Clustering a building stock towards representative buildings in the context of air-conditioning electricity demand flexibility

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Energy modeling for the prediction of energy use in buildings, especially under novel energy management strategies, is of great importance. In buildings there are several flexible electrical loads which can be shifted in time such as thermostatically controllable loads. The main novelty of this paper is to apply an aggregation method to effectively characterize the electrical energy demand of air-conditioning (AC) systems in residential buildings under flexible operation during demand response and demand shaping programs. The method is based on clustering techniques to aggregate a large and diverse building stock of residential buildings to a smaller, representative ensemble of buildings. The methodology is tested against a detailed simulation model of building stocks in Houston, New York and Los Angeles. Results show good agreement between the energy demand predicted by the aggregated model and by the full model during normal operation (normalized mean absolute error, NMAE, below 10%), even with a small number of clusters (sample size of 1%). During flexible operation, the normalized mean absolute error rises (around 20%) and a higher number of representative buildings becomes necessary (sample size at least 10%). Multiple cases for the input data series were considered, namely by varying the time resolution of the input data and the type of input data. These characteristics of the input time series data are shown to play a crucial role in the aggregation performance. The aggregated model showed lower NMAE compared to the original model when clustering is based on a hybrid signal resolved at 60-minute time intervals, which is a combination of the electricity demand profile and AC modulation level.

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1. Introduction

The building sector, given its large share in the total energy use, plays a central role in energy policy. It accounts for about 40% of the total energy use both in Europe and in the US (EIA 2017; EU 2010). Therefore, energy modeling for demand forecasts or for assessing the impact of energy management strategies in the building sector is of high importance. To this aim, accurate simulation tools for large scale evaluations of the integrated supply-demand energy system are necessary. However, a proper trade-off between the fidelity of representation and the resultant computational effort has to be found. Clustering techniques (Jain, Murty, and Flynn 1999), which group similar data objects in the same cluster, can be used in order to select representative buildings of the overall building stock and use them to simplify its representation. This paper presents and evaluates such a methodology.

Several studies in the literature report the use of clustering techniques for different applications. Nahmmacher et al. (2016), for example, used clustering algorithms to select representative days for long-term power systems modeling. In this way, it is possible to select a small number of days that adequately reflect the characteristic fluctuations of the renewable energy sources in the generation mix, thus reducing the computational effort, while maintaining the necessary diversity in temporal profiles. Buttitta, Turner, and Finn (2017) applied a similar approach to define realistic building occupant behavior, representative of a large number of households, based on available survey data.

As far as the building sector is concerned, often buildings are grouped on the basis of their characteristics. Gao and Malkawi (2014) showed the advantages of a multi-dimensional clustering approach that enables energy benchmarking among different types of buildings. This was done by taking the most relevant characteristics into account to define the building energy performance. Jones, Lannon, and Williams (2001) developed a method to group buildings on the basis of some parameters related to their energy performance: heated ground floor area, facade, window to wall ratio, exposed end area and age. Santamouris et al. (2007) applied intelligent fuzzy clustering techniques to classify school building energy data around clusters of similar characteristics. Moreover, Gaitani et al. (2010) proposed a clustering methodology based on principal components analysis to group school buildings in Greece and to define the typical building of each energy class by considering seven variables (heated surface, age of the building, insulation of the building, number of classrooms, number of students, school's operating hours per day, age of the heating system). The representative buildings can then be used to perform analysis on the potential energy savings for the specific group of school buildings.

Geyer, Schlüter, and Cisar (2017) considered a clustering method based on the sensitivity of buildings to retrofit strategies. In this way it is possible to effectively perform the retrofit of a large building stock by selecting the best retrofit measures, not only related to building age and type. Other studies, instead, tried to directly cluster the building load curves from time series data (Jota, Silva, and Jota 2011) to provide useful instruments to the energy manager to predict buildings loads and peak demand. For instance, Yang et al. (2017) proposed a clustering method based on k-shape algorithm to identify shape patterns in time-series data, thus detecting building-energy usage patterns at different levels. The clustering result was further utilized to improve the accuracy of forecasting models.Yamaguchi, Shimoda, and Mizuno (2007) showed a district clustering modeling approach, where a district instead of a single building was considered as reference unit, in order to evaluate energy management at the city level. Iacovella et al. (2015) presented an algorithm for determining up to five representative appliances with artificial parameters to represent a larger set of thermostatically controlled loads.

The state of the art review highlights that clustering techniques in buildings can be used in different fashions and for different purposes. In each case, the starting point is represented by available data about building features or its behavior (e.g. energy performance. . .), grouped by means of techniques appropriate for the final knowledge purpose of the analysis. In this paper the main goal behind clustering of buildings is the representation of their energy flexibility in an efficient and effective way. As shown in previous work of the authors (Patteeuw, Henze, and Helsen 2016), it is very important to anticipate the electricity demand of a building stock during flexible operation. The aim of this paper is to demonstrate how the representative buildings of the clusters can be used in aggregated simulation models maintaining the necessary accuracy. Given the relevance of demand response (DR) programs to manage the electric energy demand in buildings, there is a growing need for proper models to simulate integrated energy systems, where both the supply side and the demand side and their interaction are represented with sufficient detail (Patteeuw et al. 2015). In particular, Goy and Finn (2015) highlighted the necessity to develop demand response estimation tools at a large scale considering the buildings characteristics for electrically driven heating and cooling systems (i.e. heat pumps and chillers).Other approaches, rather than clustering, have been used by different authors to represent the energy demand in integrated simulations. E.g. Callaway (2009) uses a hybrid state discrete time model to mimic thermostatic controlled loads (TLC) with a probability distribution of the TLCs population, while Hedegaard et al. (2012) proposes a thermal building model add-on for the software Balmoral applied to the building stock of existing individually heated one-family houses in Denmark in 2030.

This paper presents, instead, the application of a method called cluster-center-aggregation (CCA) in building stock simulation and evaluates its performance. This CCA method is based on clustering techniques for energy flexibility evaluations in building stocks. The aim of CCA is to reduce the overall building stock to a number of representative buildings able to assess, with sufficient accuracy, the total building electric energy demand dynamics to be used in integrated power system representations. The clustering algorithm is applied to electric power or AC staging data obtained by means of a simulation tool, written in Java, that reproduces in detail all the buildings contained in a considered building stock. The total electricity demand profile from such a comprehensive simulation tool is then compared with the prediction of the aggregated demand side model that scales up the electricity demand of the representative buildings. The objective of this comparison is the determination of the proper number of representative buildings (i.e., number of clusters) in order to balance the opposing needs of reduced computational burden and loss of accuracy when assessing the demand flexibility of a building stock. The electric energy demand of buildings consists of deferrable loads, among them thermostatically controlled loads (e.g. cooling and heating by chillers, heat pumps or electric resistance), which can be shifted in time providing flexibility to the electric grid. The ability to represent and foresee such flexibility plays a crucial role in order to assess the demand shaping potential of the building stock. The proposed CCA methodology offers a simplified and reliable representation of thermostatically controlled electrical loads to be used in the evaluation of the economic and societal value of demand flexibility. In this piece of work the focus, and main novelty, lies in capturing the flexibility of the building stock by means of an aggregated demand side model obtained through clustering techniques.

2. Methodology

This section describes the CCA methodology and how its performance has been assessed. First, the general CCA methodology is described in Section 2.1) after which the specific application in the context of air-conditioning electricity demand flexibility is shown (Section 2.2). This methodology is compared to random sampling as the benchmark in Section 2.3 by means of the performance metrics introduced in Section 2.5. Section 2.4 presents the case study that is used to test the performance of cluster-based sampling in representing the building stock flexibility.

2.1. *General Cluster Center Aggregation (CCA)*

The goal of the Cluster Center Aggregation (CCA) is to draw a number of samples from a population and use these samples to represent the entire population. Figure 1 illustrates the basis steps of this CCA: cluster, center selection, and scale up. First, a number of fea-

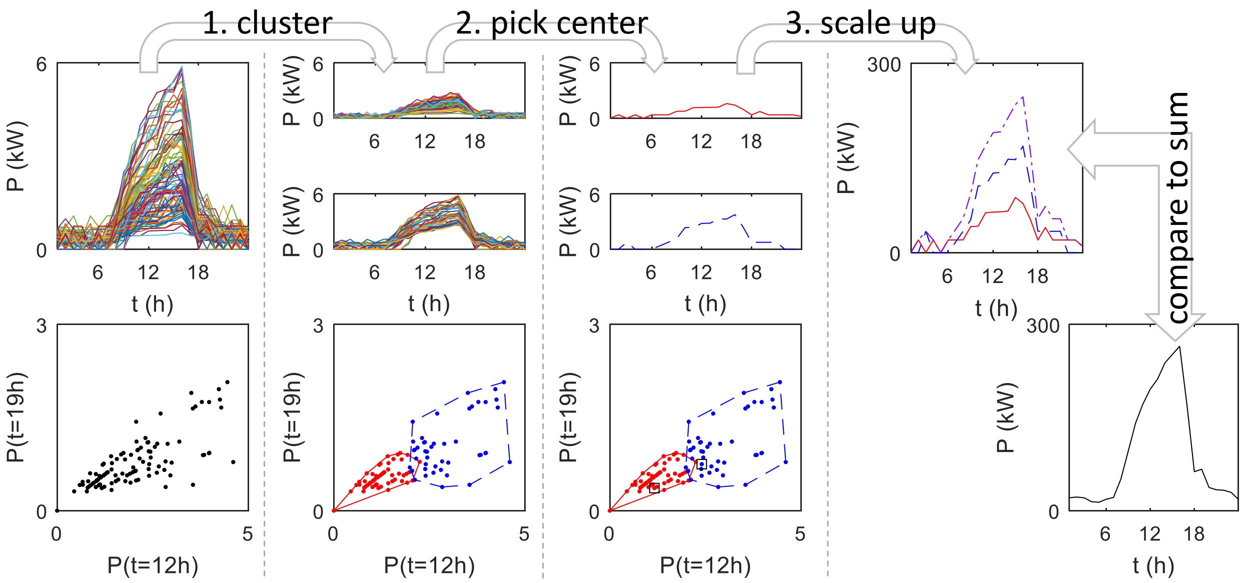


Figure 1.: Illustration of the CCA principle on 100 AC electricity demand profiles (top row). The clustering is performed for 24 time steps (i.e. 24 hours in a day) and hence in 24 dimensions. Since a 24 dimensional plot is not possible, only two of these time steps are illustrated (bottom row). In step 1, all profiles are clustered into two clusters. In step 2, the profile closest to the cluster centroid is selected as representative for that cluster. In step 3, each cluster's representative profile is scaled up with the number of profiles within that cluster. Last, it is evaluated how well the resulting electricity demand profile of these 3 steps (purple dash-dot line) compares to the sum of all 100 profiles (black line).

tures need to be selected from each member of the population in order to group the members of the population in clusters. In the second step, the central member of the cluster is picked up as a representative member of that cluster. In the third step, the features of this selected member are scaled up with the number of members in that cluster, in an attempt to imitate the features of the entire population. The main issue for application of the CCA method is to justify whether the second and third steps are allowed in a certain context or not. Throughout this paper, the context of building flexibility is considered.

2.2. *CCA in air-conditioning electricity demand flexibility context*

The novelty of this paper lies in investigating the usefulness of the CCA methodology in the context of air-conditioning electricity demand flexibility. The population to start from is a large number of buildings. In this paper, this large number of buildings is modeled as described in Section 2.4 and is referred to as the 'full model' throughout this paper. This model consists of thousands of residential buildings equipped with central air-conditioning (AC) units and smart thermostats[1]. The aim of this paper is to attain an aggregated model which consists of representative buildings taken from the full model, whose AC electricity demand can be rescaled to replicate the full model electricity demand. Such an aggregated model can then be used e.g. in integrated representations of the electric power system to assess the flexibility potential of the building stock. Fig. 2 illustrates the CCA procedure in this context.

In this paper, the features upon which to perform the clustering are the measurement data of the buildings, taken from the output of the 'full model'. In the first step of CCA, this output data from the full model, called 'training data' throughout the rest of the pa-

[1] In this paper, a smart thermostat is defined as a thermostat which is connected to the internet in order to communicate indoor air temperature, set-point and the control signal it sends to the AC unit. Additionally, it is able to perform model predictive control in response to a price profile.

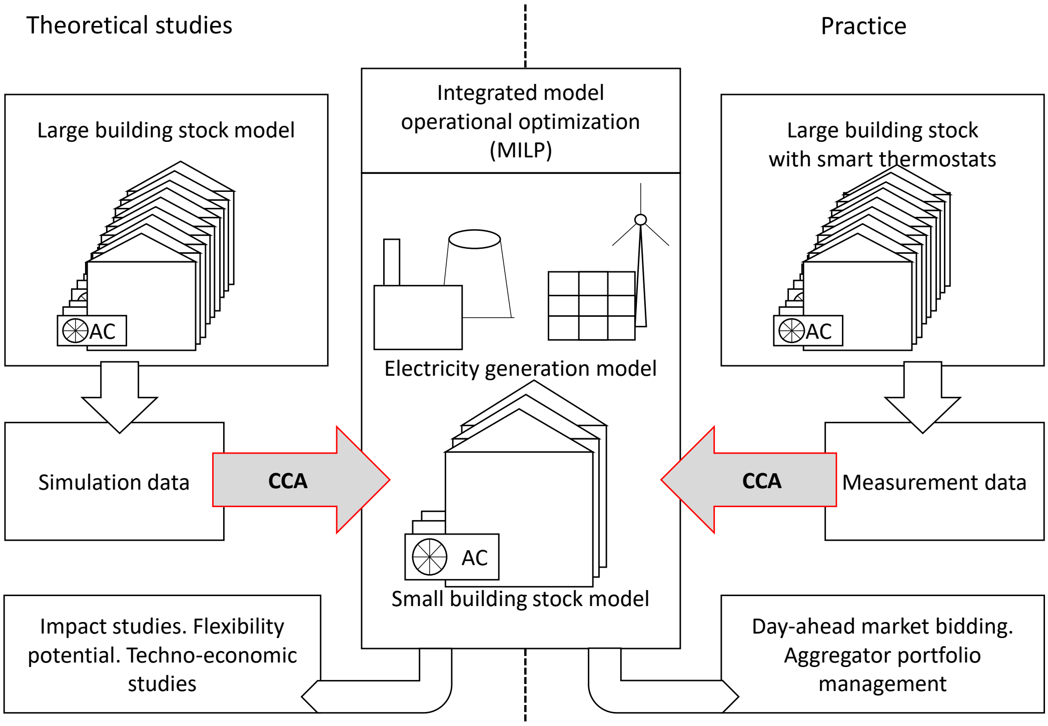


Figure 2.: Schematic representation of the use of CCA for demand response purposes in theoretical studies and in practice.

per, is taken and clustered. The data from the full model mimics the data that could be available through the use of smart thermostats in real applications in practice. In one case, this smart thermostat could obtain direct measurements of the 'electricity demand' (ED) profile through a communication with the AC unit. ED data is reported in W and varies between 0 and the maximum power of the building. The highest instantaneous electricity demand of one building is 13500 W in this study.

If the communication with the AC unit is not available, the smart thermostat only has information on the control signals sent to the AC unit. Since the control signals are typically in the form of an on-off signal or staging signal, the smart thermostat only has information of the modulation of the AC unit. This input data is referred to in the remainder of the text as 'AC modulation data' (ACMD). ACMD can only take up the values 0, 1 and 2, e.g. the stages of the AC unit.

In the case where both ED and ACMD data are available, a 'hybrid' data input can be defined. In this hybrid method, the input data is compiled of two sets of data: a period of ED and the ACMD of the same period. The ACMD data is rescaled[2] in order to achieve the same order of magnitude as the ED input data. Hence, both input data have equal importance in the clustering step.

Furthermore, this data could be fed to the clustering algorithm at 5-minute or 60-minute resolution. These two resolutions are the typical lowest and highest resolutions used for HVAC data. Intermediate resolutions are not studied in order to limit the number of cases in this paper. The 60-minute resolution is obtained by averaging the 5-minute resolution data, which largely filters out the on-off cycling of the AC unit.

The full model output data is summarized in a set of vectors: the ED or ACMD profile for each building, for a particular period in time (one week has been considered in this analysis). For the hybrid method, both data profiles of the same week are put adjacent to each other, so the input data profile is twice as long. A clustering algorithm then clusters these build-

[2]Based on Fig. 9, the ACMD data in this paper is multiplied by a factor of 10, while the ED data is expressed in kW. In this manner, both ED and ACMD input data are of the same order of magnitude.

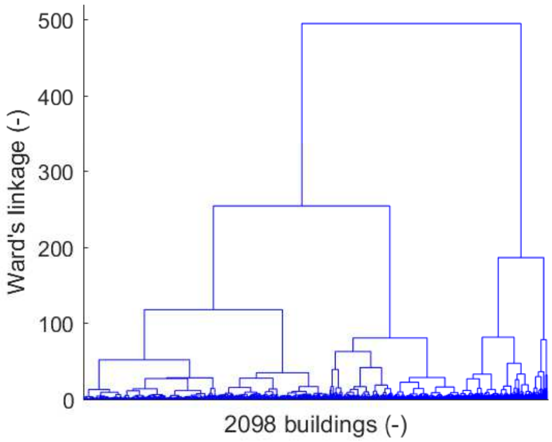


Figure 3.: Dendrogram of hierarchical clustering on ED data in kW and 60-minute resolution for the first week of July in Houston (see also Figure 5).

ings in groups of buildings with similar ED or ACMD profiles. This similarity is based on the Euclidean distance between the ED or ACMD profiles. Hence, in this paper, the clustering starts from data in multiple dimensions: the number of time steps. This paper employs the hierarchical clustering with Ward's minimum variance method (Ward Jr 1963). There are numerous clustering algorithms which could be used in this context and comparing all of them is out of the scope of this paper. Hierarchical clustering is employed here since it leads to a single reproducible result, as opposed e.g. to k-means clustering where the random starting conditions influence the result. This hierarchical clustering is performed by the Matlab script clusterdata.m (MathWorks 2017a), using Euclidean distances and Ward's method for linkage. This linkage between two joined clusters a and b is calculated as the increase in $d(a, b)$, the total within-cluster sum of the squares of the distances between all objects in the cluster and the centroid of the cluster (MathWorks 2017b):

$$d(a,b) = \sqrt{\frac{2n_a n_b}{n_a + n_b}} \|\bar{x}_a - \bar{x}_b\|_2 \qquad (1)$$

with n_a the number of elements in cluster a, $\|\|_2$ the Euclidian distance and $\bar{x}_a$ the centroid of cluster a. Fig. 3 shows an example of a resulting dendrogram using this clustering method. The only remaining user-defined parameter for the clustering is the number of clusters (i.e., the number of representative buildings for the aggregated model) to consider. This can be interpreted in Fig. 3 as 'cutting the cluster tree' at a certain value of Ward's linkage. The number of clusters is varied, and reported in a relative metric called sample size:

$$\text{sample size}\,(\%) = \frac{\#\text{clusters} \cdot 100}{\#\text{buildings in full model}} \qquad (2)$$

In the second step of CCA, the clusters are translated to a set of representative buildings. For each cluster, the center is determined as the average profile of the ED or ACMD profiles. The building whose profile is closest to this center is selected as the representative building. This paper investigates the suitability of this building in representing its cluster, especially when different operational strategies are applied (e.g. DR programs). Applying this centering methodology for all clusters, yields a set of representative buildings, which is a sample from the total set of buildings.

In the third step of CCA, the electricity demand profiles of the representative buildings, P^{rb}, are rescaled. For each representative building of cluster i, the electricity demand profile P_i^{rb} is multiplied by the number of buildings in the corresponding cluster, $N_{b,i}$. The resulting electricity demand profile of the aggregated model, P^{CCA} is hence calculated as:

$$P^{CCA} = \sum_{i=1}^{N_c} N_{b,i} P_i^{rb} \qquad (3)$$

with N_c the number of clusters in this case.

Eventually such electricity profile of the aggregated model is used to represent the building stock in integrated models for demand response analysis, as illustrated in Fig 2.

2.3. *Random sampling as reference*

In this paper, random sampling is used as a benchmark for the aggregation performance. In the case of an aggregation with N_c clusters and hence N_c representative buildings, it is best to compare this to a random sampling

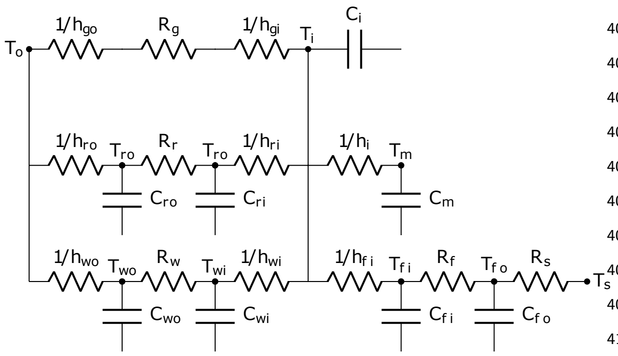


Figure 4.: The RC network representing the heat transfer in the reference building model (Corbin and Henze 2017a). The building is modeled as one thermal zone at a temperature T_i. The floor (f), external walls (w) and roof (r) are represented by two thermal capacities each, while the glazing (g) has no thermal capacity. The internal walls and furniture are lumped within one 'thermal mass' capacity (m). Heat exchange is present in the model with the outside air (o) and soil (s).

with also N_c representative buildings. The aggregation based on random sampling consists of two steps. In a first step, N_c random buildings are taken from the population. In a second step, the electricity demand profiles of each randomly chosen building P_i^{random} is scaled up by an equal factor:

$$P^{aggr,random} = \sum_{i=1}^{N_c} \frac{N_p}{N_c} \cdot P_i^{random} \quad (4)$$

with N_p the total number of buildings in the population. The random sampling is performed multiple times (for this study 20 times, see Section 3.3) in order to get an image of the spread of the performance of random sampling.

2.4. *Diverse Building Stock Case Study*

The performance of the CCA methodology is tested on output data of a building stock model that simulates the cooling demand of a large number of US buildings. This detailed dynamic simulation model was developed by Corbin and Henze (Corbin and Henze 2017a,b) and validated with respect to BESTEST-EX (Judkoff et al. 2010) by Corbin (Corbin 2014). The model comprises three cases of building stocks in different US climate zones: Houston (Texas), New York (New York) and Los Angeles (California). The Texas case consists of 2146 buildings from which 2098 are equipped with AC. For New York this is 1506 (1114 with AC) and for Los Angeles this is 1326 (711 with AC). In this study, the non-HVAC electricity demand, which is also an output from the model, is not taken into account. Each of the buildings differ in type (mobile, detached or appartment), floor area, cooling set point and building integrity. This results in different parameters for the insulation of the roof, walls, floor and windows as well as a different infiltration rate and thermal mass. For each climate zone separately, these values are randomly sampled from the Residential Energy Consumption Survey (U.S. Energy Information Administration 2009) data that was collected and made available by the US Energy Information Administration. This results in different thermal properties of the buildings depending on the climatic zone, as illustrated in Table 1.

Each building is modeled as one thermal zone. The heat transfer in the building is modeled through a network of thermal resistances and capacities as illustrated in Fig. 4 for which all R and C values are constant. The only exceptions to this are the exterior film coefficients that depend on the wind speed. The solar heat gains are based on Liu and Jordan (1960) for an isotropic clear sky. The buildings are equipped with a central air conditioning. The main component of the AC is the single and dual stage electric direct expansion air cooling coil (UIUC and LBNL 2005). This cooling coil is complemented with a constant volume fan. The building modeling was validated with BESTEST-EX (Judkoff, Neymark, and Polly 2011). The internal heat gains from occupants are based on a relaxed seated person while the gain from appliances are modeled based on nominal energy demand, schedules and sensible heat fraction (Corbin 2014). The temperature set points vary among the different buildings but are constant during the day. The AC control of each building is performed independent of the other buildings, by means of a dual mode thermostat with a hysteresis of $0.5K$. In addition, each building is assumed to have a model predictive controller

Table 1.: Home characteristics for each climatic zone selected for study, taken from Corbin and Henze (2017a)

		Percentage of homes		
		New York	Los Angeles	Houston
Home type	Apartment	16.8	18.5	18.2
	Detached	77.4	73.2	73.5
	Mobile	5.8	8.4	8.3
Floor area (m^2)	$\leq$ 200	67.3	88.2	52.7
	$>$ 200	32.7	11.8	47.3
Roof insulation (Km^2/W)	$\leq$ R - 3.3	55.1	38.0	38.2
	$>$ R - 3.3	44.9	62.0	61.8
Wall insulation (Km^2/W)	$\leq$ R - 1.9	67.9	51.3	51.5
	$>$ R - 3.3	32.1	48.7	48.5
Floor insulation (Km^2/W)	$\leq$ R - 3.3	77.4	63.2	62.3
	$>$ R - 3.3	22.6	36.8	37.7
Window type	Single pane	24.2	11.8	12.4
	Double pane	60.7	64.6	62.4
	Triple pane	15.1	23.6	25.2
Infiltration (air changes per hour)	$\leq$ 0.4	44.0	62.5	61.6
	$>$ 0.4	56.0	37.5	38.4
Air conditioning	Central	74.1	54.3	97.9
	None	25.9	45.7	2.1

(MPC) that uses a particle swarm optimization (PSO) (Corbin 2014) based on the canonical formulation of Eberhart and Kennedy (1995). This formulation is enhanced with a taboo list for previous candidates and familiar box constraints. The increment is 0.1 and a maximum velocity is 0.25. The MPC can alter the upper and lower bound for the hysteresis controller between certain predefined limits. A fully detailed description of the reference model can be found in Corbin (2014).

Fig. 5 shows some typical input and output data of the building stock model for Houston. The first two figures show the solar heat gains, ambient air temperature and wind speed. These weather input conditions are used for all buildings in the Houston model. The last two figures show the output of the model for one building (left axis, blue) and for all buildings with AC (right axis, orange). What can be observed first is the strong cycling of the AC, both in the indoor temperature and in the electricity demand. When considering the 2098 buildings with AC in Texas, the electricity demand shows a strong correlation with the solar gains and outdoor temperature.

2.5. *Sampling Performance Evaluation*

The interest of this paper lies in the performance assessment of demand flexibility and, in particular, how well normal operation data suits the aggregation methodology in predicting flexible building operation in response to DR and demand shaping signals. The aggregated electricity demand profile should match the full electricity demand profile as accurately as possible, evaluated by the mean absolute error (MAE) over h time steps with index j:

$$MAE = \frac{\sum_{j=1}^{h} |P_j^{full} - P_j^{CCA}|}{h}. \quad (5)$$

The MAE is normalized by the mean value μ of the full electricity demand profile in order to have a metric comparable for the different considered case studies:

$$NMAE = MAE/\mu = \frac{\sum_{j=1}^{h} |P_j^{full} - P_j^{CCA}|}{h \cdot \frac{\sum_{j=1}^{h} P_j^{full}}{h}}. \quad (6)$$

To evaluate the behavior in the flexible regime, all buildings within one case are sub-

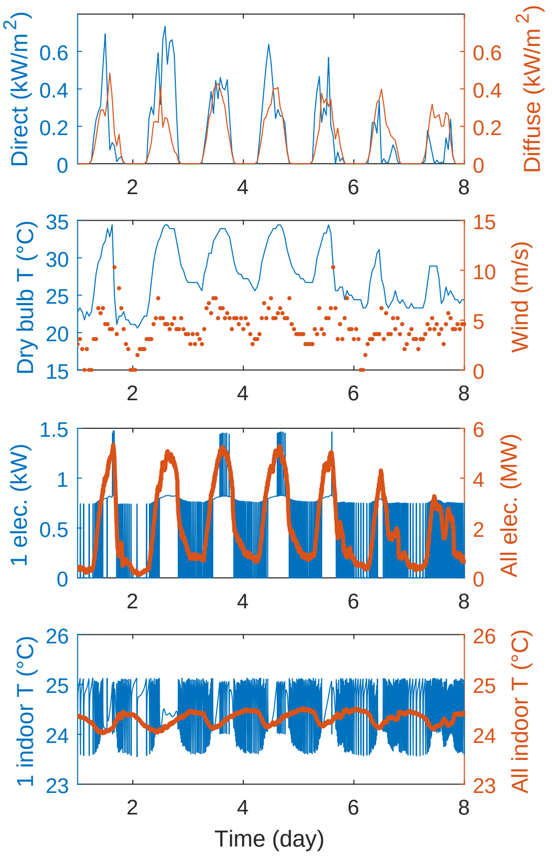


Figure 5.: Data for the first week of July in Houston, Texas. From top to bottom: direct (left) and diffuse (right) solar heat gains; outside dry bulb temperature (left) and wind speed (right); HVAC electricity demand of one building (left) and all buildings combined (right); indoor air temperature of one building (left) and all buildings combined (right).

jected to the same price profile, to which they all respond individually based upon their dedicated MPC operation. Two scenarios are studied: normal operation and price responsive operation, denoted as 'normal' and 'price', respectively. In this context, the energy flexibility is defined as the power consumption deviation of a system from its normal operation to a new profile aimed at compensating power imbalances in the grid. The energy flexibility can be activated by means of demand response mechanisms, intended to achieve changes in electric usage patterns in response to changes in the price of electricity.

Under the normal operation scenario, the price profile is flat and the temperature bounds for comfort are constant. Hence, the objective function for the MPC is the minimization of the electricity consumption:

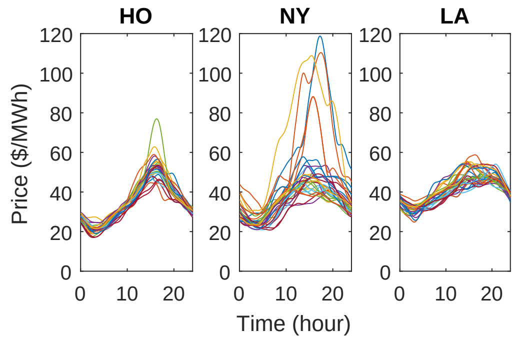


Figure 6.: Electricity price profiles for every day of July for the cases of Houston (HO), New York (NY) and Los Angeles (LA).

$$\min \sum_{j=1}^{H} P_j^{HVAC} \tag{7}$$

with P_j^{HVAC} the electric power of the HVAC system during time step j over a time horizon of H time steps. Under price responsive operation, the electricity price e_j triggers the MPC to use the flexibility of the building. The objective function becomes

$$\min \sum_{j=1}^{H} e_j \cdot P_j^{HVAC}. \tag{8}$$

The electricity price profiles shown in Fig. 6 are used for each day of the month. These profiles are based on the wholesale market prices corresponding to the region in which the cities are located. Based on historical wholesale market prices, Corbin (2014) determined these price profiles for the typical weather file used throughout the model. In the scenario of price responsive operation, the temperature bounds for comfort are relaxed to allow for a stronger response to the price profile. Before 8 a.m. and after 6 p.m., the lower bound on the indoor temperature is lowered by $2K$ in order to allow for precooling. During absence of the occupants, between 8 a.m. and 6 p.m., the upper bound of the indoor temperature is increased by $3K$ while the lower bound is decreased by $5K$. Hence, in this period of absence there is a significant potential for load shifting. The plots ‘normal’ and ‘price’ in Fig. 7 show that the combination of the variable price profile and the wide band on temperature set-point can lead to extreme electricity demand profiles. The results for the ’price’ scenario are hence for a fairly extreme flexibility scenario.

3. Results

In Section 3.1 the results of the application of the CCA methodology are illustrated. In particular, the impact of the choice of input data (i.e. sampling time and type of signal) on the performance of CCA is analyzed (Section 3.2). Finally, the performance of CCA is compared to a random sampling approach in Section 3.3.

The evaluation of the CCA methodology is common in the context of unsupervised machine learning. Measurements for a couple of days are used as training data for CCA (see Fig. 7 (top)). The goodness of fit (NMAE in this study) of the resulting representative buildings and their factors N_c are tested on this training data. But more importantly, the goodness of fit is validated on validation data, which is data stemming from the same system but for a different time period (see Fig. 7 (bottom)).

3.1. *CCA Methodology Application*

Fig. 7 illustrates the application and performance of the CCA. The aim of the aggregation is to predict the electricity demand profile of the full building stock P^{full} (‘Full’ in Fig. 7). The CCA aggregation methodology reconstructs the electricity demand profile with a limited number of representative buildings P^{CCA}. The model is trained in normal operation for a summer week in July and then tested for the whole month. The results are shown for multiple numbers of representative buildings, normalized to a sample size expressed in percentage (Eq. 2). As can be seen in Fig. 7, the performance of the aggregation on the training data is very good, even for a small sample size of 1%. Also, in the case of testing with a flat electricity price (‘Normal’ case in Fig. 7), the aggregated representation performs well. Yet, when price responsive MPC is applied in order to assess the flexible behavior as explained in Section 2.5 (‘Price’ case in Fig. 7), the MAE rises and it is evident that better performance is achieved by increasing the sample size. In this case, a sample size of 1% gives a MAE in predicting the electricity demand of $0.50MW$. This reduces to $0.23MW$ for a sample size of 10%.

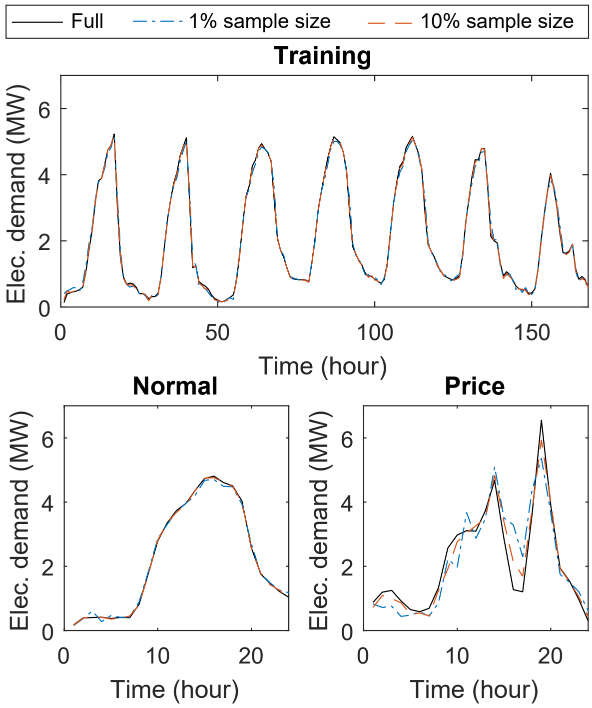


Figure 7.: Reconstruction of the electricity demand profile for Houston, Texas. Clustering based on electricity demand data for a week in hourly resolution. Aggregation performance illustrated for the training data of a week. The performance is also shown for July 19th, for both normal operation and for responsive price for both a 1% and 10% sample size of buildings.

3.2. *Choice of Input Data*

This section investigates the importance of the choice and pre-processing of the input data used for clustering, as introduced in Section 2.2. The data could either consist of direct measurements of electricity demand (ED) or in the absence of these, AC modulation data (ACMD). This data could be attained in 5 or 60-minute resolution. For these four input preprocessing options, Fig. 8 illustrates the normalized mean absolute error (NMAE) between the estimated and actual feeder electricity demand for multiple cases (Houston (HO), New

York (NY) and Los Angeles (LA)). Moreover, both normal operation with a flat price and the price responsive profiles are considered. The latter is used to assess the performance for flexible operation.

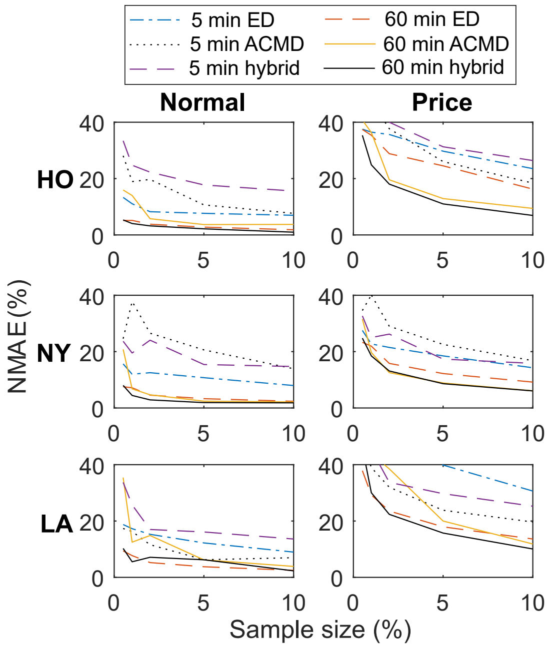


Figure 8.: Normalized mean absolute error (NMAE) as a function of the sample size, determined for normal operation and operation under price incentives (Fig. 6) for the month of July for Houston (HO), New York (NY) and Los Angeles (LA). Comparison of six clustering options, based on clustering of profiles in five minute (5 min) or 60-minute (60 min) resolution of electricity demand (ED), AC modulation data (ACMD) or both ED and ACMD (hybrid).

Regarding the resolution of input data, Fig. 8 shows that providing the clustering methodology with input data in 60-minute resolution generally outperforms 5-minute resolution data. The shorter resolution still contains the AC cycling artefacts, which appears to hamper the clustering in finding good representative buildings.

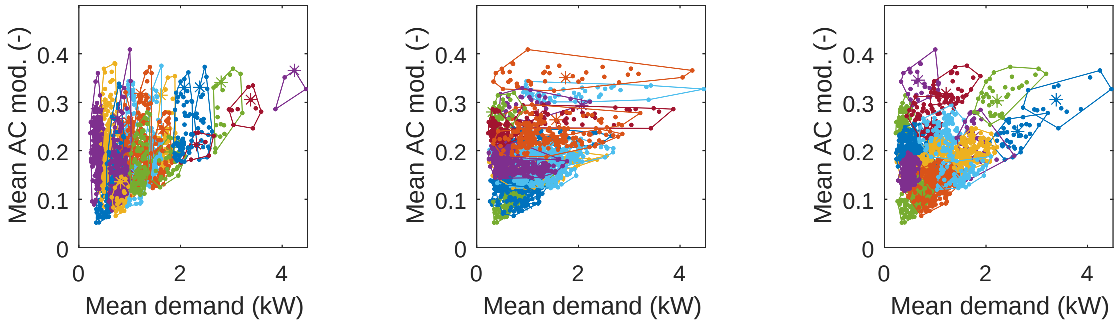
Regarding the type of input data, no clear preference between using directly electricity demand data ('ED' in Fig. 8) or AC modulation data ('ACMD' in Fig. 8) emerges. The former performs the best in the scenario of a flat electricity price. In this scenario, the available demand flexibility of the buildings is not utilized and all buildings follow their regular cooling schedule. Using electricity demand measurements as input data for the clustering performs well in this scenario, leading to a NMAE below 5%. Clustering focusses strongly on the absolute value of the input profiles and hence a good representation is attained. When the flexibility is activated with a price profile, ACMD outperforms ED and shows lower errors for most cases. What emerges from this analysis is that focussing on the modulation of the air conditioning captures the demand flexibility better.

Generally speaking, a variable electricity price appears to have a significant impact on aggregation performance. When there is no electricity price incentive ('Normal' in Fig. 8), the NMAE stays easily below 10% of the mean electricity demand. With electricity price incentives ('Price' in Fig. 8), the NMAE is higher and quickly rises to 20% of the mean electricity demand. From this, it appears that flexible operation is harder to capture for aggregation.

The use of electricity demand data ('ED') delivers better results for normal operation while AC modulation data ('ACMD') delivers better results for flexible operation. The resulting clusters from both methods with a sample size of 1% for Houston (21 samples, 60-minute resolution) are illustrated in Fig. 9. Observing the cluster arrangement, it can be seen how clustering based on ED ignores the AC modulation level contained in the ACMD profile (Fig. 9a), while clustering based on ACMD ignores the information contained in the ED profile (Fig. 9b).

As introduced in the Section 2.2, the 'hybrid' method uses both ED and ACMD data. Figure 9c shows how clustering on both data simultaneously leads to fairly different clusters. The performance of the hybrid method is assessed in Fig. 8. The hybrid method based on 5-minute resolution data shows equally poor performance as the other 5-minute data types. However, the hybrid method with data at 60-minute resolution, clearly outperforms ED and ACMD in most cases. For normal operation, it gets close or slightly improves upon using ED data. For flexible operation, it outperforms both ED and ACMD, sometimes by a significant margin.

The results in Fig. 8 are shown for an entire month. There appeared to be no clear cor-



(a) Clustering based on electric power

(b) Clustering based on AC modulation

(c) Clustering based on electric power and AC modulation

Figure 9.: Illustration of resulting clusters based on electricity demand as input (Fig. 9a), AC modulation data as input (Fig. 9b) and a mix of both input data (Fig. 9c) which is coined 'hybrid' method. The clusters are illustrated by showing the mean electricity demand over the period on the x-axis and the mean AC modulation data (called 'mean AC mod.') on the y-axis. Buildings in the same cluster have the same color and are also surrounded by a convex hull for clarity.

relation between the NMAE per day and the variance of the price profile for the corresponding day. In other words, there is no significant difference in aggregation performance for days with either a strong or a weak price incentive.

The CCA methodology was repeated with input data stemming from multiple price-responsive days. The result from this repetition are generally in line with using normal operation days as input, as shown in Fig. 8. Hence, the results from this variation are not shown separately.

Finally, the performance of the CCA methodology was also tested for normal operation during the month of May. In other words, representative buildings which were chosen based on data in July were tested for normal operation measurements in May. The results are very similar to Figure 8 and are hence not repeated here. From this, it appears that the CCA methodology can also be used to predict the full electricity demand profile during periods of lower cooling demand.

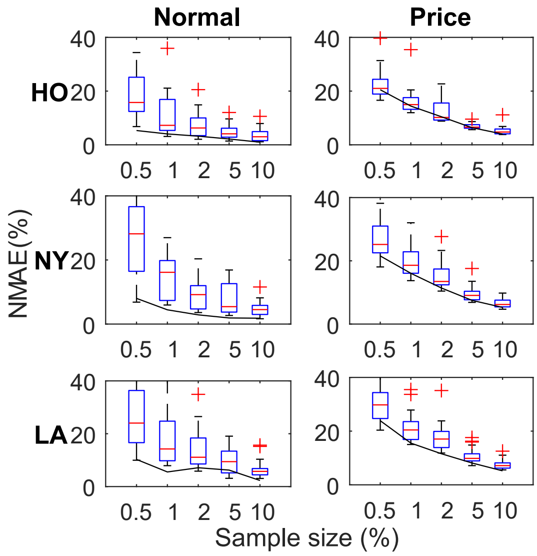


Figure 10.: Second evaluation of the normalized mean absolute error (NMAE) normalized by the mean of the full electricity demand as a function of the sample size. The full line shows the results for the aggregation based on the hybrid case in 60-minute resolution. The box plots show the results for random sampling, repeated 20 times. The red plus signs show the outliers of the box plot.

3.3. *Comparison to Random Sampling*

As described in Section 2.3, the results are compared to the benchmark of random sampling. Fig. 10 compares this random sampling to the best performing CCA method, using hybrid data in 60-minute resolution. What can be noted first is the excellent performance of CCA compared to random sampling in case of a flat price profile. The NMAE of CCA is in most cases smaller than 90% of the random sampling results. This illustrates how well CCA performs in predicting the normal operation of a large set of buildings.

In the scenario of flexible operation ('Price' in Fig. 10), it can be seen that CCA outperforms random sampling less drastically. Overall, CCA outperforms 60 to 90% of the random sampling results. For Houston, CCA outperforms around 60% of the random sampling cases. For New York and Los Angeles, CCA is even better, outperforming 75 to 90% of the random sampling results.

The advantage of CCA in this context is that it directly leads to a single set of representative buildings that do a fairly good job at capturing the flexibility of the population of buildings. This cannot be said from the random sampling, which on average shows good performance but with a wide spread in performance. For example, taking a sample of 0.5% buildings in the New York case with price incentive, could lead to a NMAE between 18 and 39% compared to the average electricity demand during that day.

4. Discussion

As far as the sample size (i.e., number of representative buildings) is concerned, the sample size quickly needs to be 10% of the population size in this paper in order to obtain good results in responsive price profiles, as can be seen in Figs. 7 and 8. A sample size of 10% is fairly large and represents a complexity reduction of only a factor 10. Although it must be noted that in this paper, the population sizes of buildings with AC are pretty low: 2098 for Texas, 1114 for New York and 711 for Los Angeles. Given a limited population size, this automatically leads to a high relative sample size needed (Krejcie and Morgan 1970). For example, for a confidence level of 95%, a margin of error of 5% and a population size of 2098, a classical sample size calculation (Krejcie and Morgan 1970) advises a sample size of 325 or 15%. If we increase the population size to 1,000,000 buildings, this sample size calculator advises 384 samples or 0.00038%. Hence, if the aggregation methodology presented in this paper is used on larger population sizes, it can be expected that the relative complexity reduction will be larger.

When the aggregation is based on AC modulation data, the performance in terms of NMAE in flexible operation approaches that of CCA with hybrid data (see Fig. 8). This is an interesting result in the context of smart thermostats. As many smart thermostats do not have ED data available, they can only rely upon AC modulation data. In this context, they could perform the CCA methodology in order to attain a representative set of buildings. In practice, specifically only these buildings could be equipped with smart meters. The measurements of these smart meters can then be scaled up in order to get a good estimate of the full building population's electricity demand during flexible operation. However, care should be taken that the absence of a smart meter in a building is not correlated to certain building characteristics, which could create a bias in the sampling. Note that in this study, we use data stemming from a simulation model. If measurement data is used as input for the CCA method, this data should be reliable by avoiding wrong or absent measurements. A check for corrupt measurement data is thus needed, after which this data should be removed from the data set to be used in the CCA method.

Furthermore, this paper illustrates that applying CCA leads to an error and hence an uncertainty on a building stock's electricity demand profile. Such clustering can be used in DR programs (Iacovella et al. 2015). Bruninx et al. (2017) showed that a large uncertainty on the building stock's electricity demand can limit its perceived controllability and hence lower the value of DR for a system operator. Hence, when combining the representative building models with an electricity generation model in an integrated modeling framework (Patteeuw et al. 2015), an appropriate sample size needs to be chosen. A too small sample size will lead to large uncertainty on the building stock's electricity demand and make the DR scheduling unreliable. A too large sample size will lead to impractical calculation times.

5. Conclusion

The main novelty of this paper is the application of a cluster-center-aggregation (CCA) methodology in representing the flexibility of a diverse building stock AC electricity demand. Hierarchical clustering is used to group buildings on the basis of their electricity demand (ED) or AC modulation data (ACMD) for the electrical cooling system. For every cluster, the building with the electric energy demand profile closest to the average ED or ACMD profile of that cluster is selected as a representative building.

The model has been tested on three cases composed of buildings stocks in different cities and climate zones (Houston, New York or Los Angeles) with 2098, 1114 or 711 modeled buildings respectively. The proposed model is intended for the estimation of demand flexibility provided by the electricity for thermostatically controllable loads, such as central AC systems and heat pumps for cooling and heating. In order to represent the flexible operation, different price profiles have been considered. Results show the crucial role of data pre-processing to obtain low NMAE values for estimating the full building stock electricity demand profile. An appropriate time resolution for input data is 60-minutes, with the use of ED showing better results for normal operation and, conversely, ACMD for flexible operation. Combining both signals (ED and ACMD) outperforms all the other clustering options when a dynamic price profile is considered. When electricity demand profiles are not available, AC modulation data at 60-minute resolution still performs well during flexible operation, which can be useful for smart thermostats that do not have electric demand information at their disposal. Finally, the electricity demand profile is harder to estimate during flexible operation, since the NMAE is higher in all studied cases. For example for hybrid data (a mix between ED and ACMD data) in 60-minute resolution, the NMAE is typically 5% during normal operation for a sample size of 1%. In other words, the model size can be reduced with a factor 100 with only a NMAE of 5%. For flexible operation, the NMAE is typically 10% at a sample size of 5 to 10%, hence for a model size reduction of 10 to 20.

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