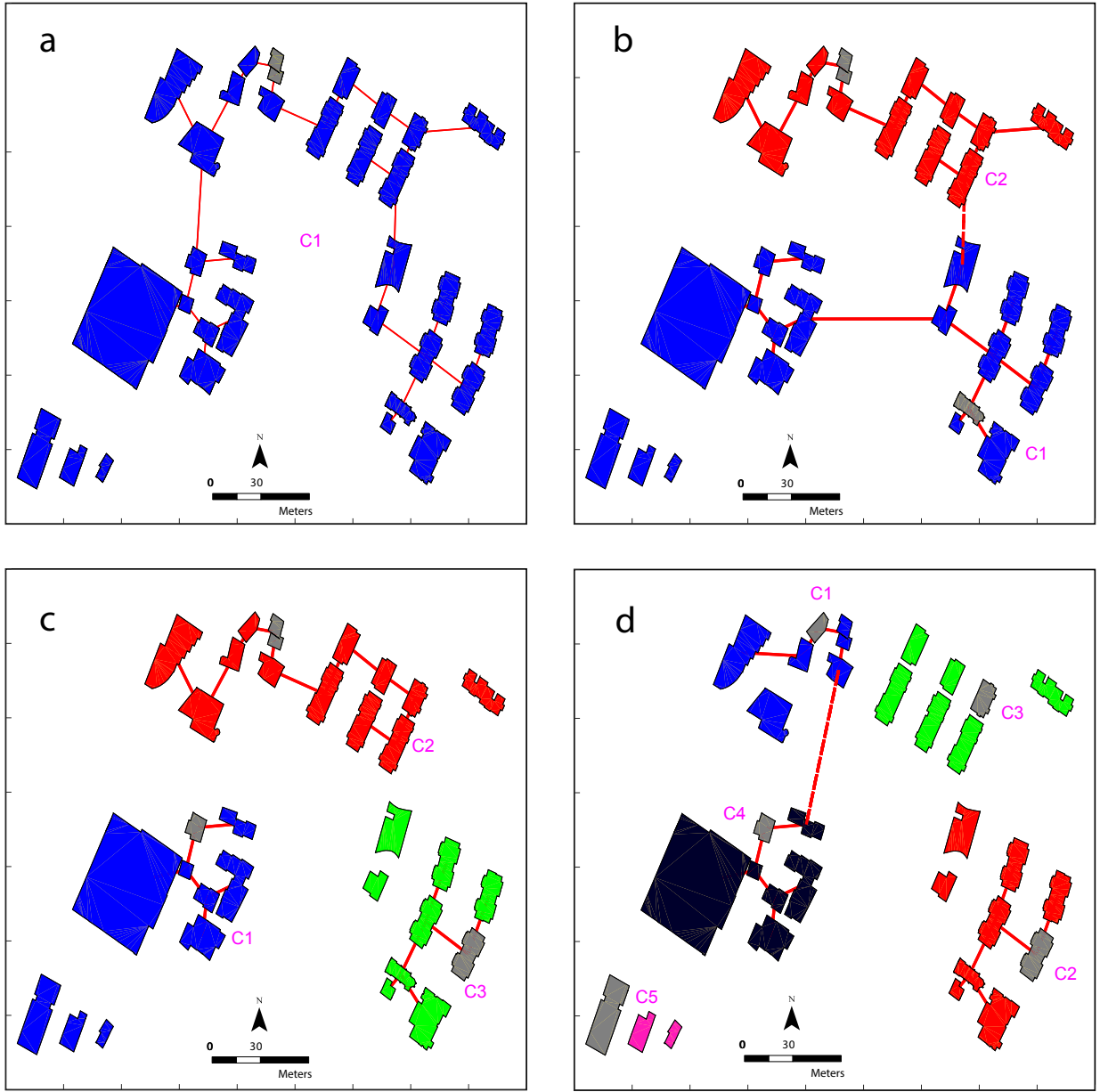


Figure 8: Influence of clustering on DH network shape: a. 1 cluster, b. 2 clusters, c. 3 clusters and d. 5 clusters.

4. Case study

4.1. Overview

The goal of the multi-scale framework is to overcome computational limitations when studying the design of multiple energy systems and operations in the urban context. We applied the framework to an urban context composed of heterogeneous districts to study the relative economic benefits of a more centralised vs. distributed energy strategy. For the study case, different technologies are assumed to be available: natural gas boilers, combined heat and power

(CHP) engines, heat storage devices and photovoltaic panels. The technology range of sizes, efficiencies and economies of scale prices based on the maximal power range can be found table 4, based on various sources: Beith (2011), Omu et al. (2013b), Pöyry (2009). Step-wise price and efficiency is implemented in the model to account for the fact that the size of possibly installed technologies can vary from few kW to a few MWs based on the candidate technologies chosen by the optimisation problem. Indeed, the system configuration could vary from highly distributed - with numerous smaller technologies distributed amongst the buildings - to highly centralised - with fewer larger technologies. Investment costs and technologies efficiency depends linearly and step wise on the technologies size retained in order to account for economy of scale. A district heating network is considered for installation, with the cost of the network dependent on the length of the pipes. Electricity and gas grids are assumed to be installed and available to all buildings. The carbon factor used for natural gas is 0.18 kg CO₂/kWh and for electricity 0.78 kg CO₂/kWh based on Morvaj et al. (2014). The electricity grid price is 0.15 [CHF/kWh], the natural gas price is 0.08 [CHF/kWh] and the export price for electricity assumed, to not be subsidized, is 0.08 [CHF/kWh], Morvaj et al. (2015b). It is assumed that consumers receive single retail prices².

P_{tech}^{max} [kW]	η_{CHP}^{elec} [-]	$\eta_{NGboiler}^{elec}$ [-]	LC_{CHP} [CHF/kW]	$LC_{NGboiler}$ [CHF/kW]
2-20	0.25	0.8	1128	211.5
20-50	0.27	0.8	775.5	176.25
50-180	0.30	0.8	564	131.13
180-350	0.30	0.8	564	111.39
350-500	0.30	0.8	564	91.65
500-5000	0.32	0.8	493.5	42.35
Technology	Efficiency	Fix cost	Linear cost	Life time
NG-boiler	$\eta_{NGboiler}^{elec}$	2'820 [CHF]	$LC_{NGboiler}$	20 years
CHP	2 (HP)	4'260 [CHF]	LC_{CHP}	20 years
PV panels	0.15	2'000 [CHF]	500 [CHF/m ²]	20 years
Storage	0.96 ch/disch 0.99 self	800 [CHF]	80 [CHF/kWh]	20 years
DH-network	4% [km]	[-]	240 [CHF/m]	40 years

Table 4: Table with cost and efficiency per technology and size band based on Beith (2011), Omu et al. (2013b), Pöyry (2009).

The case study consists of 221 buildings situated on the right side of Geneva, grouping residential and mixed residential-commercial buildings. Data are based on open data collected from the SITG (Geneva Territorial Information System) extraction tool available on their website³. The extracted zone for the case study is marked in red in Figure 10a. A detailed map of building shapes in the concerned area and their energy demand is shown in Figure 10. Data available from the website comes in the form of polygons representing the owners of one or multiple houses. Yearly energy consumption and shape area are available for each polygon. Data have been concatenated in order to get the yearly mean energy consumption per building when data were available for multiple layer of floors or juxtaposing buildings (in the raw data a polygon can represent an apartment, a floor or a building based on the ownership, floors and apartments have been grouped at the building scale). In order to calculate the optimal operating strategy according to a simultaneously optimally designed solution, hourly energy demand profile data per building are required. The annual heating and electricity demand profiles are deduced from variable profile based on paper of Evins et al. (2016) by grouping building occupancy and fitting to the area and yearly energy consumption of the actual buildings. In order to consider photovoltaic (PV) panels as a possible supply system, the solar radiation used to generate demand profiles is scaled to the annual sum of measured data in Geneva for the year 2011 (data available in Ineichen (2013)). Data

²Time series for time of use pricing can be easily added to the model, however this study is not in the scope of the paper presenting here a methodology.

³SITG data collector website: <https://www.etat.ge.ch/geoportail/pro/?method=showextractpanel>

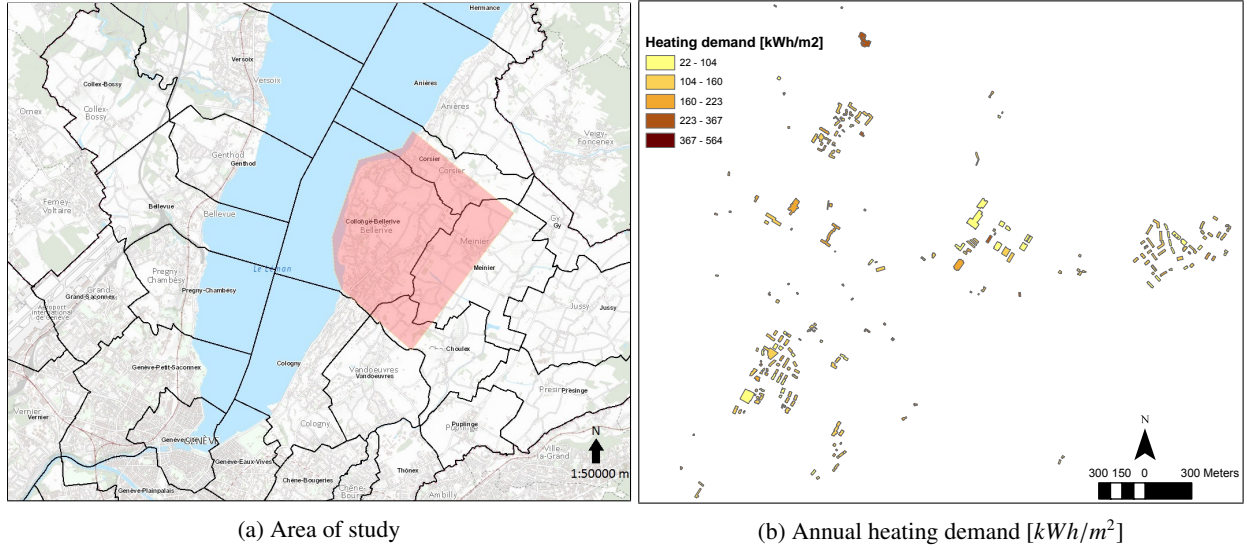


Figure 10: Case study map

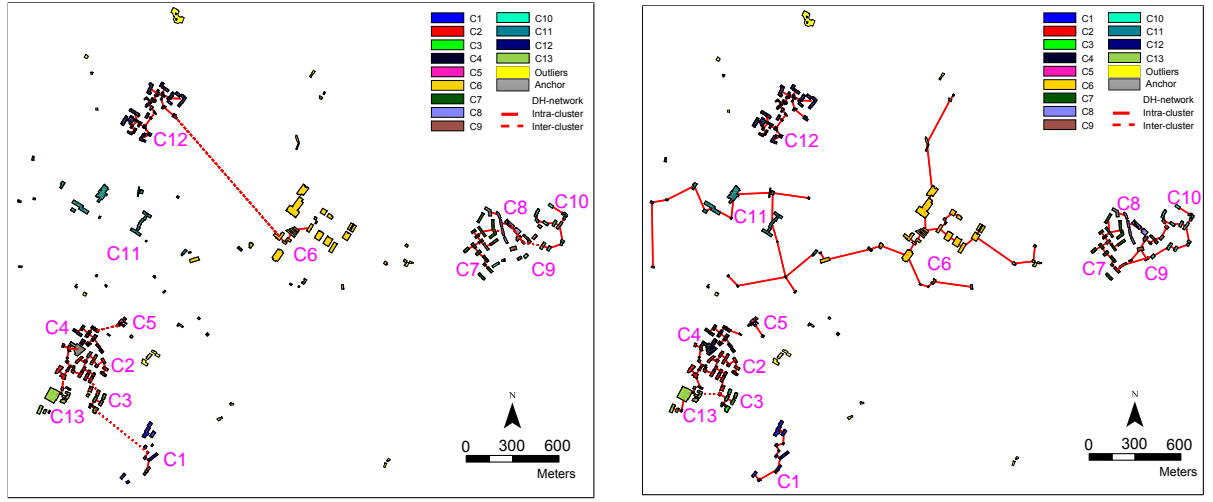
corresponds to the global radiation on a 35° degrees tilted and 0° degree oriented plane (south= 0° degree) expressed in $[Wh/m^2]$ at hourly resolution.

4.2. Parameters used in the framework

Clustering parameters are chosen according to the preceding results and computed using the OPTICSxi algorithm. The optimal number of clusters depends on the problem formulation. A large amount of smaller clusters is necessary for computationally intensive problems including a large number of binary variables often due to time dependent constraints. For a simpler problem a small amount of large clusters is recommended, reducing the error in objective function (see Figure 6). The maximum size of a cluster is fixed to 40 entities (chosen according to the power growth of the computational time with the number of entities for model D, see figure 5). The minimum number of points to form a cluster is fixed to 4 entities and the Minkowski Euclidean distance matrix is selected with a 200 meters distance as the maximum reachability distance (known as EPS-reachability distance).

4.3. Clustering

Based on the preliminary results on clustering map, the presented method is applied to the case study described in section 4.1. The post-processed clustering result leads to the following clustering map, see figure 12 divided into 13 clusters and considering 25 buildings as outliers. The outlier buildings are represented in yellow on the map. Map 12a represents the cost optimal solution in term of Equivalent Annual Costs (EAC) when minimising the EAC. Map 12b represents the carbon optimal solution for a carbon emissions minimisation. The carbon emissions minimisation is optimised in two steps. First the minimum value for the carbon emissions is found and then the EAC are minimised using the minimum carbon emissions, found in the first step, as carbon limit (adding a carbon constraint). This is done in order to assure that the carbon minimum is achieved at least costs, without over sizing the energy systems. There is a contrast in the number of buildings connected to district heating networks between the cost optimal vs. carbon optimal solutions. In the cost optimal solution only the buildings from cluster C12 are fully interconnected through a district heating network, buildings from other clusters are only partially interconnected or fully independent as it is the case for clusters C11, C9, C8 and C14 (outliers), as can be seen in map 12a and figure 11. Whereas for the carbon minimisation solution, buildings from all clusters are fully interconnected through district heating networks. At the inter-cluster level, only close clusters are interconnected for the carbon minimisation result, whereas for the cost minimisation results more distant clusters are interconnected. This is a consequence of the economy of scale, favouring the installation of larger systems in the intra-cluster optimisation when minimising costs, allowing the creation of larger networks at the inter-cluster optimisation step.



(a) Intra and inter-cluster DH network's design for the Equivalent Annual Costs (EAC) minimisation

(b) Intra and inter-cluster DH network's design for the carbon emissions minimisation

Figure 12: DH network's design maps for the cost and carbon optimal solution

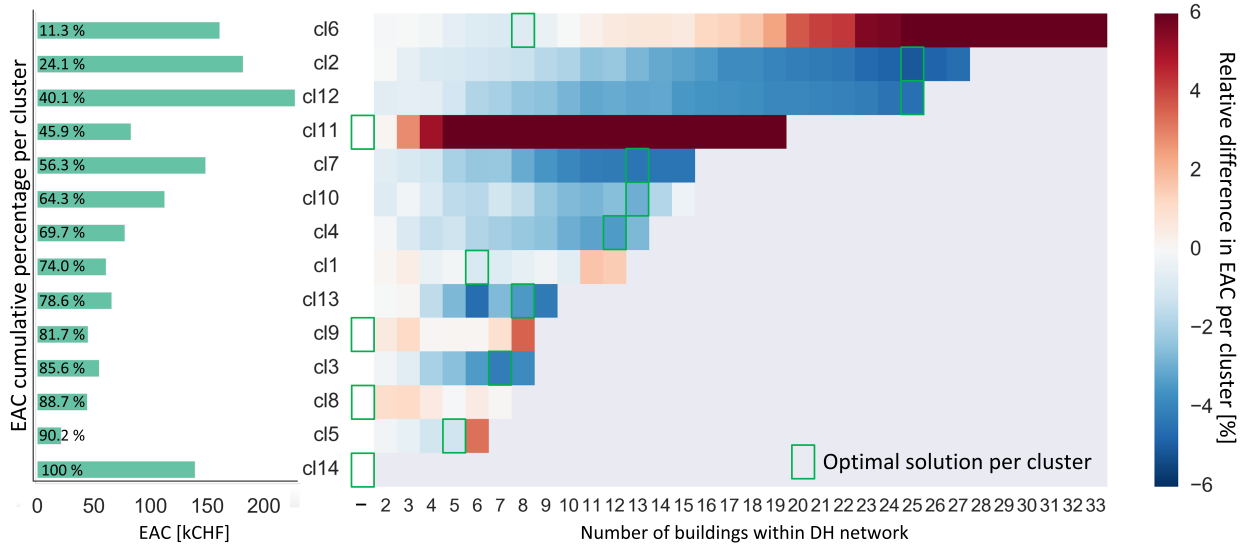


Figure 11: Relative difference in Equivalent Annual Cost (EAC) with distributed energy system case per clusters, for the costs minimisation problem

4.4. Global optimum per clusters lead to a local optimum when optimising between clusters

A global optimum solution based on investment and operating costs is obtained per cluster and illustrated in figure 11, for the costs minimisation problem. The left plot shows the equivalent annual costs per cluster for the fully decentralised case, where all buildings have their own energy systems. The case without a district heating network is considered as the reference case (state of the art). The right plot shows the relative difference to the reference case (illustrated in white, referred with x-axis equal 1, 1 representing the anchor building) per cluster and district heating network generation. Starting from the reference case, buildings are interconnected to create a growing network from 2 up to the maximum number of buildings possible to include in a cluster.

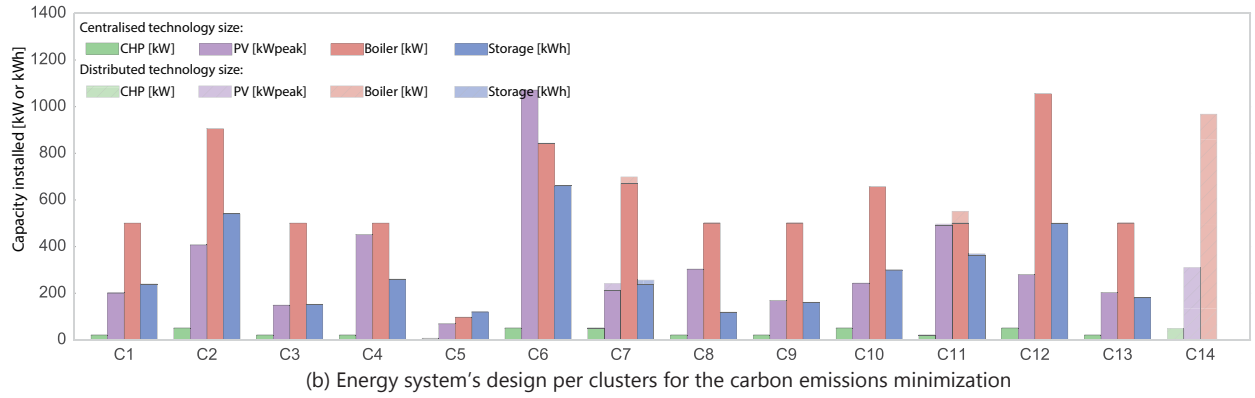
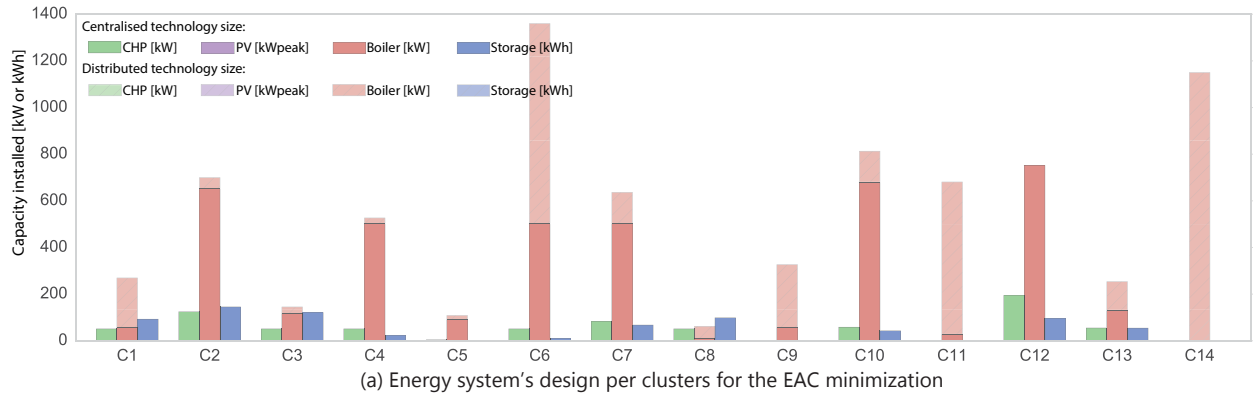


Figure 13: Energy system's design per cluster: a. for the equivalent annual costs minimisation, b. for the carbon emissions minimisation.

The results show the optimum cluster pattern considering all possible anchor buildings per cluster. The green square indicates the optimal solution per cluster. Based on this optimal selection per clusters, an inter-cluster problem is run. Figure 12a illustrates the optimal district heating network connection between buildings per clusters as solid red lines. Fragmented lines illustrate the results of the inter-cluster optimisation problem. By increasing the investment costs by 47 kCHF, from 157 kCHF (11% of the total costs) to 204 kCHF (14.4% of the total costs), it is possible to cut the operating costs by 252 kCHF realising an overall saving of 205 kCHF in equivalent annual costs. This is done by installing a district heating network covering certain districts, splitting the investment cost into energy supply system costs 6.7% and network costs 7.7%. Figure 14a illustrates the cost-optimal results of map (figure 12a) and highlights the 14.4% savings possible to realise annually (on equivalent annual costs) compared to the case where distributed energy systems would be installed to supply the energy demand of the city scale case study. Figure 13a presents the system's design per clusters for the cost optimal solution when minimising the EAC. For the cost optimal solution the total amount of carbon emissions is 3374 tons of CO₂, which represents a decrease of 3.7 % in the carbon emissions compared to the reference solution without a DH network (installing energy systems proper to each buildings). The carbon emissions can be furthermore decreased, by 8.7 % representing 279 tons of CO₂ saved, by increasing the size of the DH network as seen in the carbon optimal solution, when minimising carbon emissions (12b). In this carbon emissions minimisation problem, the PV system⁴ which is not selected in the cost optimum solution appears in all clusters, figure 12b. There is also a large increased of locally centralised system per clusters as well as storage systems. However the investment costs double and it impacts the EAC, increasing them by 28.6 %.

5. Discussion

Results indicate the existence of a correlation between highly dense clusters and the need for interconnecting buildings within a network, which leads to cost and energy savings. The density coefficient of each cluster is calculated as the reversed unity-based normalisation of the mean of the inter-building distance matrix per cluster (for a density coefficient value close to 1 it means that the buildings of the cluster are confined in a small area relatively to the other clusters, for a value close to 0, it means the buildings are sparse within the cluster). This correlation is illustrated in Figure 14b, where the percentage of buildings interconnected by a DH network per cluster is shown by the x-axis (for the cost minimisation problem). Denser clusters (higher than 0.7) tend to be more likely highly interconnected (more than 70% of the buildings are part of the network). However the density characteristic is not the only parameter driving network design. For instance, C6 and C12, though far apart, are interconnected. Other parameters such as load shifting and load magnitude also contribute to the need to interconnect buildings (this will be explained in more details below). Figure 15 shows both of these parameters per cluster on the two heat-map diagonals and the evolution of those parameters when two clusters are grouped, which can be seen as interconnecting two clusters.

Figure 15a shows the Homogeneity Index (HI) as defined by Jafari-Marandi et al. (2016), which is calculated for the heating demand profiles. This index represents the average value of the correlations in the heating load time series between houses within a cluster (on the diagonal), or within houses of two different clusters (on the upper or lower triangle). A decrease of the homogeneity index indicates an increase in the heterogeneity of the cluster, meaning the possibility of having shifted loads between energy consumers. It is calculated per cluster according to the definition of Jafari-Marandi et al. (2016), where i is the index of different clusters and $M_j^{cl_i}$ is the j -th building member of cluster i . N_{cl_i} is the number of buildings within a cluster:

$$HI_{cl_i} = \frac{\sum_{j=1}^{N_{cl_i}} \sum_{k=j+1}^{N_{cl_i}} Corr(M_j^{cl_i}, M_k^{cl_i})}{N_{cl_i} \times (N_{cl_i} - 1) / 2} \quad (13)$$

Figure 15a can be seen as a matrix of the possibility of flattening the load curve which ensues from aggregating building loads within a cluster (in the diagonal) or with another cluster. The lower and greener the HI, the more

⁴ A peer to peer energy exchange system through existing grid network is assumed for the centralised PV system solution. Indeed, the PV are still installed in a distributed manner: all the available roof area of the corresponding buildings within the network boundaries is used and the generated electricity can be transmitted through the buildings incorporated within the network without additional costs, using existing infrastructure. This assumption is already valid as part of new rules in exchange of energy at community level in Switzerland in Arnold (2017) and Niederhusern (2017).

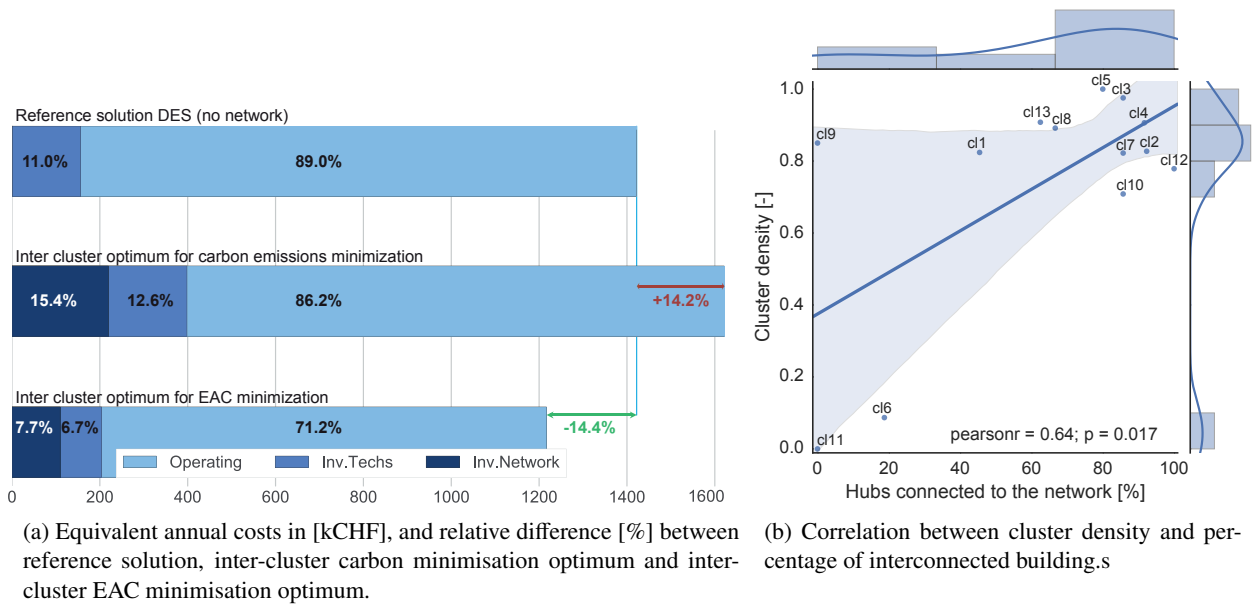


Figure 14: Costs comparison between reference case and inter-cluster optimum solution and correlation between density indicator and network relative size per cluster

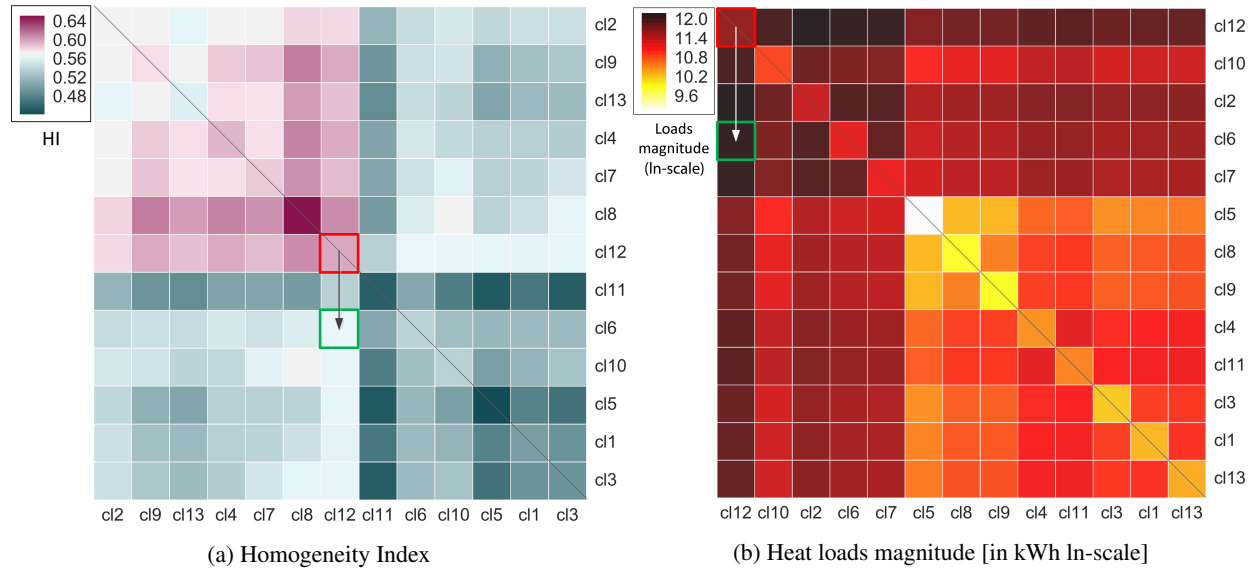


Figure 15: Homogeneity Index and heating loads magnitude per cluster (diagonal) and inter-cluster

heterogeneously are the loads of the different buildings distributed in the corresponding clusters. This indicates load shifting potential within the various demand profiles, and thus the potential to reduce the difference between the peak loads and average loads of the aggregated demand. This is of interest when installing large-size CHP engines and operating them within a part-load efficiency constraint.

Figure 15b shows the magnitude of the heating loads calculated by aggregating the loads of representative days of each building per cluster. This value allows understanding the importance of total heating demand per cluster. A Natural logarithmic scale is used here to visualise the cluster diversity. A darker colour indicates an increase of the load magnitude, meaning of the heating demand of a cluster. This allows to compare the heating demand within a

cluster, and the change of the global heating demand when clusters are combined.

The combination of both parameters can explain the results of the inter-cluster district heating network connection between cluster 12 (cl12) and cluster 6 (cl6). For example a CHP engine of 195kW is installed within cl12 and operates with the CHP engine of 51kW installed in cl6. This is enabled by the increase of the loads' heterogeneity (decreasing the HI index of cl12 alone when grouping it with buildings of cl6). The decrease of HI by grouping cl12 with cl6 can be seen in figure 15a. The HI decreases by 0.1 point when shifting from cl12 diagonal (red square) to the intersection of cl12 and cl6 (green square), and the HI changes from red (more homogeneous loads) to green (more heterogeneous loads). At the same time, there is an increase in the load magnitude when cl12 is grouped with cl6, as seen in figure 15b. Combination of increase of heterogeneity in the loads as well as their magnitudes is an explanation of the deployment of a DH network connection between cl6 and cl12.

These results raise questions about whether these indicators could be included in the clustering step to orient the clustering results. Are these indicators the only ones which could steer the design of networks? If they should be included to the clustering step, which rules (order of importance of the indicators and thresholds values) would be applied to form clusters based on these indicators? Finally, is it possible to generalise an approach allowing to form clusters of fully centralised vs. fully decentralised urban energy systems only based on these indicators? These questions are triggered by the developed framework, which allows for preserving considerable detail at the building level, while still allowing for optimisation of large-scale systems. In the context of future research, it will be investigated to what degree indicators such as load diversity and magnitude themselves may be suitable for identifying optimal energy systems configurations, and under what conditions comprehensive multi-scale optimisation is necessary. The framework developed in this paper is an essential basis for this.

Effort of further research will be concentrated on the use of the developed framework at different scales. Indeed the framework can be directly applied at a city scale in order to investigate and quantify the need for better interconnected energy systems and carriers per districts. It is done by evaluating the trade-off between centralised or distributed approaches in order to help decision makers, urban planners in their investigations of energy and cost saving potentials per districts which are realised by improving network infrastructures. The framework gives an overview on potentially interesting districts where combinations of energy systems could lead to savings. The potential savings are estimated and quantified through the framework then more detailed investigations can be lead in the focus zone of interests.

6. Conclusion

A framework allowing city-scale optimisation of distributed energy systems while retaining detailed building-level resolution has been presented. To enable large-scale optimisation of urban energy systems, new modelling formulations have been introduced and evaluated at neighbourhood scale. They are analogous to the rolling horizon method but applied for the spatial rather than the temporal dimension. The framework demonstrates an ability to reduce computation time by 10 to 100 times with minimal sacrifice in terms of solution accuracy (contained error of 1% relative to a non nested schema). Combining this at neighbourhood scale with a clustering method in the context of a bi-level approach enables the modelling of large-scale systems while preserving building-scale levels of detail. This also allows for the tracking of errors in the modelling of large-scale systems.

Results from the application of the approach to a specific case study show decreased equivalent annual costs by 14.4% relative to the standalone approach which does not consider any network possibilities. This solution also allows to decrease the carbon dioxide emissions by 3.7%. This is achieved by optimally clustering buildings into small-scale district heating networks, and then optimally linking these clusters with further network connections, which reduces necessary supply technology investments and enables effective leveraging of economies of scale.

The influence on the results of the clustering techniques is also discussed. It is important to optimally tune the clustering algorithm based on the problem specifics to converge faster toward the global optimal. Clustering can group together objects based on similarities, but can also be applied to dissimilarities. In this work, they are used to reduce the size of the optimisation problem i.e. the number of variables. Here, the focus is on spatial clustering methods applied in a "divide and conquer" fashion in order to enable solving of large-scale models.

The limitations of the approach can be found in the nesting or division per district implied by the one direction clustering step. Thus, creating the possibility to end up with a sub-optimal solution, limited by the clustering schema. To ensure an optimal clustering associated to a minimisation of the objective function, an iteration loop combined with a genetic optimisation algorithm tuning the clustering parameters based on the optimisation is necessary.

Further research will be dedicated to the clustering methods in order to intelligently divide a large optimisation problem into a set of multiple tractable problems already driven by the entities' characteristics (buildings characteristics) and optimisation results. This would be studied and finally applied to a larger scale case study (thousands of buildings), for which the detailed results and correlation in term of technologies, energy performance and carbon emissions will be investigated.

Acknowledgement

This research has been financially supported by CTI within the SCCER FEEB&D (CTI.2014.0119).

References

- Allegrini, J., Orehounig, K., Mavromatidis, G., Ruesch, F., Dorer, V., Evins, R., 2015. A review of modelling approaches and tools for the simulation of district-scale energy systems. *Renewable and Sustainable Energy Reviews* 52, 1391–1404.
- Ankerst, M., Breunig, M. M., Kriegel, H.-P., Sander, J., 1999. Optics: ordering points to identify the clustering structure. In: *ACM Sigmod Record*. Vol. 28. ACM, pp. 49–60.
- Arnold, C., 2017. Swissolar: Neue situation auf dem strommarkt. =<http://www.ee-news.ch/de/solar/article/35165/swissolar-neue-situation-auf-dem-strommarkt>, accessed: 2017-05-12.
- Beith, R., 2011. Small and micro combined heat and power (CHP) systems: advanced design, performance, materials and applications. Elsevier.
- Bischi, A., Taccari, L., Martelli, E., Amaldi, E., Manzolini, G., Silva, P., Campanari, S., Macchi, E., Aug. 2014. A detailed MILP optimization model for combined cooling, heat and power system operation planning. *Energy*.
URL <http://www.sciencedirect.com/science/article/pii/S0360544214001765>
- Bouffard, F., Kirschen, D. S., 2008. Centralised and distributed electricity systems. *Energy Policy* 36 (12), 4504–4508.
- Carvalho, M., Lozano, M. A., Serra, L. M., 2012. Multicriteria synthesis of trigeneration systems considering economic and environmental aspects. *Applied Energy* 91 (1), 245–254.
- Casali, M., Pinamonti, P., Reini, M., Dec. 2009. Optimal lay-out and operation of combined heat & power (CHP) distributed generation systems. *Energy* 34 (12), 2175–2183.
URL <http://www.sciencedirect.com/science/article/pii/S0360544208002594>
- Chinese, D., Sep. 2008. Optimal size and layout planning for district heating and cooling networks with distributed generation options. *International Journal of Energy Sector Management* 2 (3), 385–419.
URL <http://www.emeraldinsight.com/doi/abs/10.1108/17506220810892946>
- da Graça Carvalho, M., 2012. {EU} energy and climate change strategy. *Energy* 40 (1), 19 – 22.
URL <http://www.sciencedirect.com/science/article/pii/S0360544212000175>
- Dasika, M., Gupta, A., Maranas, C., 2003. A mixed integer linear programming (milp) framework. In: *Pacific Symposium on Biocomputing 2004: Hawaii, USA, 6-10 January 2004*. World Scientific, p. 474.
- Dimitriadis, A. D., Shah, N., Pantelides, C. C., 1997. RTN-based rolling horizon algorithms for medium term scheduling of multipurpose plants. *Computers & Chemical Engineering* 21, S1061–S1066.
URL <http://www.sciencedirect.com/science/article/pii/S0098135497876430>
- Domínguez-Muñoz, F., Cejudo-Lpez, J. M., Carrillo-Andrs, A., Gallardo-Salazar, M., Nov. 2011. Selection of typical demand days for CHP optimization. *Energy and Buildings* 43, 3036–3043.
URL <http://myscidir.cjb.net/science/article/pii/S037877881100329X>
- Evins, R., Orehounig, K., Dorer, V., 2016. Variability between domestic buildings: the impact on energy use. *Journal of Building Performance Simulation* 9 (2), 162–175.
- Fazlollahi, S., Becker, G., Maréchal, F., 2014a. Multi-objectives, multi-period optimization of district energy systems: Iii. distribution networks. *Computers & Chemical Engineering* 66, 82–97.
- Fazlollahi, S., Girardin, L., Maréchal, F., 2014b. Clustering urban areas for optimizing the design and the operation of district energy systems. In: *Proceedings of the 24th European Symposium on Computer Aided Process Engineering*. Vol. 33. Elsevier, pp. 1291–1296.
- Fazlollahi, S., Marchal, F., Feb. 2013. Multi-objective, multi-period optimization of biomass conversion technologies using evolutionary algorithms and mixed integer linear programming (MILP). *Applied Thermal Engineering* 50 (2), 1504–1513.
URL <http://www.sciencedirect.com/science/article/pii/S1359431111006636>
- Fishbone, L. G., Abilock, H., 1981. Markal, a linear-programming model for energy systems analysis: Technical description of the bnl version. *International journal of Energy research* 5 (4), 353–375.
- Fonseca, J. A., Schlueter, A., 2015. Integrated model for characterization of spatiotemporal building energy consumption patterns in neighborhoods and city districts. *Applied Energy* 142, 247–265.
- Geidl, M., Koeppel, G., Favre-Perrod, P., Klckl, B., Andersson, G., Frhlich, K., 2007. The energy huba powerful concept for future energy systems. In: *Third annual Carnegie Mellon Conference on the Electricity Industry*, Pittsburgh. pp. 13–14.
- General Secretariat of the Council, E. C., 2011. Communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions, energy roadmap 2050. European Commission, 1–20.
URL <http://eur-lex.europa.eu/legal-content/EN>
- General Secretariat of the Council, U. C., 2014. European council (23 and 24 october 2014), conclusions. European Commission, 1–15.
URL <http://www.consilium.europa.eu>

- Gerber, L., Fazlollahi, S., Maréchal, F., 2013. A systematic methodology for the environomic design and synthesis of energy systems combining process integration, life cycle assessment and industrial ecology. *Computers & Chemical Engineering* 59, 2–16.
- Grossmann, I. E., 2012. Advances in mathematical programming models for enterprise-wide optimization. *Computers & Chemical Engineering* 47, 2–18.
URL <http://www.sciencedirect.com/science/article/pii/S0098135412002220>
- Gustafsson, S.-I., Oct. 1998. Mixed integer linear programming and building retrofits. *Energy and Buildings* 28 (2), 191–196.
URL <http://www.sciencedirect.com/science/article/pii/S037877889800019X>
- Hiremath, R. B., Shikha, S., Ravindranath, N. H., Jun. 2007. Decentralized energy planning; modeling and applicationa review. *Renewable and Sustainable Energy Reviews* 11 (5), 729–752.
URL <http://www.sciencedirect.com/science/article/pii/S1364032105000894>
- Ineichen, P., 2013. Solar radiation resource in geneva: measurements, modeling, data quality control, format and accessibility. 333.7-333.9, iD: unige:29599.
URL <http://archive-ouverte.unige.ch/unige:29599>
- Jafari-Marandi, R., Hu, M., Omitaomu, O. A., 2016. A distributed decision framework for building clusters with different heterogeneity settings. *Applied Energy* 165, 393–404.
- Jakob, M., Ott, W., Kiss, B., Fulop, L., Maneschi, D., Ungureanu, V., Bolliger, R., Kallio, S., Chobanova, H., Nägeli, C., et al., 2014. Integrated strategies and policy instruments for retrofitting buildings to reduce primary energy use and ghg emissions.
- Jones, T., 2008. Distributed energy systems. *Transitions: Pathways towards sustainable urban development in Australia*, 411–424.
- Keirstead, J., Jennings, M., Sivakumar, A., 2012a. A review of urban energy system models: Approaches, challenges and opportunities. *Renewable and Sustainable Energy Reviews* 16 (6), 3847–3866.
- Keirstead, J., Samsatli, N., Pantaleo, A. M., Shah, N., 2012b. Evaluating biomass energy strategies for a uk eco-town with an milp optimization model. *biomass and bioenergy* 39, 306–316.
- Keirstead, J., Samsatli, N., Pantaleo, A. M., Shah, N., Apr. 2012c. Evaluating biomass energy strategies for a UK eco-town with an MILP optimization model. *Biomass and Bioenergy* 39, 306–316.
URL <http://www.sciencedirect.com/science/article/pii/S0961953412000232>
- Kerr, T., 2016. From paris to implementation: The role of international climate initiatives. *Sustainability: The Journal of Record* 9 (1), 12–16.
- Koestler, A., 1972. Beyond atomism and holismthe concept of the holon. *The rules of the game: cross disciplinary essays in models in scholarly thought*. London: Tavistock.
- Kok, K., Karnouskos, S., Nestle, D., Dimeas, A., Weidlich, A., Warmer, C., Strauss, P., Buchholz, B., Drenkard, S., Hatzigiorgiou, N., et al., 2009. Smart houses for a smart grid. In: *Electricity Distribution-Part 1, 2009. CIRED 2009. 20th International Conference and Exhibition on. IET*, pp. 1–4.
- Kong, X., Wang, R., Huang, X., 2005. Energy optimization model for a cchp system with available gas turbines. *Applied Thermal Engineering* 25 (2), 377–391.
- Li, F., Qiao, W., Sun, H., Wan, H., Wang, J., Xia, Y., Xu, Z., Zhang, P., 2010a. Smart transmission grid: Vision and framework. *IEEE transactions on Smart Grid* 1 (2), 168–177.
- Li, Y. F., Li, Y. P., Huang, G. H., Chen, X., Oct. 2010b. Energy and environmental systems planning under uncertaintyAn inexact fuzzy-stochastic programming approach. *Applied Energy* 87 (10), 3189–3211.
URL <http://www.sciencedirect.com/science/article/pii/S0306261910000619>
- Liu, S., Pinto, J. M., Papageorgiou, L. G., 2008. A tsp-based milp model for medium-term planning of single-stage continuous multiproduct plants. *Industrial & Engineering Chemistry Research* 47 (20), 7733–7743.
- Lozano, M. A., Ramos, J. C., Carvalho, M., Serra, L. M., Oct. 2009. Structure optimization of energy supply systems in tertiary sector buildings. *Energy and Buildings* 41 (10), 1063–1075.
URL <http://www.sciencedirect.com/science/article/pii/S037877880900111X>
- Makkonen, S., Lahdelma, R., Jun. 2006. Non-convex power plant modelling in energy optimisation. *European Journal of Operational Research* 171 (3), 1113–1126.
URL <http://www.sciencedirect.com/science/article/pii/S0377221705001293>
- Marquant, J., Omu, A., Orehounig, K., Evins, R., Carmeliet, J., 2015a. Application of spatial-temporal clustering to facilitate energy system modelling. In: *Building Simulation, BS2015 Proceedings*, ISBN: 978-93-5230-118-8.
- Marquant, J. F., Evins, R., Carmeliet, J., 2015b. Reducing computation time with a rolling horizon approach applied to a milp formulation of multiple urban energy hub system. *Procedia Computer Science* 51, 2137–2146.
- Mehleri, E. D., Sarimveis, H., Markatos, N. C., Papageorgiou, L. G., Aug. 2012a. A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level. *Energy* 44 (1), 96–104.
URL <http://linkinghub.elsevier.com/retrieve/pii/S036054421200103X>
- Mehleri, E. D., Sarimveis, H., Markatos, N. C., Papageorgiou, L. G., 2012b. A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level. *Energy* 44 (1), 96–104.
- Moniz, E. J., Jacoby, H. D., Meggs, A., Armstrong, R., Cohn, D., Connors, S., Deutch, J., Ejaz, Q., Hezir, J., Kaufman, G., 2011. *The future of natural gas*. Cambridge, MA: Massachusetts Institute of Technology.
- Moreno, R., Moreira, R., Strbac, G., Jan. 2015. A MILP model for optimising multi-service portfolios of distributed energy storage. *Applied Energy* 137, 554–566.
URL <http://www.sciencedirect.com/science/article/pii/S0306261914008915>
- Morvaj, B., Evins, R., Carmeliet, J., 2014. Optimal selection and operation of distributed energy resources for an urban district. *Proceeding EngOpt* 2014.
- Morvaj, B., Evins, R., Carmeliet, J., 2015a. Bi-level optimisation of distributed energy systems incorporating non-linear power flow constraints. In: *Proceedings of International Conference CISBAT 2015 Future Buildings and Districts Sustainability from Nano to Urban Scale*. No. EPFL-CONF-213433. LESO-PB, EPFL, pp. 859–864.

- Morvaj, B., Evins, R., Carmeliet, J., 2015b. The impact of low energy buildings on the optimal design of distributed energy system and networks. In: Building Simulation.
- Morvaj, B., Evins, R., Carmeliet, J., 2016a. Optimising urban energy systems: Simultaneous system sizing, operation and district heating network layout. *Energy* 116, 619–636.
- Morvaj, B., Evins, R., Carmeliet, J., Jun. 2016b. Optimization framework for distributed energy systems with integrated electrical grid constraints. *Applied Energy* 171, 296–313.
URL <http://www.sciencedirect.com/science/article/pii/S0306261916304159>
- Morvaj, B., Evins, R., Carmeliet, J., 2016c. Optimization framework for distributed energy systems with integrated electrical grid constraints. *Applied Energy* 171, 296–313.
- Morvaj, B., Evins, R., Carmeliet, J., 2017. Decarbonizing the electricity grid: The impact on urban energy systems, distribution grids and district heating potential. *Applied Energy* 191, 125–140.
- Nease, J., Adams, T. A., Sep. 2014. Application of rolling horizon optimization to an integrated solid-oxide fuel cell and compressed air energy storage plant for zero-emissions peaking power under uncertainty. *Computers & Chemical Engineering* 68, 203–219.
URL <http://linkinghub.elsevier.com/retrieve/pii/S009813541400180X>
- Niederhuser, A., 2017. Pv-tagung: Von der energiestrategie ber forschung und solarflieger bis zu farbigen modulen. =<http://www.ee-news.ch/de/solar/article/35733/pv-tagung-von-der-energiestrategie-uber-forschung-und-solarflieger-bis-zu-farbigen-modulen>, accessed: 2017-05-12.
- Omu, A., Choudhary, R., Boies, A., Oct. 2013a. Distributed energy resource system optimisation using mixed integer linear programming. *Energy Policy* 61, 249–266.
URL <http://www.sciencedirect.com/science/article/pii/S0301421513003418>
- Omu, A., Choudhary, R., Boies, A., 2013b. Distributed energy resource system optimisation using mixed integer linear programming. *Energy Policy* 61, 249–266.
- Pantaleo, A. M., Giarola, S., Bauen, A., Shah, N., Jul. 2014. Integration of biomass into urban energy systems for heat and power. Part II: Sensitivity assessment of main techno-economic factors. *Energy Conversion and Management* 83, 362–376.
URL <http://www.sciencedirect.com/science/article/pii/S0196890414002507>
- Pfenniger, S., Hawkes, A., Keirstead, J., 2014. Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews* 33, 74 – 86.
URL <http://www.sciencedirect.com/science/article/pii/S1364032114000872>
- Pirouti, M., Bagdanavicius, A., Ekanayake, J., Wu, J., Jenkins, N., 2013. Energy consumption and economic analyses of a district heating network. *Energy* 57, 149–159.
- Pöyry, A., 2009. The potential and costs of district heating networks. UK Department.
- Pruitt, K. A., Braun, R. J., Newman, A. M., Feb. 2013. Evaluating shortfalls in mixed-integer programming approaches for the optimal design and dispatch of distributed generation systems. *Applied Energy* 102, 386–398.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0306261912005521>
- Ren, H., Gao, W., 2010. A milp model for integrated plan and evaluation of distributed energy systems. *Applied Energy* 87 (3), 1001–1014.
- Ren, H., Zhou, W., Nakagami, K., Gao, W., 2010. Integrated design and evaluation of biomass energy system taking into consideration demand side characteristics. *Energy* 35 (5), 2210–2222.
- Silvente, J., Kopanos, G. M., Pistikopoulos, E. N., Espua, A., Oct. 2015. A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids. *Applied Energy* 155, 485–501.
URL <http://www.sciencedirect.com/science/article/pii/S0306261915007230>
- Sugihara, H., Tomioka, H., Tsuji, K., 2008. A competitive evaluation of urban energy systems from viewpoints of energy conservation and mitigating environmental impact. *Electrical Engineering in Japan* 164 (2), 71–79.
- Uhlemair, H., Karschin, I., Geldermann, J., Jan. 2014. Optimizing the production and distribution system of bioenergy villages. *International Journal of Production Economics* 147, Part A, 62–72.
URL <http://www.sciencedirect.com/science/article/pii/S0925527312004227>
- Wagner, M., Weyell, C., Geyer, P., Schlter, A., Schlegel, M., Steubing, B., Hellweg, S., Gruber, S., Mavromatidis, G., Frmelt, A., Cisar, S., Christiaan, K., Mikoleit, A., Orehounig, K., Carmeliet, J., Zaug, H., 2015. Zerne Energie 2020 - Leitfaden. Tech. rep.
URL <https://doi.org/10.3929/ethz-a-010577816>
- Weber, C., Shah, N., 2011. Optimisation based design of a district energy system for an eco-town in the united kingdom. *Energy* 36 (2), 1292–1308.
- Wolfe, P., 2008. The implications of an increasingly decentralised energy system. *Energy Policy* 36 (12), 4509 – 4513, foresight Sustainable Energy Management and the Built Environment Project.
URL <http://www.sciencedirect.com/science/article/pii/S0301421508004722>
- Yang, Y., Zhang, S., Xiao, Y., 2015. Optimal design of distributed energy resource systems coupled with energy distribution networks. *Energy* 85, 433–448.
- Yokoyama, R., Hasegawa, Y., Ito, K., Apr. 2002. A MILP decomposition approach to large scale optimization in structural design of energy supply systems. *Energy Conversion and Management* 43 (6), 771–790.
URL <http://www.sciencedirect.com/science/article/pii/S0196890401000759>