A new Combined Clustering Method to Analyse the Potential of District Heating Networks at Large-scale

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Abstract:
For effective integration of large amounts of renewables and high-efficiency energy technologies, their benefits have to be quantified. Network-level energy optimisation approaches can determine the optimal location of generation technologies within a region and the optimal layout of energy distribution networks to link them. Mixed-integer linear programming (MILP) formulations are generally employed and this is often a burden for large scale models as the computational time drastically increases with the problem size.
Most methods used to reduce the complexity of MILP problems focus on the temporal scale or use aggregated demand profiles for the spatial dimension. There is a lack of a method addressing the spatial complexity to assess the potential of interlinked energy networks at large scale. Therefore, this paper introduces a new combined clustering schema enabling quantification of the potential of district heating networks based on results from building scale energy optimisation problems and taking into account building characteristics.
A city-scale case is divided into multiple districts based on the output of a density based clustering algorithm. The parameters taken into account by the clustering method are the cluster density, homogeneity index and load magnitude. The analysis of the clustering map along with building characteristics of each cluster reveals the required characteristics for the installation of a district heating network or distributed energy systems.

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

Nomenclature

CHP	combined heat and power
COP	conference of the parties
CRF	capital recovery factor, calculated with a discount rate of 3% [-]
DB	Davies-Bouldin index
DES	distributed energy systems
DHN	district heating network
EAC	equivalent annual cost
ELDC	error in the load duration curve
LP	linear programming problem
MILP	mixed integer linear programming problem
MST	minimum spanning tree algorithm
NPV	net present value

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OPTICS ordering points to identify the clustering structure
PV photovoltaic solar panel
REH receding horizon
RH rolling horizon
TS thermal storage
TSP travelling salesman problem

Greek symbols

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

Roman symbols

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

Subscripts

$+$ discharging storage
$-$ charging storage
cl_x cluster x
e energy hub e
j j-th member of cluster x

t time step [hour]

$tech$ technology available

1. Introduction

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

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

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

1.1. Distributed energy systems optimisation

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

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

1.2. Clustering methods enabling large scale energy optimisation

Considering multiple energy systems in a MILP problem becomes computationally demanding in terms of solving time when increasing the problem space by augmenting the number of integer variables (exponential increases of the solving time [9]). This is often the case when adding specific constraints on technologies (minimum part-loads, banded efficiencies and/or costs), or when increasing the spatial or temporal dimensions of the problem. Commonly in research, large scale optimisation of DES is made possible by applying different reduction techniques.

Those techniques are first applied at the temporal scale for problems including more than one building in the energy optimisation problem, but for which the spatial scale remains limited to a neighbourhood scale (tens of buildings). Average days are employed in [20] to represent a full year of operation at hourly resolution with an average day per month. Typical days [15], [28] or periods [13], [29] approaches are commonly employed to reduce the temporal scale by representing a full year horizon using shorter periods, which may be selected using k-medoids or k-means clustering methods [28], [30]. Other approaches, such as rolling horizon, can also be employed to divide the entire problem horizon into sub-problems solved sequentially, thus reducing the number of decision variables per interval [9], [17]. Receding horizon techniques, derived from rolling horizon techniques and related to Model Predictive Control (MPC), allow an aggregated view on the full horizon problem for each planning interval. They have been applied in [9], [17], [31], [32], allowing to consider the seasonality of storage systems, often linked to optimisation problem including intermittent sources of energy. Those decomposition techniques, rolling or receding horizon are mostly used in optimisation problems looking at the optimal operating strategy of given set of energy carriers and sources. They have to be employed with heuristic techniques for the design of energy system problem, as it has been done in [33], where a rolling horizon schema is employed for the optimal operating scheduling problem and combined with a genetic algorithm for the design of the set of candidates energy technologies.

Spatial scale reduction techniques are employed conjointly with temporal reduction techniques for problem larger than the neighbourhood scale. Indeed, they are employed for district scale [34], [35] or city scale [12], [36] problems. Often aggregation techniques are employed to represent the energy demand of many buildings by a single node [15], [37]. Those spatial dimensionality reductions have been effectuated manually in previous studies by aggregating buildings and their energy demands based on spatial location or building use classes to compute district-level distributed energy systems optimisation problems [12], [34], [38], [39]. Recently, mathematical algorithms have been used to aggregate buildings into clusters based on specific characteristics. Those distance-based or density based clustering methods allow grouping buildings into clusters while assessing the quality of the aggregation. The *k*-means or *k*-medoids distance based clustering algorithms have been employed to group and aggregate buildings in districts [37] and to enable district-level DES design [40]. OPTICS density-based clustering algorithm [41], [42] and Self Organizing Maps (SOM) [35] or the Geo-Self Organising Map (Geo-SOM) tool [43] have also been used to cluster buildings considering their spatial location and also the homogeneity or heterogeneity (when clustered on dissimilarity) of their energy loads [44].

However, there is a lack of a method addressing the full spatial and temporal complexity and assessing the potential of interlinked energy networks at large scale, while considering a building scale level of detail to avoid sub-optimal solutions. In the methodology developed in [42] allowing to consider a building level of detail at larger scale in a bottom-up framework, a critic is emitted on the influence of the clustering method, purely spatially based, on the results of the energy optimisation problem. Indeed if in this previous study, the clustering algorithm allows to reduce the spatial dimensionality by dividing a large problem in sub-problems, solved iteratively, the limitation of the approach arose in the nesting approach, implied in a one direction clustering step, thus limiting the possibilities of exchange of energy at a building level within the respective districts delimited by the spatial clustering algorithm.

A novel approach has been developed in this paper to ensure a near optimal energy design solution, by providing a feedback loop between the energy problem and the clustering algorithm results. We present a method formulated as a bottom-up approach, considering each building individually, with their spatial location and including their temporal dimension, considering their energy demand profile in the optimisation problem, by combining the energy optimisation problem with a clustering method using an evolutionary metaheuristic genetic algorithm. The combined clustering algorithm is presented in Section 3. Results, in Section 4, demonstrates the effectiveness of the combined clustering method taking into account the spatial and temporal dimension of the load profiles at the building level for district or city scale problems.

2. Methodology

The multi-scale hierarchical approach for DES optimisation presented in [44] is employed and integrated with a combined clustering approach in order to enable solving of large scale DES problems while considering building scale level of detail. This is done in an iterative manner between the clustering method and a bottom-up optimisation framework. This section first introduces the optimisation problem and gives an overview of the multi-scale hierarchical approach used. Full details of the multi-scale approach can be found in [44]. A city-scale case is divided into multiple clusters based on the output of the clustering algorithm. The optimisation problem is run individually for each cluster before being run between clusters at the higher scale (inter-cluster) based on the optimal results from the cluster scale.

2.1. The energy hub approach

The energy hub framework [45] is employed for the MILP formulation of the optimisation problem. The energy hub formulation allows representing the efficiency of multiple energy systems within a matrix coupling energy demand and supply [46] as shown in Fig. 1.

Objective function

The objective function (1) is to minimize the equivalent annual cost for design (2) and operations (3) of multiple urban energy systems including networks.

$$min \sum_{e=1}^{n_e} \left\{ I_{tech} \times CRF + \sum_{t=1}^{horizon} OC_{tech}(t) \right\} \tag{1}$$

The investment costs are multiplied by the capital recovery factor (CRF). A discount rate of 3% is used, with a lifespan of 20 years for the technologies and 40 years for the network pipelines in order to calculate the CRF. The operating costs are calculated for a year of operation.

$$I_{tech} = \sum_{tech=1}^{n_{tech}} \delta_{tech} \times C_{tech}^{linear} \times P_{\text{tech}}^{max} \tag{2}$$

The investment costs (2) represent the costs of each technology installed taking into account economies of scale (see Table 1) where the price per kW of each technology depends on its size band. δ_{tech} is a binary variable for the design optimisation problem which takes the value 1 or 0, based on the installation or not of a specific technology. A detailed formulation explaining the linearization of the multiplication between integer and binary variables, to consider the economy of scale formulation, can be found in [47]

$$OC_{tech}(t) = \sum_{tech=1}^{n_{tech}} P_{tech}(t) \times C_{supply} \tag{3}$$

The operating costs (3) are calculated based on the sum of the costs of electricity imported from the grid, the gas used by the boiler and CHP engine minus the electricity produced and sold to the grid. C_{supply} represents the cost of the energy resources per technology and $P_{tech}(t)$ the power consumed or generated by a technology at every time step. Electricity and gas grids are assumed to be installed and available to all buildings. 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]. It is assumed that consumers receive single retail prices. The carbon emissions are calculated in (4). The carbon factor used for natural gas is 0.18 kg CO2/kWh and for electricity 0.78 kg CO2/kWh based on [20]

$$Carb_{tech}(t) = \sum_{tech=1}^{n_{tech}} P_{tech}(t) \times Carb_{supply}^{em} \tag{4}$$

Energy demand constraints

The following energy demand constraints (5) ensure that the electricity and heating demand is met at each time step at a building level $L(t)$. The efficiency of the technology, based on the size of the energy systems selected by the optimisation problem, appears in the coupling matrix represented by Θ. The storage continuity is modelled by equation (6), where the state of charge E depends of the storage flux Q, subjects to charging $A_{\_}$ and discharging A_{+} efficiencies given in Table 1.

$$L(t) = \Theta \times P_{tech}(t) + A_{\_}Q_{\_}(t) - A_{+}Q_{+}(t) \tag{5}$$

$$E(t+1) = n_s \cdot E(t) + Q_{+}(t) - Q_{\_}(t) \tag{6}$$

Specific constraints (7-8) are added to take into account the operating characteristics of dispatchable technologies in multi-energy systems, for example part-loads constraints for CHP engines, considering a minimum load of 50% to guaranty that the CHP engines are not operating at lower efficiency [48]. B is an arbitrary large number, employed for the 'big-M' constraint method to formulate binary constraints [27], and δ_{CHP}^{on} is a binary variable for the on/off constraint of the CHP engine at every time step.

$$\eta_{CHP} \cdot P_{CHP}(t) \le B \cdot \delta_{CHP}^{on}(t) \quad \forall t \tag{7}$$

$$0.5 \cdot P_{CHP}^{\max}(t) \le \eta_{CHP} \cdot P_{CHP}(t) + B \cdot \left\{1 - \delta_{CHP}^{on}(t)\right\} \quad \forall t \tag{8}$$

At the inter-cluster level, the district heating network formulation (9) is based on [49].This formulation allows to consider the possibility of transferring heat from one entity (at the cluster level) to another through the district-heating network whose structured is optimally determined during the inter-cluster MILP solving. Q_{ji} represents the heat transferred from entity *j* to *i* and (10) ensures that heat is transferred in only one direction at every time step.

$$L(t) = \Theta \times P_{tech}(t) + A_{\_}Q_{\_}(t) - A_{+}Q_{+}(t) + \sum Q_{ji}(t) \times HL_{ij} - \sum Q_{ij}(t) \tag{9}$$

$$Q_{ij}(t) \le \delta_{ij} \times B \quad , \delta_{ij} + \delta_{ji} \le 1 \tag{10}$$

There is no loop of heat possible with the constraint formulation (11) employed in [13] and motivated by the Travelling Salesman Problem [50].

$$O_j \ge o_i + 1 - N_e(1 - \delta_{ij}) \qquad \forall\, i,j \qquad i \ne j \tag{11}$$

The available energy systems considered in this study are natural gas boiler (NG), combined heat and power engine (CHP), photovoltaic panel (PV), thermal storage (TS) and district heating network (DHN), considering that gas and electrical networks are already connected to all buildings. CHP engines and NG boilers sizes can vary from mini-CHP or NG boiler of 2kW to large size CHP plant or boiler of 5MW.

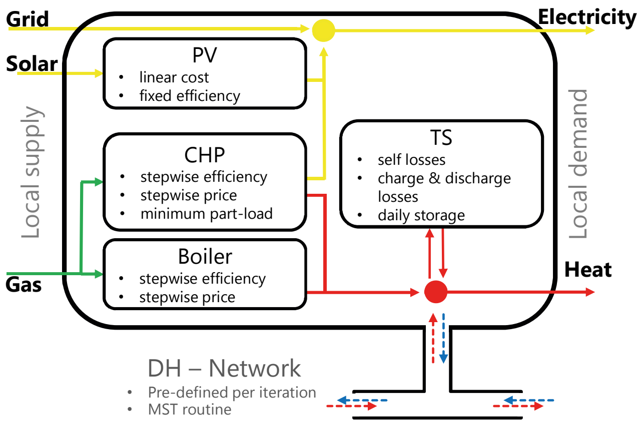


Fig. 1. Energy hub design space

The maximum allowable size of PV panels is constrained by the total roof area available per building. Similarly the total capacity of thermal storage available per area depends on the number of buildings considering a fixed maximum capacity of 20 kWh per building. Cost and efficiency depend on the technology size which is a design variable of the optimisation problem. Size price and efficiency bands are obtained from various sources [15], [51], [52] and harmonized with Swiss prices in Table 1.

Table 1. Size band cost and efficiency per technology [51], [52]

$P_{Tech.}^{max}$ [kW]	η_{CHP}^{elec} [-]	η_{NG-b}^{elec} [-]	c_{CHP}^{linear} [CHF/kW]	c_{NG-b}^{linear} [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	η_{NG-b}^{elec}	2820 [CHF]	c_{NG-b}^{linear}	20 years
CHP	η_{CHP}^{elec}	4260 [CHF]	c_{CHP}^{linear}	20 years
PV panels	0.15	2000 [CHF]	500 [CHF/m^2]	20 years
Storage	0.96 ch/disc 0.99 self	800 [CHF]	80 [CHF/kWh]	20 years
DH-network	5% [km]		240 [CHF/m]	40 years

2.2. Iterative hierarchical multi-scale framework to facilitate large scale optimisation

The hierarchical multi-scale optimisation framework developed in [44] is combined with a genetic algorithm and a combined clustering algorithm in order to avoid sub-optimal solution, by considering only one clustering result as input for the energy optimisation problem. The combined framework is presented in Fig. 2. It is divided in three phases (a,b,c in Fig. 2):

1. a structuring phase (a), during which the clustering algorithm divide the problem space in multiple sub-problems (clusters);
2. an optimisation phase (b) run per cluster at a district level;
3. a general optimisation between clusters (c) based on optimal solutions at the cluster level.

Fig. 2 presents the workflow coloured based on the software used at each step. The building locations and load profiles are given as input to the energy optimisation problem, as is the set of technologies available to supply the energy demand. Each building is considered as an energy hub and energy systems can be installed at any location. A first density based clustering algorithm creates a set of hierarchically nested clusters as a tree structure. Those pre-clusters are ordered and grouped based on a combined clustering score function, developed Section 3.2. Based on the results of this combined clustering approach a set of clusters is created. The energy hub optimisation problem is then considered per cluster. In each cluster, multiple network shapes are generated based on a minimum spanning tree algorithm, interconnecting at each generation a growing number of buildings within each cluster from no district heating network to fully connected DH network, as presented in [47]. Per network generation, the loads of the buildings included in the DHN are aggregated and losses considered as a linear relation with the network size. Aggregated buildings which are part of the network are considered as a single energy hub, with the other remaining buildings considered as individual hubs. The energy hub optimisation problem is solved per hub, and this is done per network generation and per cluster, as described in Fig. 2 (b). Finally once the optimisation problem has been run per cluster, the optimal solution is retained and the design variables are passed to an inter-cluster scale optimisation problem (9). This ultimate optimisation problem consider the possibility of interconnecting clusters as an integer design variable, as in [49].

The iterative loop between the result of the optimisation steps (b,c) and the clustering algorithm (step a) is developed in order to avoid ending up with sub-optimal solutions driven by the clustering algorithm output. The feedback loop between the inter-clustering network optimisation results and the combinatorial clustering algorithm is created and tuned by the genetic algorithm (GA). The cluster set as output from the combined clustering is based on building location and load profiles, reflected by density indices, load homogeneity and load magnitude of given clusters, explained in Section 3.2. The clusters are formed based on the output of the GA at every iteration, taking into account the results of the energy optimisation problems at the intra and inter-cluster phases.

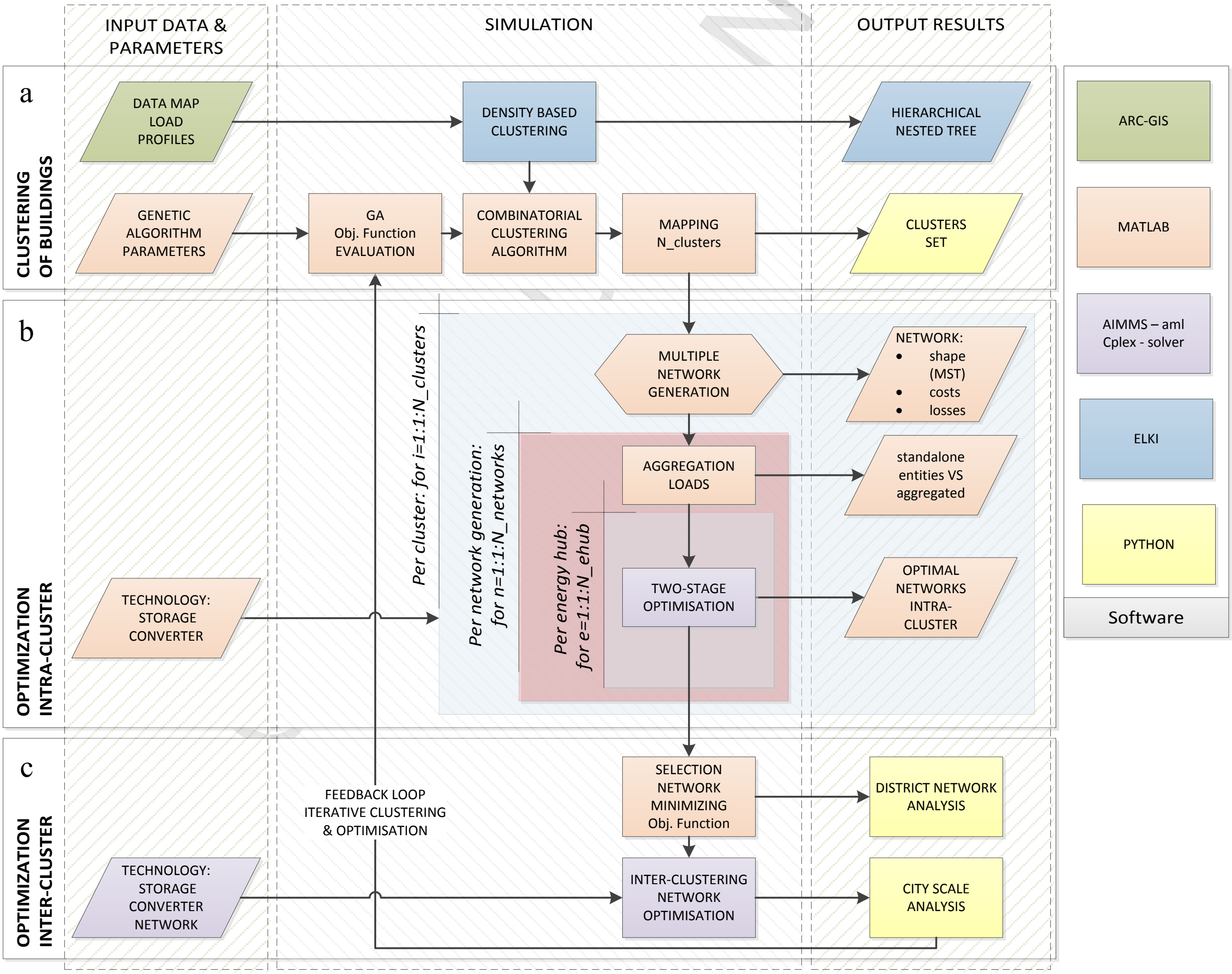


Fig. 2. Iterative multi-scale optimisation of DES

3. Combined clustering approach

Clustering methods drastically reduce the computational time in a 'divide and conquer' fashion. This can be done without significantly reducing the problem accuracy, e.g. lower than 2% difference in the objective function in [44]. However, the clustering schema has an influence on the results and design of the DHN due to the limitations imposed on the building interconnections at an inter-cluster level based on the intra-cluster optimisation results. The following section highlights the different characteristics influencing the design of the DHN as well as the technology design variables. Finally, the combined clustering algorithm is presented to explore optimal solutions under different clustering maps, based on different building characteristics.

3.1. Spatial clustering and its limitations

The density distribution represents how far each object is from another object. A density-based and hierarchical algorithm is employed, called OPTICSxi (Ordering Points To identify the Clustering Structure). Density based algorithms evaluate for each object of a cluster that there is a minimum number of objects *MinPts* in a maximal neighbourhood distance *EpsDist*. The *xi* parameter is a contrast parameter defining the relative drop in density. More details on OPTICS can be found in [53]. 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 selecting the number of clusters in advance. This number depends only on the minimum number of points to form a cluster, the maximal reachability distance and the data.

3.1.1. Density based clustering

Fig. 3 shows the district heating network connections for a small case comprised of three different clusters where the difference between Fig. 3a and Fig. 3b is the demand profiles of the buildings. On Fig. 3b, buildings are considered as residential, and profiles from one building to another are highly correlated (correlation coefficient is higher than 0.5, calculated in (12) as defined in [35]). This implies the same behaviours in the consumption patterns of building occupants. The graph on the bottom (Fig. 3d) shows the similarities in the hourly profiles, represented here for 12 optimally selected typical days (288 hourly time steps). The demand profiles have been randomly generated based on an approach presented in [54] where data are re-sampled per blocks of hourly period to maintain specific energy patterns. The correlation coefficient is lower than 0.5 for those demand profiles. The building types are similar to those from a mixed-use area.

The first clustering indicator essential to define the possibility of having a DH network is the distance between energy hubs: for highly dense clusters (e.g. 8 or 2 in Fig. 3a and Fig. 3b), even with different energy demand behaviour, it is worthwhile to install a district heating network. For cluster 8, the highest density, even the design variables fixing the sizes of the selected technologies remain the same after optimisation. 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) [42].

3.1.2. Loads based clustering

Load distribution reflects building use (sector) and user behaviour. The Homogeneity Index (HI) on the load profile per cluster is calculated in (12) as defined by [35]. It is calculated per cluster where x is the index of different clusters and $M_j^{cl_x}$ is the j-th building member of cluster x with N_{cl_x} number of buildings.

$$HI_{cl_x} = \frac{\sum_{j=1}^{N_{cl_x}} \sum_{k=j+1}^{N_{cl_x}} Corr(M_j^{cl_x}, M_k^{cl_x})}{N_{cl_x} \times (N_{cl_x} - 1)/2} \quad (12)$$

This index represents the average value of the correlations in the heating load time series between buildings within a cluster. A decrease of the homogeneity index indicates an increase in the heterogeneity of the cluster, meaning the possibility of having an increase in the shifted loads between energy consumers within a cluster.

The results from C8 in Fig. 3 indicate the importance of the load distribution as reflected in the Homogeneity Index (HI), which can be used as a clustering parameter. For cluster 9 the HI of the clustering has an influence. Indeed in cluster 9 in Fig. 3b, there is only a small network (interconnecting the highest energy consumer with two other buildings) and mostly distributed energy systems with gas boilers installed. Whereas in Fig. 3a for the same cluster 9, there is a full network deployed and a larger share of storage and CHP systems installed. Energy demand profiles and load peaks are different for a zone consisting only of residential buildings or a zone of pure commercial and office space buildings. Indeed, the energy consumption in the residential sector is mostly happening at different times from the offices. In a mixed zone with residential and office buildings there are possibilities of having a levelling out of the consumption curve when aggregating together multiple profiles, reducing the difference between peaks and average energy consumption. This opens up the possibility of decreasing the total energy consumption by an exchange of energy between buildings with different energy profiles. This is made possible by favouring the installation of large size CHP engines running at higher efficiency (which could not have been operated otherwise due to minimum part load constraints) in parallel with storage devices. The final result is a DH network interconnecting a large share of the buildings as seen in Fig. 3b. The deployment of the DHN is driven here by the decrease of the homogeneity index for a mixed case compare to a residential case. It is then the increase of the heterogeneity (the complement of the homogeneity index) of the cluster which leads to a fully interconnected cluster 9 in Fig. 3a.

To summarize, the results from the design optimisation problem in Fig. 3 are important to understand the role of the clustering parameters, encountered in the following Section 3.2 on the combinatorial clustering. Indeed the design results are different in Fig 3a from Fig. 3b, due to the different in the load profiles; we can deduce that the temporality of the load profiles plays a role in the determination of the set and sizing of the optimal energy systems. In Fig. 3a the load profiles associated to the building energy demand are typical of a mixed zone area whereas in Fig. 3b only purely residential buildings are considered. Stochasticity has been introduced in the demand profile to simulate the behaviour of a mixed zone typical consumption. In Fig. 3a, the value of the Homogeneity Index (HI) is lower than 0.5, reflecting a zone where the loads are temporally more diverse (peaks are not synchronised), and can be qualified as heterogeneous in the load profile schedules, reflected by the overlapping and diversity of load profiles represented in Fig 3c. Whereas in the case in Fig. 3b, districts are constituted of purely residential buildings, thus, the energy demand appear to be more homogenously temporally distributed between consumers. Those differences alternate the sizing of, both the DHN and the selected technologies, for cluster 2 and cluster 9, whereas cluster 8 remains the same. This is explained by the three characteristics of the clusters: density, load homogeneity and load magnitude. Buildings of cluster 8 are in both cases, Fig 3a and Fig 3b, fully interconnected by a DHN, demonstrating the impact of the density coefficient; the density is higher for cluster 8 than for cluster 9. We can conclude that for dense cluster the temporality of the loads does not have such an influence on the design solution, as long as the load magnitude remains similar (peak loads). Whereas for a sparse cluster, as cluster 9, the temporality of the loads has to be taken into account, as it leads to different DES and DHN design solutions. When the homogeneity index of the loads is increased, from the mixed case (Fig. 3a) to the residential case (Fig. 3b), the CHP and storage capacities are decreased and replaced by a larger boiler. Indeed, the CHP and storage systems no longer benefit from the heterogeneity of the loads, traduced in a load shifting potential.

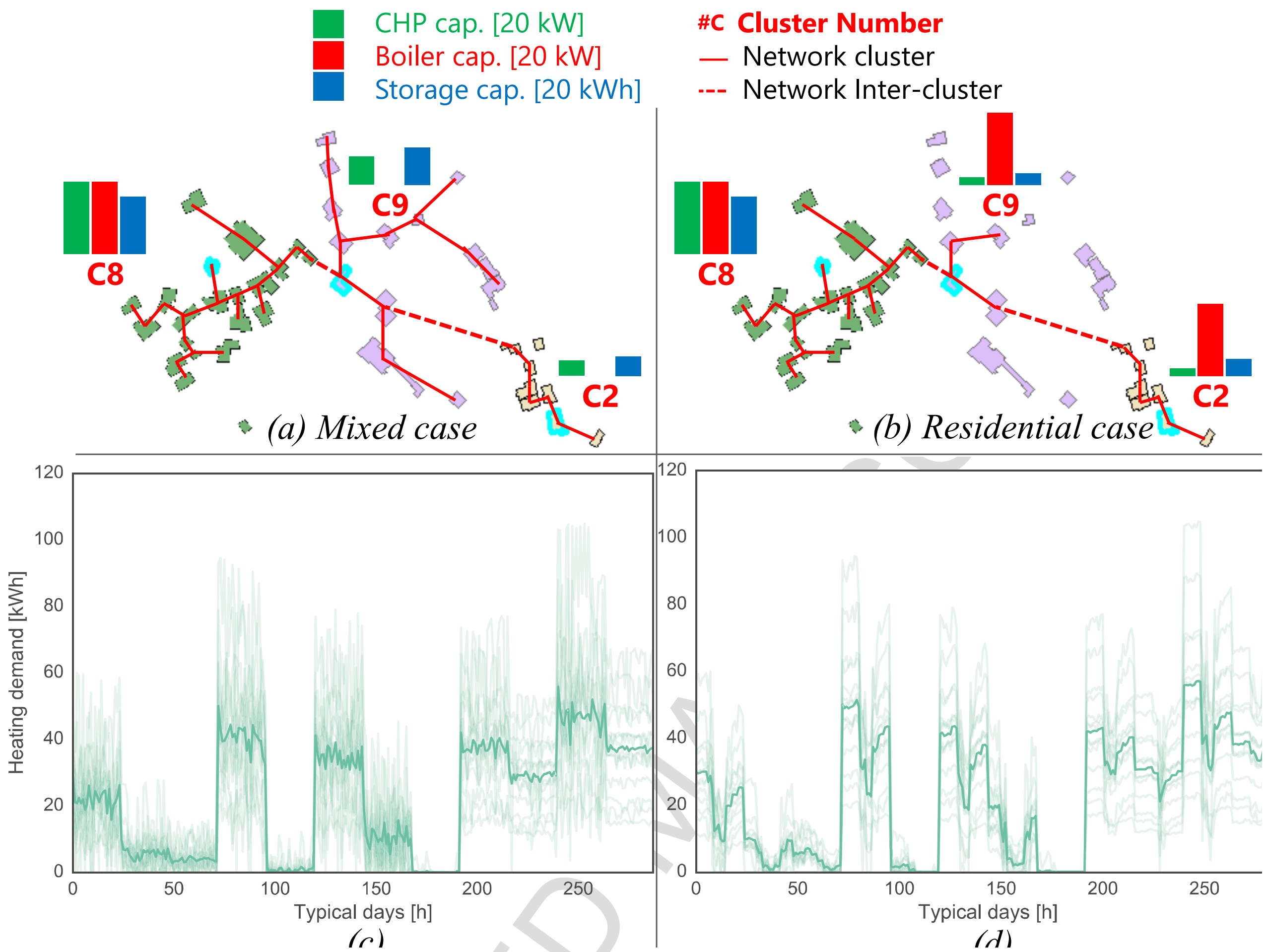


Fig. 3. Comparison for 3 clusters between mixed-case (HI < 0.5) and residential case (HI > 0.5) on DHN designs based on demand profile variations: (a) DH network design and technologies installed per cluster and inter-cluster corresponding to (c) heating demand for a mixed-case of residential and office buildings for cluster 9. (b) DH network design and technology for residential buildings obtain after optimisation and (d) demand profiles for buildings of cluster 9.

The load magnitude is calculated as the sum of the heating demand over a full year. A higher load should be considered as an input to the clustering algorithm, as its inclusion in a cluster can have a large influence on the overall results. It can be used to balance the grid or as an energy centre and creates the possibility of installing a large energy system with higher efficiency curves. The case where a large load should be part of a particular cluster can only be considered by adding the load based dimension to the clustering algorithm.

3.2. Combined clustering algorithm

A combined clustering algorithm is developed in order to take into account spatial and temporal aspects of building characteristics. This is done with the help of a feedback loop between the clustering output and the results of the energy optimisation at the cluster and inter-cluster level. Fig. 4 presents the clustering framework in which inputs are tuned using an evolutionary approach. First a set of clusters is determined (a) based on the hierarchical tree of clusters resulting from OPTICSxi density based algorithm. The clusters are extracted from the lowest branches of the hierarchical nested tree where clusters are characterized by different density. Clusters are ordered based on their density and the following characteristics are calculated (b) per cluster and per combination of existing clusters (i.e. at each node of the hierarchical tree):

density function, homogeneity index and load magnitude. The thresholds are evaluated to ensure that clusters of very low density are not considered. A score is calculated based on the weights α, β, γ by multiplying respectively the normalized density, homogeneity and load magnitude indices, (c):

$$\alpha \cdot DY + \beta \cdot (1 - HI) + \gamma \cdot MAG \qquad (13)$$

Clusters of different density, magnitude and homogeneity indexes are combined (all combinations from 1 to 3 clusters are considered) and grouped based on a maximisation of the score function. Before finalising the result of a clustering iteration, a last refinement is evaluated (d) by looking for a possible improvement of the score function. This is done by taking into account outlier entities (and created new clusters), which were not considered at the first density based clustering iteration (a). This is made possible by increasing *xi*, the relative drop in density from 0.1 in the first iteration to 0.5, which allows sparser clusters. The *MinPts* parameter is fixed at two entities, enabling the creation of a cluster of outliers from 2 buildings. *EpsDist* the maximal reachability distance is fixed at 200 meters for the density based step, in order to not consider density-based clusters including very distant buildings.

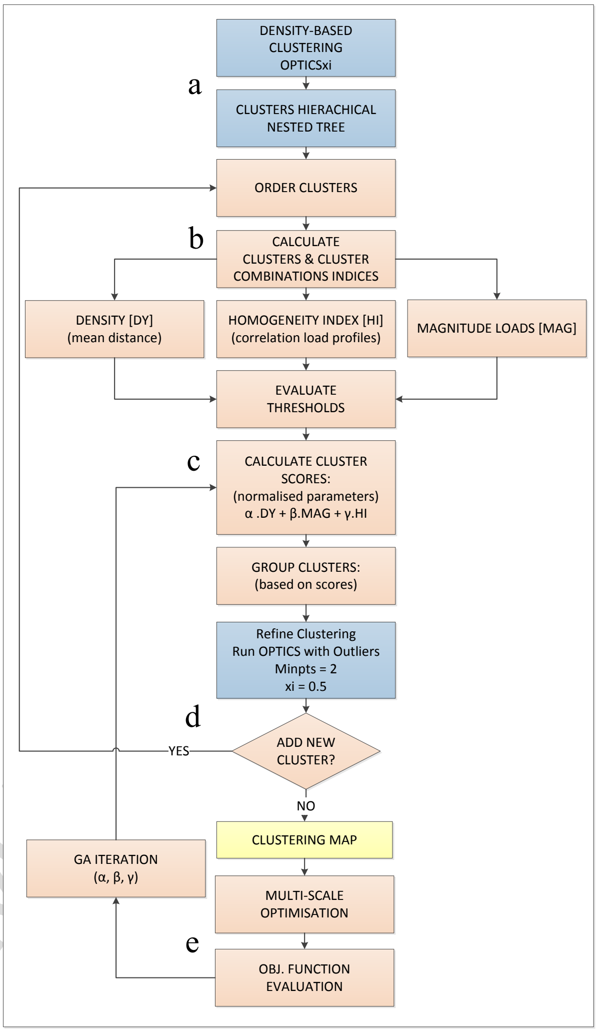


Fig. 4. Combined nested clustering algorithm

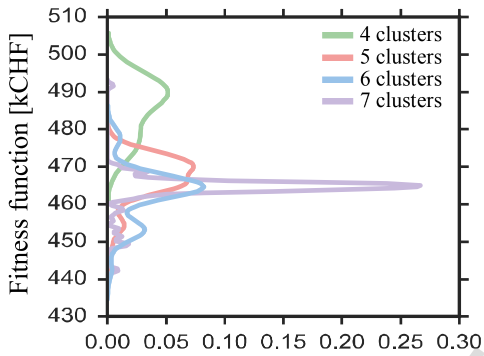
Finally, a clustering map is generated and the optimisation problem objective function can be evaluated using the multi-scale framework presented in Fig. 2. A genetic algorithm (MATLAB built-in algorithm [55], [56]) is used to evaluate the result of the objective function and to tune the weights of the score function, α, β, γ positive continuous decision variables bounded in the interval [0 - 1]. The choice of the genetic algorithm is motivated by the large discontinuous search space. Elitism is enabled preserving the best solution across generations. The crossover fraction is 0.8; crossover is biased with a ratio of 1.5 towards the better parent; the mutation rate is 0.2. The GA optimisation takes 250 hours for 50 generations with a population of 10 individuals.

4. Results

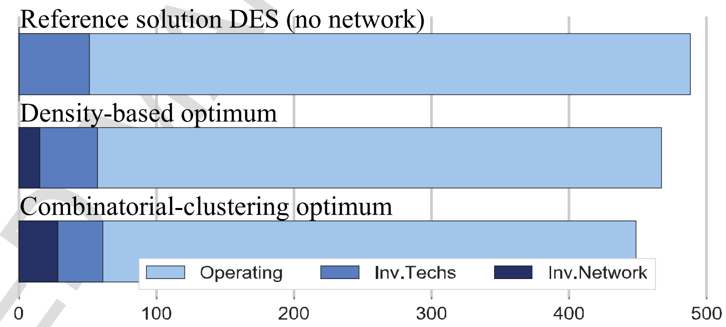
The case study for evaluation consists of 32 buildings of a mixed residential-commercial area on the South-East side of Geneva. Buildings location and characteristics are extracted from an open data source SITG (Geneva Territorial Information System). The hourly heating and electricity demand profiles per building are based on variable profiles generated based on building occupation levels [57], and fitted to the actual buildings size and yearly energy consumption. The objective function studied here is the equivalent annual costs (EAC) for the supply of the total energy demand of the considered buildings, including design and operating of the distributed energy systems.

The problem is computed using CPlex solver on a machine which has an Intel Xeon 3.1 GHz CPU with 8 cores and 64 Gb of RAM. The number of constraints per energy hub for the intra-cluster problem is 9001 including 4924 variables, whom 302 integers, taking an average of 7.8 seconds per solving. For the inter-cluster optimisation problem, the number of constraints for a 4 clusters problem for example is 18'454 including 14996 variables, whom 1164 integers, taking an average of half-hour to solve with fixed design constraint passed from the intra-clustering results. The optimal solution is retained after a GA optimisation of 250 hours for 50 generations with a population of 10 individuals. For comparison, without using the framework developed in Section 2, the intra-cluster optimisation problem takes up to 30 hours for solving a 4 energy hub case study without fixed design constraints [42]. As the solving time increase exponentially with the problem complexity for solving MILP problems, an increase of the spatial scale to 32 energy hubs would make the problem unsolvable in a reasonable time and with the limited CPU.

By tuning the weights α, β, γ of the score function (13) of the clustering algorithm, the resulting map for optimisation is divided in a number k of clusters, between 4 and 7, leading to different values of the fitness function Fig. 5a. The density distribution indicates that for the lowest number of division in 4 clusters, the fitness value increases. A higher number of clusters seems to provide a higher probability of leading to a better solution. This is also reflected in Fig. 6 where the division into 6 and 7 clusters minimized the objective function. Results are comparing the design obtained and objective function for a density-based solution where the clustering step only includes the spatial dimension (α=1, β=0, γ=0), against a solution where the temporal dimension of the loads and their magnitude has been taken into account (α=0.95, β=0.95, γ=0.15). The combined solution obtained considering the loads distribution and spatial dimension appears on Fig. 6 as the best solution determined by the GA algorithm. The fitness function of those two solutions is compared with a reference solution where the possibility of a DHN is not considered Fig. 5b.



(a) Kernel Density Estimation



(b) EAC Objective function [kCHF]

Fig. 5. Difference in the optimal solution for different weights of the clustering score function: (a) Fitness function kernel density estimation. (b) Equivalent annual cost (EAC) for the reference case, density-based case and combined clustering case.

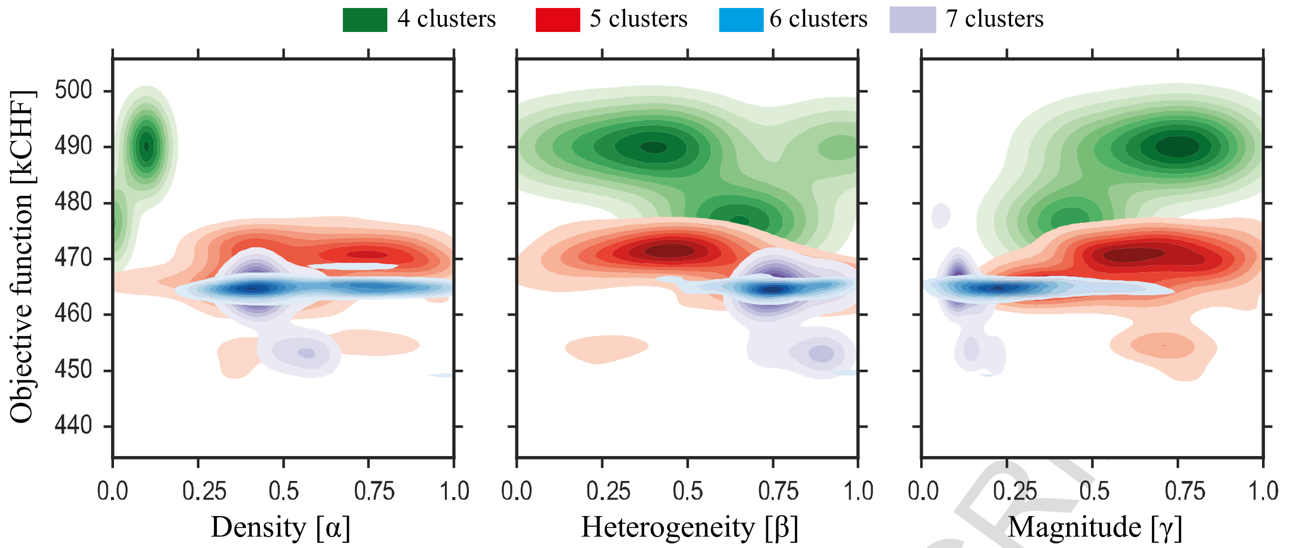


Fig. 6. Density estimation of the fitness value after optimisation based on the weights of the combined clustering algorithm: density (α), heterogeneity index (β) and loads magnitude (γ).

By considering the possibility of installing a district heating network, the equivalent annual costs (EAC) are decreased by 60.5 kCHF Fig. 5b, when the optimisation map is achieved using a density-based clustering method; the clustering is shown in Fig. 7. The EAC can be even further decreased (by 79.2 kCHF in Fig. 5b) when the temporal aspect is also considered in the clustering step using combined clustering; the clustering is shown in Fig. 8. Considering altogether the density coefficient *DY* and the load heterogeneity index (*1-HI*) creates cluster 2 in Fig. 8 with distant buildings. This enables the design of a large network connection within cluster 3, which is then connected to cluster 2 at the inter-clustering optimisation level. Whereas in the density based optimisation problem, restricted by the definition of cluster 5, the optimisation problem ends up with a sub optimal solution by not being able to consider this large connection, as the optimal solution for cluster 2 is the installation of fully distributed energy systems.

From the results of Fig. 6, the role of the load magnitude index is not clear. The optimal solution retained after a GA optimisation of 250 hours for 50 generations with a population of 10 individuals, is a division of the problem space into 6 clusters with the weights (α=0.95, β=0.95, γ=0.15), showing a balance between the importance of density and load heterogeneity and a weak impact of the load magnitude.

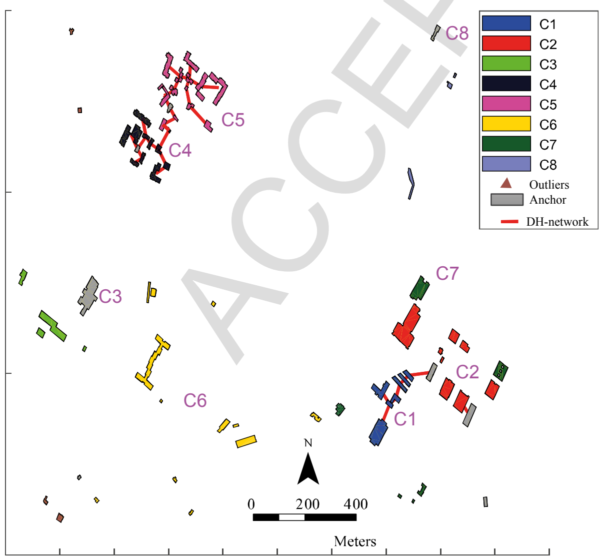


Fig. 7. Density based clustering

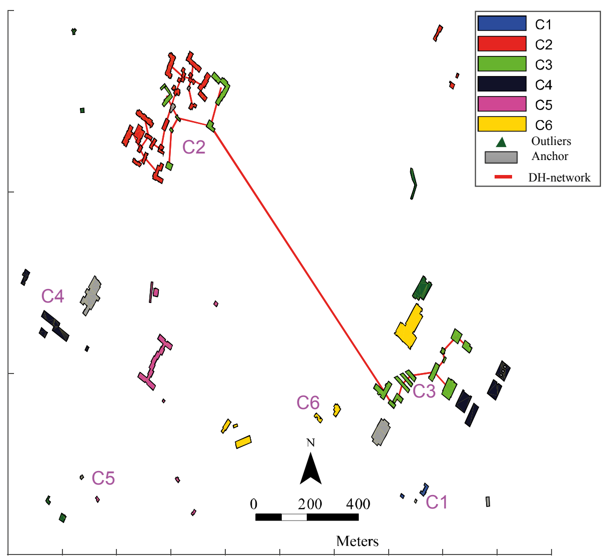


Fig. 8. Density and loads based clustering

5. Conclusion

Clustering methods are shown to be a promising approach to facilitate large scale modelling and optimisation of urban energy systems. By alleviating limitations of MILP model, clustering methods enable the formulation and the solution of large scale optimisation problems for the exploration of design possibilities for the 4th generation DHN [58].

The combined framework of the multi-scale approach with a clustering algorithm presented in this work allows the execution of optimisation problem at large scales. The framework's formulation maintains a high resolution level of details on the building scale, and by sub-dividing a large problem in sub-problems to reduce the computational burden it does not omit an optimal solution. This technique allows defining the building characteristics intrinsic to the cluster definition along with an optimisation problem.

In future work, the calibration of the clustering method across multiple cases will improve the ability to find good clustering patterns, which will allow assessing the durability of the role of spatial and temporal indicators for the deployment of energy streams. Indeed correlations seem to appear between the cluster characteristics, as density, homogeneity or magnitude of the load profiles, and the systems design solutions; district heating network dimensions and energy systems sizes and characteristics. A statistical regression model will be employed in future studies to be able quantifying the potential of district heating networks combined to multiple energy systems at regional scales based on cluster characteristics combined to energy system design solutions.

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References

[1] C. J. Rhodes, "The 2015 Paris Climate Change Conference: COP21," *Sci. Prog.*, vol. 99, no. 1, pp. 97–104, Mar. 2016.

[2] "Paris Agreement - Status of Ratification." [Online]. Available: http://unfccc.int/paris_agreement/items/9444.php. [Accessed: 24-Jan-2017].

[3] D. Arvizu *et al.*, "Technical Summary," *IPCC Spec. Rep. Renew. Energy Sources Clim. Change Mitig.*, 2011.

[4] J. F. Marquant, R. Evins, L. A. Bollinger, and J. Carmeliet, "A holarchic approach for multi-scale distributed energy system optimisation," *Appl. Energy*, vol. 208, pp. 935–953, Dec. 2017.

[5] L. G. Fishbone and H. Abilock, "Markal, a linear-programming model for energy systems analysis: Technical description of the bnl version," *Int. J. Energy Res.*, vol. 5, no. 4, pp. 353–375, Jan. 1981.

[6] X. Q. Kong, R. Z. Wang, and X. H. Huang, "Energy optimization model for a CCHP system with available gas turbines," *Appl. Therm. Eng.*, vol. 25, no. 2–3, pp. 377–391, Feb. 2005.

[7] S. Makkonen and R. Lahdelma, "Non-convex power plant modelling in energy optimisation," *Eur. J. Oper. Res.*, vol. 171, no. 3, pp. 1113–1126, Jun. 2006.

[8] H. Ren, W. Zhou, K. Nakagami, W. Gao, and Q. Wu, "Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects," *Appl. Energy*, vol. 87, no. 12, pp. 3642–3651, Dec. 2010.

[9] A. D. Dimitriadis, N. Shah, and C. C. Pantelides, "RTN-based rolling horizon algorithms for medium term scheduling of multipurpose plants," *Comput. Chem. Eng.*, vol. 21, pp. S1061–S1066, 1997.

[10] R. Yokoyama, Y. Hasegawa, and K. Ito, "A MILP decomposition approach to large scale optimization in structural design of energy supply systems," *Energy Convers. Manag.*, vol. 43, no. 6, pp. 771–790, Apr. 2002.

[11] D. Chinese, "Optimal size and layout planning for district heating and cooling networks with distributed generation options," *Int. J. Energy Sect. Manag.*, vol. 2, no. 3, pp. 385–419, Sep. 2008.

[12] J. Keirstead, N. Samsatli, A. M. Pantaleo, and N. Shah, "Evaluating biomass energy strategies for a UK eco-town with an MILP optimization model," *Biomass Bioenergy*, vol. 39, pp. 306–316, Apr. 2012.

[13] E. D. Mehleri, H. Sarimveis, N. C. Markatos, and L. G. Papageorgiou, "A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level," *Energy*, vol. 44, no. 1, pp. 96–104, Aug. 2012.

[14] K. A. Pruitt, R. J. Braun, and A. M. Newman, "Evaluating shortfalls in mixed-integer programming approaches for the optimal design and dispatch of distributed generation systems," *Appl. Energy*, vol. 102, pp. 386–398, Feb. 2013.

[15] A. Omu, R. Choudhary, and A. Boies, "Distributed energy resource system optimisation using mixed integer linear programming," *Energy Policy*, vol. 61, pp. 249–266, Oct. 2013.

[16] A. Bischi *et al.*, "A detailed MILP optimization model for combined cooling, heat and power system operation planning," *Energy*, Aug. 2014.

[17] J. F. Marquant, R. Evins, and J. Carmeliet, "Reducing Computation Time with a Rolling Horizon Approach Applied to a MILP Formulation of Multiple Urban Energy Hub System," *Int. Conf. Comput. Sci. ICCS 2015 Comput. Sci. Gates Nat.*, vol. 51, no. 0, pp. 2137–2146, 2015.

[18] R. Moreno, R. Moreira, and G. Strbac, "A MILP model for optimising multi-service portfolios of distributed energy storage," *Appl. Energy*, vol. 137, pp. 554–566, Jan. 2015.

[19] J. Silvente, G. M. Kopanos, E. N. Pistikopoulos, and A. Espuña, "A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids," *Appl. Energy*, vol. 155, pp. 485–501, Oct. 2015.

[20] B. Morvaj, R. Evins, and J. Carmeliet, "Optimization framework for distributed energy systems with integrated electrical grid constraints," *Appl. Energy*, vol. 171, pp. 296–313, Jun. 2016.

[21] Z. Beihong and L. Weiding, "An optimal sizing method for cogeneration plants," *Energy Build.*, vol. 38, no. 3, pp. 189–195, Mar. 2006.

[22] K. Kok *et al.*, "Smart houses for a smart grid," in *CIRED 2009 - 20th International Conference and Exhibition on Electricity Distribution - Part 1*, 2009, pp. 1–4.

[23] P. Wolfe, "The implications of an increasingly decentralised energy system," *Energy Policy*, vol. 36, no. 12, pp. 4509–4513, Dec. 2008.

[24] F. Bouffard and D. S. Kirschen, "Centralised and distributed electricity systems," *Energy Policy*, vol. 36, no. 12, pp. 4504–4508, Dec. 2008.

[25] R. Loulou and M. Labriet, "ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure," *Comput. Manag. Sci.*, vol. 5, no. 1–2, pp. 7–40, Feb. 2007.

[26] S. Pfenninger, "Dealing with multiple decades of hourly wind and PV time series in energy models: A comparison of methods to reduce time resolution and the planning implications of inter-annual variability," *Appl. Energy*, vol. 197, pp. 1–13, Jul. 2017.

[27] H. Hijazi, P. Bonami, G. Cornuéjols, and A. Ouorou, "Mixed-integer nonlinear programs featuring 'on/off' constraints," *Comput. Optim. Appl.*, vol. 52, no. 2, pp. 537–558, Jun. 2012.

[28] F. Domínguez-Muñoz, J. M. Cejudo-López, A. Carrillo-Andrés, and M. Gallardo-Salazar, "Selection of typical demand days for CHP optimization," *Energy Build.*, vol. 43, pp. 3036–3043, Nov. 2011.

[29] H. Yang, T. Xiong, J. Qiu, D. Qiu, and Z. Y. Dong, "Optimal operation of DES/CCHP based regional multi-energy prosumer with demand response," *Appl. Energy*, Nov. 2015.

[30] S. Fazlollahi, S. L. Bungener, P. Mandel, G. Becker, and F. Maréchal, "Multi-objectives, multi-period optimization of district energy systems: I. Selection of typical operating periods," *Comput. Chem. Eng.*, vol. 65, pp. 54–66, Jun. 2014.

[31] P. M. Castro, I. Harjunkoski, and I. E. Grossmann, “Rolling-Horizon Algorithm for Scheduling under Time-Dependent Utility Pricing and Availability,” *Comput. Aided Chem. Eng.*, vol. 28, pp. 1171–1176, 2010.

[32] J. Nease and T. A. Adams, “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,” *Comput. Chem. Eng.*, vol. 68, pp. 203–219, Sep. 2014.

[33] J. F. Marquant, G. Mavromatidis, R. Evins, and J. Carmeliet, “Comparing different temporal dimension representations in distributed energy system design models,” *Energy Procedia*, vol. 122, pp. 907–912, Sep. 2017.

[34] M. Pirouti, A. Bagdanavicius, J. Ekanayake, J. Wu, and N. Jenkins, “Energy consumption and economic analyses of a district heating network,” *Energy*, vol. 57, pp. 149–159, Aug. 2013.

[35] R. Jafari-Marandi, M. Hu, and O. A. Omitaomu, “A distributed decision framework for building clusters with different heterogeneity settings,” *Appl. Energy*, vol. 165, pp. 393–404, Mar. 2016.

[36] S. Fazlollahi, G. Becker, and F. Maréchal, “Multi-objectives, multi-period optimization of district energy systems: III. Distribution networks,” *Comput. Chem. Eng.*, vol. 66, pp. 82–97, Jul. 2014.

[37] J. A. Fonseca and A. Schlueter, “Integrated model for characterization of spatiotemporal building energy consumption patterns in neighborhoods and city districts,” *Appl. Energy*, vol. 142, pp. 247–265, Mar. 2015.

[38] A. Omu, R. Choudhary, and A. Boies, “Distributed energy resource system optimisation using mixed integer linear programming,” *Energy Policy*, vol. 61, pp. 249–266, Oct. 2013.

[39] C. Weber and N. Shah, “Optimisation based design of a district energy system for an eco-town in the United Kingdom,” *Energy*, vol. 36, no. 2, pp. 1292–1308, Feb. 2011.

[40] S. Fazlollahi, L. Girardin, and F. Maréchal, “Clustering Urban Areas for Optimizing the Design and the Operation of District Energy Systems,” in *Computer Aided Chemical Engineering*, vol. Volume 33, P. S. V. and P. Y. L. Jiří Jaromír Klemeš, Ed. Elsevier, 2014, pp. 1291–1296.

[41] M. Ankerst, M. M. Breunig, H.-P. Kriegel, and J. Sander, “OPTICS: ordering points to identify the clustering structure,” in *ACM Sigmod record*, 1999, vol. 28, pp. 49–60.

[42] J. F. Marquant, R. Evins, L. A. Bollinger, and J. Carmeliet, “A holarchic approach for multi-scale distributed energy system optimisation,” *Appl. Energy*, vol. 208, no. Supplement C, pp. 935–953, Dec. 2017.

[43] F. Bação, V. Lobo, and M. Painho, “Geo-Self-Organizing Map (Geo-SOM) for Building and Exploring Homogeneous Regions,” in *Geographic Information Science*, 2004, pp. 22–37.

[44] J. F. Marquant, R. Evins, A. Bollinger, and J. Carmeliet, “A holarchic approach for multi-scale distributed energy system optimisation,” *Appl. Energy*, Submitted for publication.

[45] M. Geidl, “Integrated modeling and optimization of multi-carrier energy systems,” ETH Zurich, 2007.

[46] M. Geidl, G. Koeppel, P. Favre-Perrod, B. Klöckl, G. Andersson, and K. Fröhlich, “The Energy Hub–A powerful concept for future energy systems,” in *Third annual Carnegie Mellon Conference on the Electricity Industry, Pittsburgh*, 2007, pp. 13–14.

[47] J. Marquant, A. Omu, R. Evins, and J. Carmeliet, “Application of spatial-temporal clustering to facilitate energy system modelling,” in *Building Simulation*, 2015.

[48] E. Moniz, “The Future of Natural Gas,” p. 33.

[49] B Morvaj, R Evins, and J Carmeliet, “Optimal selection and operation of distributed energy resources for an urban district,” in *Engineering Optimization 2014*, 0 vols., CRC Press, 2014, pp. 709–714.

[50] S. Liu, J. M. Pinto, and L. G. Papageorgiou, “A TSP-based MILP Model for Medium-Term Planning of Single-Stage Continuous Multiproduct Plants,” 24-Sep-2008. [Online]. Available: https://pubs.acs.org/doi/abs/10.1021/ie800646q. [Accessed: 17-Mar-2018].

[51] A. Pöyry, “The potential and costs of district heating networks,” *UK Dep.*, 2009.

[52] R. Beith, *Small and Micro Combined Heat and Power (CHP) Systems: Advanced Design, Performance, Materials and Applications*. Elsevier, 2011.

[53] M. Ankerst, M. M. Breunig, H.-P. Kriegel, and J. Sander, "OPTICS: ordering points to identify the clustering structure," in *ACM Sigmod Record*, 1999, vol. 28, pp. 49–60.

[54] G. Mavromatidis, K. Orehounig, and J. Carmeliet, "Evaluation of photovoltaic integration potential in a village," *Sol. Energy*, no. 0.

[55] C. Houck, J. Joines, and M. Kay, "A Genetic Algorithm for Function Optimization: A Matlab Implementation." NCSU-IE TR 95-09, 1995.

[56] V. Punnathanam, C. Sivadurgaprasad, and P. Kotecha, "On the performance of MATLAB's inbuilt genetic algorithm on single and multi-objective unconstrained optimization problems," in *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, 2016, pp. 3976–3981.

[57] R. Evins, K. Orehounig, and V. Dorer, "Variability between domestic buildings: the impact on energy use," *J. Build. Perform. Simul.*, vol. 9, no. 2, pp. 162–175, Mar. 2016.

[58] H. Lund *et al.*, "4th Generation District Heating (4GDH)," *Energy*, vol. 68, pp. 1–11, Apr. 2014.

Highlights:

- Multi-scale hierarchical approach for optimal system design and operating strategy.
- Combined clustering method for distributed energy system optimization.
- Aggregation schema to enable optimization of urban energy systems at large scale.
- New modelling formulations reducing computational time while preserving accuracy.
- District heating networks allow a decrease of system's costs and environmental impact.