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Locating Multi Energy Systems for A Neighborhood In Geneva Using K-Means Clustering

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Abstract

To determine the optimum location for non dispatchable renewable energy systems, this study comes up with an integrated tool to place energy systems considering distributed energy demand and renewable energy potential.
The Citysim urban energy planning software is used to compute the hourly heating demand of 371 buildings in Jonction, a neighborhood in Geneva. Hourly solar irradiation on the roof tops of each building is computed using the Citysim model. The electricity demand profile for each building is generated using the hourly profile for Geneva using the databases of Swissgrid and Swiss building database. Subsequently, k-means algorithm is used to cluster the buildings based on spatial distribution. An energy economic model is used to evaluate the losses in the thermal and electrical distribution networks and initial investment. Sensitivity of cluster size is evaluated using the energy economic model to obtain an optimum number of clusters and the locations for the energy systems.

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Keywords: distributed energy systems; energy-economic analysis; K-means clustering; thermal networks; urban energy systems

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1. Introduction

Integrating renewable energy technologies into energy infrastructure is important to face the global challenges due to climate change, depletion of fossil fuel resources etc. Distributed energy systems such as hybrid energy systems, energy hubs, multi-vector energy systems etc. can play an important role in this context [1]. These systems can support integration of more non dispatchable renewable energy technologies such as Solar PV (SPV) and wind energy, which are challenging to integrate directly to the main grid beyond a certain limit. However, designing such distributed energy systems is a challenging task due to the fluctuation in demand and non-dispatchable energy sources. A number of recent studies have focused on this aspect [2]–[5]. When moving into urban scale, it is required to consider more than one distributed energy system. One of the main challenges in this context is locating these energy systems. Hourly time series of the demand for multi energy services and losses in the distribution networks among others should be carefully considered in this context. Several recent studies have focused on this topic from the perspective of combined energy system optimization [6], [7].

This study focuses on applying clustering algorithms to locate distributed energy systems in Jonction, a neighbourhood in Geneva. This provides a detailed case study combining the building simulation model Citysim, an energy flow model developed in Matlab and data gathered from Swissgrid and SITG. Results obtained from the case study are subsequently discussed in detail. The research paper is organized as follows; Section 2 of the paper presents a concise overview about the demand model used, cost model developed and the energy flow model used for the study. Section 3 presents the clustering algorithm developed for this study. Finally, Section 4 presents the results obtained using the clustering algorithm.

2. Computational model

The computational model developed in this study combines the demand for heating, electricity and solar energy potential for each building that are obtained using different sources with the clustering algorithm. A concise overview of the demand, cash and energy flow models used in this context are given in this section.

2.1. Computational model for heating and electricity demand

The energy demand for electricity and heating and the solar PV production of each building in the Jonction neighbourhood are presented in this section. The coordinates of each building are gathered through the ArcGIS software using the map of Jonction obtained from the SITG web database (Fig. 1). Then the software computes the corners of each building and creates a centre for each one. This data is exported to a spreadsheet. In this case, each building is linked to a BuildingID number, which corresponds in total to 836 buildings. The hourly electricity demand has been modelled using different sources. First, the annual consumption data for each building has been obtained from SITG. Each data is linked to an EGID number which corresponds to a building number. Since we are interested in the hourly consumption over the whole year, we need to downscale each building's annual consumption to an 8760-hour time series. We use aggregated hourly profiles for each Swiss canton provided by Swissgrid [9] (Fig. 2).

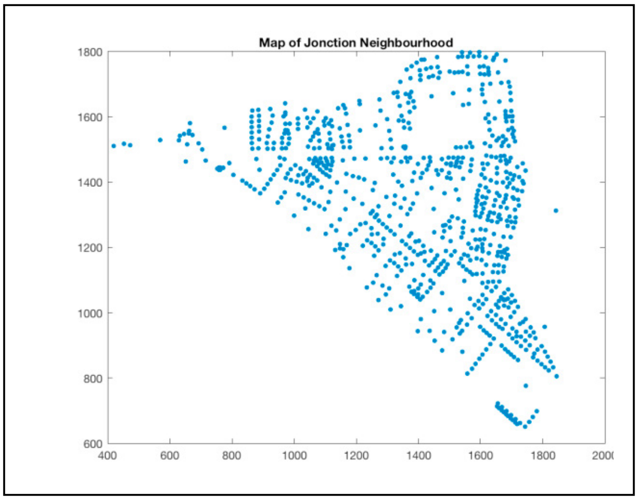

Fig. 1. Map of Jonction.

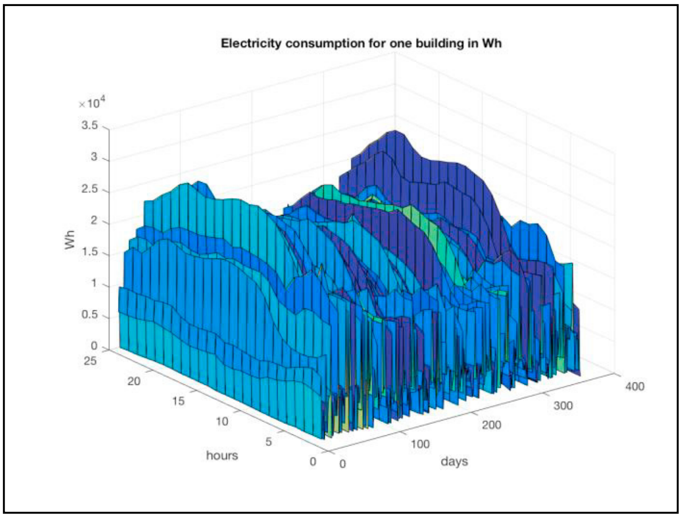

Fig. 2. Electricity consumption for one random building in Wh

The heating demand for the neighbourhood of Jonction was obtained by a detailed model of the neighbourhood using CitySim. This software, developed at EPFL in the LESO-PB lab, models each building with the actual dimensions of the building and with detailed material specification for each building, such as number of floors, type of wall etc. Thereafter, the occupancy of each building is selected with respect to a certain occupancy model. The sanitary hot water demand of 50L per person per day is also included in the heating demand. The Junction neighbourhood model contains 822 buildings. We simulate the heating hourly demand based on the measured weather of Geneva over a full year. Each time series is linked also to an EGID number, unique to a building. The heating demand for a selected building is presented in Fig. 3.

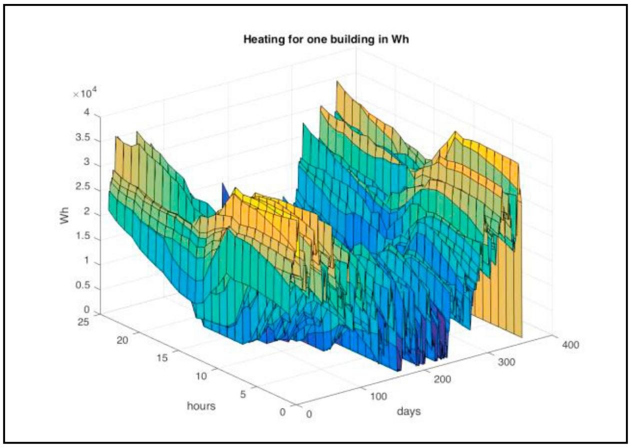

Fig. 3. Heating demand in Wh for a random building

2.2. Energy and cash flow model

The energy flow model mainly focuses on energy losses that occur in the distribution network. This includes both thermal and electrical aspects. Simple DC approximation is used for the electrical grid when calculating the losses. The heat losses in the thermal network are taken as a function of exp(-x-1) of the distance. In addition to that, pressure losses are considered for the distribution network. Finally, the total thermal losses, pressure losses and pump losses are taken into account for the model. Costs for developing the thermal network and operation are considered under the cost model. Unfortunately, the length computed by the algorithm corresponds to the sum of the lengths of each building to its centroid while in reality the district heating networks are built in spanning trees or meshed grids[4]. Heat pumps were considered as the heat generation method. The initial capital costs corresponding to heat pumps are taken from Ref. [3]. Finally, the operating cost of the system is calculated based on the demand for heating the buildings within each cluster.

3. Clustering algorithm

A clustering algorithm is used to locate the energy system and to identify the buildings that are catered from the energy system. There are a wide range of clustering algorithms available in the literature which can be classified into three main groups: partitioning, hierarchical and density-based algorithms. A density based algorithm is used in this study, which is often used for similar problems in the literature. The K-means algorithm is one of the main algorithms under the class of density based algorithms. However, the main disadvantage of this algorithm is that we need to select the number of clusters at the beginning. The K-mean algorithm minimises the Euclidian distance of an observation to a cluster centroid. The main steps of the algorithm can be presented as follows [5]:

1. Initial assignment of the observations to K clusters and computation of the centroids.
2. Computation of the Euclidian distance between each observation to each centroid:
3. Assign each observation to the nearest centroid.
4. Re-update centroids.
5. Re-iterate steps 3 and 4 until convergence.

K-means has the advantage of being able to work with any size of dataset, to be very intuitive and also to select the optimal centroid for each cluster with regards to the distance measure. The algorithm is stable and robust. As stated before, the main drawback is that the algorithm does not provide the optimum number of clusters. In order to select the optimal number of cluster, the following factors were considered.

- The cost of the heating pipes

- The cost of the power losses
- The cost of a heat pump at each centroid

4. Results and discussion

First, clusters were created considering K values from one to twenty. Cluster centroids and corresponding buildings for each cluster for cases K=3,5,7,10 are plotted in Fig. 4.

When analysing the clusters it is observed that the energy losses gradually decrease as the number of clusters increases. Equally, the sum of the lengths from the energy systems to the buildings decreases, and the pumping power required decreases significantly due to the reduction in the distance the working fluid needs to be pumped. Costs due to the losses in the electricity network are negligible in all the scenarios compared to the other costs. Therefore, it can be concluded that thermal network should be carefully considered in the clustering process compared to the electricity grid.

When considering the cost, the investment cost of the heating pipes decreases with the number of clusters. With the increase of clusters the piping length of the thermal network decreases, which results in a reduction of cost, which falls from 25 to 4 million CHF when moving from a single cluster to twenty. On the other hand, the cost for heat pumps increase with the increasing number of clusters. When considering the installation and operation costs (Fig. 5) it is prudent to say that total cost significantly decreases at the beginning and gradually settles down after eight clusters. The lowest cost is observed for 14 clusters.

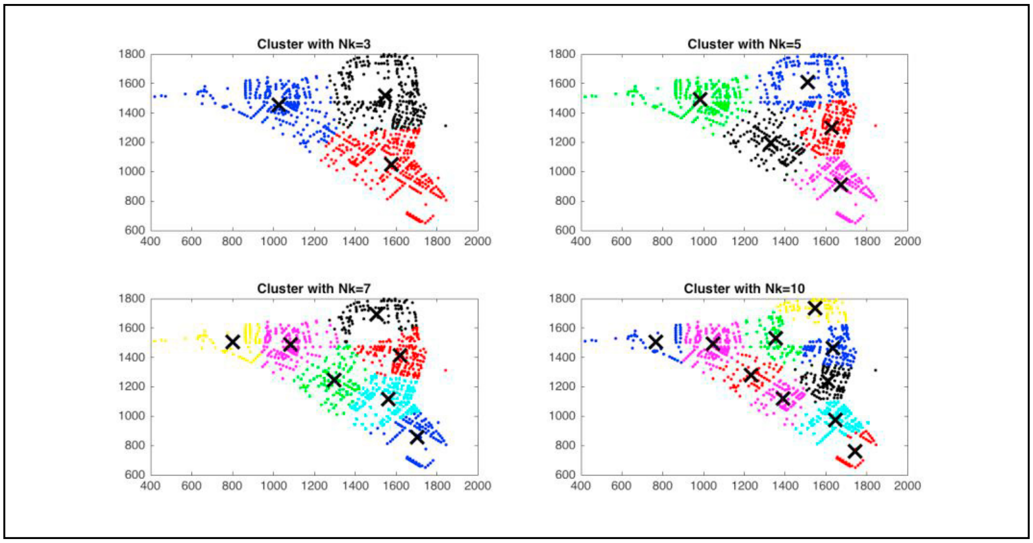

Fig. 4. Map of the Jonction district with plot of the clusters for Nk=3,5,7,10

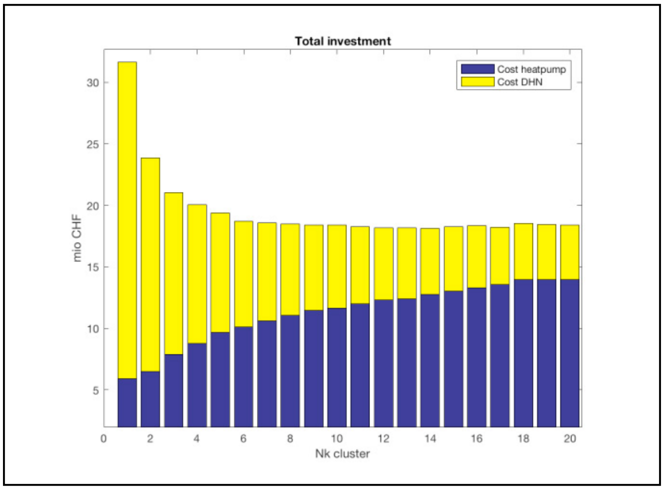

Fig. 5. Investment cost for the DHN and heating generation systems

5. Conclusions

This study presents a case-study on locating distributed energy systems for a neighbourhood in in Geneva. The K-means algorithm is used to cluster the buildings and locate the energy system. An energy-economic model is used to arrive at the best fitting K value. An optimal number of clusters can hence be determined with this methodology thereby providing useful insight for urban energy system design. The study can be further extended considering time-series clustering where energy storage can be assessed in the clustering process.

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