Comprehensive Benchmark System for Load Management Applications Using Morphological-based Load Profile Clustering

Farnaz Harirchi, *Member, IEEE,* Ramtin Hadidi[1], *Member*, *IEEE*, Bill Schroeder, Ryan Baumgartner[2]

***Abstract*— One of the main concerns in building demand management-related applications such as peak shaving, energy efficiency, tariff design and demand response is the limited knowledge from different building-type load patterns, their specifications, and features. In this regard, designing a reliable and comprehensive benchmark system for load profiles would be a critical primary task. Such an encyclopedic database plays a critical role in evaluating different demand side management approaches for buildings. In this work we aim to define an appropriate benchmark system to assess efficacy of buildings load management methods by classifying a large yearly dataset of various load types including commercial, educational, industrial, and grocery buildings. For this purpose, first, daily load patterns of each building are considered as individual load samples. Then, a morphological filtering procedure is used in order to segmentize each of these load samples. Next, a set of energy-based features is extracted from segments and is fed to a hierarchical clustering algorithm to partition this enormous dataset into an optimal number of classes. Finally, each building is assigned to different categories based on the total number of load classes it may include.**

***Index Terms*—Electrical load clustering, Pattern recognition, Feature extraction and selection, Classification, Energy micromanagement, Changepoint detection.**

I. Introduction

NOWADAYS fast and reliable energy management is a critical task for smart power systems. In this regard, understanding the pattern of load consumption plays a critical role in electricity resource optimization, and especially in green energy-based trends development. Traditionally, the load management was a subject of large-scale region analysis such as electrical network zones. However, the flow of comprehensive information through the new advents of advanced sensor networks in smart grids, opens a new topic entitled micromanagement in energy grids [1]. In this energy management level, each consumer can contribute in optimizing the demand response by following a dynamic load profile.

Micromanagent would, specifically, resolve the associated challenges related to the lack of detailed knowledge of electrical load consumption as a major barrier for demand side management in small and medium industries [2]. In order to design such a fine level autonomous and smart network-wide load management strategy, every single consumer unit should be able to dynamically respond to daily constraints dictated by the main grid. However, different load types are having distinct specifications and characteristics. Thus, to design a wise standard control strategy, we should first study the specific behavior of various load sources and then validate the effectiveness of a new strategy over such a benchmark system.

A. Overview, Problem Definition, State of the art literature

The new technology of smart metering provides a near real-time recording of the load consumption pattern from a variety of building types. Online grid-customer interaction is an interesting and widely under study field [3]. Electrical load clustering (ELC) plays a major role in designing such a fine level of energy planning or micromanagement. ELC has been mostly used as a customer grouping procedure in order to provide insightful information for dynamic tariff design. Traditionally, ELC is modelled as a multi-level Pattern Recognition (PR) problem with the following standard steps: 1) Data preprocessing, 2) Feature extraction (FE), 3) Feature selection (FS), 4) Clustering\ Classification. It is worth noting that, in the professional pattern recognition language, clustering is usually referred to a data grouping procedure where no knowledge on the optimal number of classes is available. In contrast the classification is termed to a situation where the data is labelled, or we have a predefined set of data classes where each data sample should assign to one of these limited class numbers. In load pattern categorization we, usually, work with unlabeled data and, consequently, try to solve a clustering problem. However, in the rest of this paper, without loss of generality, we may use clustering and classification terms interchangeably.

A variety of mathematical methods has been developed to implement each of these steps in the PR literature. From simple linear to highly complex and nonlinear FE, FS and classification approaches are available, and one may select the optimal approach based on the data characteristics. Using these toolboxes, consolidated approaches have been proposed in the literature for ELC. Within the 1st step, a combination of outlier removal, normalization and alignment techniques are incorporated to purify the data from the bad data recording and telemetry or any other unwanted effect.

In the 2nd step a set of features is extracted from the load patterns to reveal the associated load class. In this step any data from the original time domain is mapped to a predesigned feature space. In the literature, various features used to reveal the specific

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characteristic of each load class [4]-[6]. One may use the time samples from the original time domain representation as distinguishing features. However, it is common to, instead, form a set of shape features from the time-domain behavior of load samples. Some examples such as average to maximum power ratios, or ratios between average power at different times of the day (daylight period, night period, or the entire day), can be found in the literature [4], [7], [8], and [9]. In more modern schemes, alternative mathematical features such as harmonic-based coefficients, Fourier coefficients, and time-frequency-based features have been in [5], [10], and [6], respectively. From geometrical viewpoint, the corresponding shape of a load class within the feature space (or shape of its corresponding cluster), depends on the distribution of the extracted features.

The 3rd step is the FS procedure that is usually performed to further reduce the dimensionality of the feature space in high dimensional schemes. An appropriate FS approach can significantly decrease the time complexity (by reducing the feature space dimension) while form a more clustered-compact feature space. Principal component analysis is the most common mathematical projection recognized in this regard, while other dimensional reduction techniques such as curvilinear component analysis, or the canonical variate analysis were utilized by different researchers, in [11], [12], respectively.

Finally, in the 4th step and based on requirements of different applications, various clustering or classification algorithms have been applied to find the correct between-class boundaries in the feature space. Naturally, the overall performance of a typical classifier would be highly dependent on the prior FE and FS procedures. Geometrically, if all classes have a compact distribution (and are widely separated from each other), a simple linear classifier should be able to perfectly recognize the associated boundaries between these classes and accurately assign the correct class label to each of the load classes. A large set of supervised, semi-supervised and unsupervised approaches have been already examined in the previous work, such as k-means or fuzzy k-means clustering [13], a probabilistic neural network (PNN) [14], self-organizing maps (SOM) [15] and Gaussian mixture model (GMM) [16]. A new approach is presented in [17] that exploits the ant colony principles. A variety of other PR techniques such as the support vector clustering, dynamic time warping, and latent Dirichlet allocation have also been applied to cluster electricity customers [18]-[22].

B. Techinical Challenges and Contributions

A major limitation associated with most of the aforementioned approaches is their holistic viewpoint. Usually, these approaches have been adapted in case of very small number of load samples [23]-[24], or have been verified in case of a single building-type [25], or over a seasonal dataset [26]. On the other hand, some of these techniques are only applicable in terms of specific applications. For example, since the occurrence time of statistical features of the load patterns are not considered in the dynamic time wrapping-based frameworks, these methods are not useful in case of energy storage planning. Similarly, Fourier coefficients do not reveal useful information about the time resolution of a load peak or load variation. Time-frequency features may solve this issue but still generate a large set of features which needs postprocessing procedures to be implementable in case of large-scale datasets with tens of thousands of load patterns. To the best of our knowledge none of the aforementioned work considers a large-scale dataset with tens of thousands load profiles.

In this work we aim to design an appropriate benchmark system to assess efficacy of buildings load management methods by classifying a large yearly dataset of various load types including commercial, educational, industrial, and grocery buildings. For this purpose, first, daily load patterns of each building are considered as individual load samples results in over 35000 load samples from 100 buildings. Then, a morphological filtering procedure is used to segmentize each of these load samples. Unlike small-scale seasonal-based databases, in such a huge year-round dataset load peaks do not necessarily occur at a routine time frame, resulting in a set of load curves with similarity in shape, but with considerable amount of variation in time behavior. Thus, in contrast with former shape-based feature extraction methods, where the daily load pattern is segmented based on the day-time period [23], in this work, a set of energy-based features is extracted from segments and is fed to a hierarchical clustering algorithm to partition this enormous dataset into an optimal number of classes.

Due to enormous scale of the data space, most of state of the art clustering approaches are not easily implementable. Moreover, some techniques such as k-means chasing approaches would need the maximum number of clusters to be initially determined. Furthermore, our findings indicate that the usual clustering evaluation metrices are widely ignoring the smaller-scale clusters and are biased toward the populated clusters. To address these issues, we designed an elastic manual dendrogram cutting modification on hierarchical clustering approach that would result in the best overall performance. In the final step, each building is assigned to a hardship-analysis category based on the total number of load classes it may include.

II. Dataset Procurement and Data Parsing

Our dataset is a yearly (5 minute) demand power for 98 different buildings including 25 commercial, 25 educational, 25 food shops and, 23 industrial buildings. Figure.1, graphically displays, the statistical properties and specifications of the proposed database. Variety of buildings from different time zones, climate situations, sizes and subindustries are collected to introduce a comprehensive benchmark system. Since quarter-based time interval analysis is more common within the load profiling literature [23], using a 3rd order moving average filter, we converted 5min intervals to 15min. This filtering is usually performed to eliminate the unnecessary variations in the load shapes.

Fig.1. Dataset Specification

III. Methodology

In this paper, we will follow the stepwise PR framework to deal with the ELC problem. In this section, we present the technical details of the approaches we used to address the corresponding challenges in each of the 4 aforementioned PR steps. The final goal is to assign similar load patterns into the same group without prior knowledge of groups definition. This is widely known as a clustering problem [27]. Fig.2 shows the detailed diagram of the proposed load clustering methodology for load clustering.

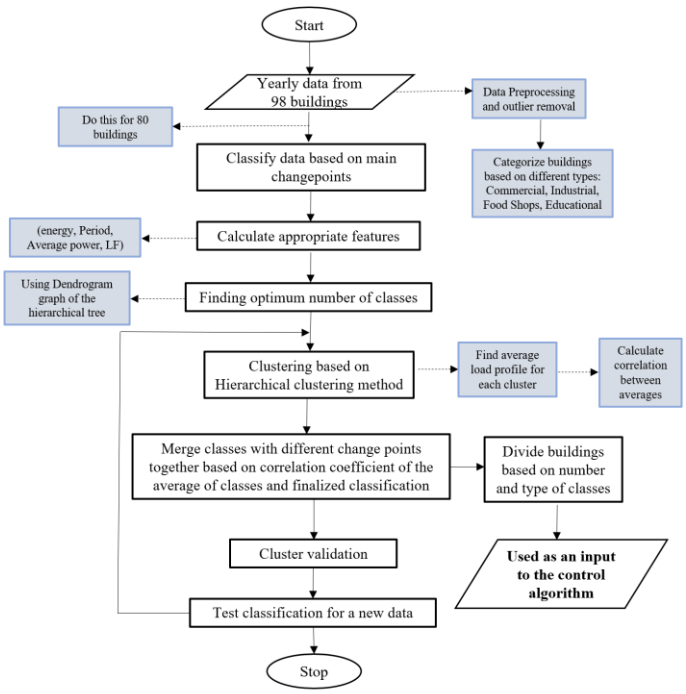

Fig. 2. Morphological-based load clustering algorithm

A. *Data Preprocessing: Morphological Filtering*

Due to the existence of a couple of outliers in the load samples, we have excluded 2 buildings from the final evaluations. As said, each daily load profile from each of 98 case studies is taken and considered as an individual sample which results in a total of 35868 load samples. To address the further requirements in energy management applications, each load sample is split into a limited number of smaller segments, based on considerable changes in the load behavior.

Unlike the usual day-time based load pattern segmentations (morning, afternoon, night), in this work an adaptive morphological filtering procedure has been applied to find the major change points in the load pattern. Reliable detection and localization of change points in the distributional pattern of a signal is a conventional and challenging problem in statistics, and a variety of methods have been developed to address this combinatorial problem. Usually, the changepoint analysis is referred to the problem of identifying of points within a signal support where one or more statistical properties are changed. This problem can be formulated in terms of a penalized (usually unconstrained) mathematical optimization.

Consider a load pattern, $\boldsymbol{x}$, of length N with a total number of K changepoints along its support occurred at the following set of ordered time samples $\{\tau_k: k = 1{:}K\}$, such that, $\tau_k = 0$ and $\tau_K = N$. These K changepoint segementize $\boldsymbol{x}$ such that, each of the $K+1$ subsections in the load pattern is happening within a time interval $\tau_k < \Delta t < \tau_{k+1}$. Now define the following loss function:

$$\sum_{k=1}^{K+1}\left[\mathcal{L}(x_{(\tau_{k-1}+1:\tau_k)}\right] + \alpha p(k) \qquad (1)$$

Minimizing this function over a set of changepoints, τ_k, can determine the optimal number and locations of change points along signal $\boldsymbol{x}$. Variety of possible mathematical formulations can be used to define the segment loss function, $\mathcal{L}$, and the linear penalize term $\alpha p(k)$. In this work we use the following mathematical minimization:

$$\Xi(\tilde{t}) = \min_{\tau\in\aleph_{\tilde{t}}}\sum_{k=1}^{K+1}\left[\mathcal{L}(x_{(\tau_{k-1}+1:\tau_k)}\right] + \alpha \qquad (2)$$

where $\Xi(0) = -\alpha$, and $\aleph_{\tilde{t}}$ denotes a possible set of changepoints $\{\hat{\tau}_k: k = 1{:}K\}$ for a typical signal $\boldsymbol{x}_{1:\tilde{t}}$. In our framework, similar to the approach that is developed in [30] we considered a constant penalized factor. The minimization problem (2) can be rewritten as follows:

$$\Xi(\tilde{t}) = \min_{t}\left\{\min_{\tau\in\aleph_t}\sum_{k=1}^{K+1}\left[\mathcal{L}(x_{(\tau_{k-1}+1:\tau_k)})\right] + \mathcal{L}(x_{(t+1:n)}) + \alpha\right\}$$
$$= \min_{t}\left\{\Xi(t) + \mathcal{L}(x_{(t+1:n)}) + \alpha\right\} \qquad (3)$$

In this work we define the loss term $\mathcal{L}(x_{(\tau_{k-1}+1:\tau_k)})$ of each segment as the residual error of each segment from its local average. In order to solve this recursion problem and find the optimal set of changepoints we have used the pruned exact linear time (PELT) partition algorithm (Algorithm.1) that is introduced in [28], however, we have, instead, replaces the internal minimization problem with the maximization over the log-likelihood of the loss function. Using this morphological filtering procedure, we found the most significant changes in each load profile.

Fig.3 illustrates an example of such a filtering on a typical load pattern with a total number of 4 changepoints along its support. Once the morphological filtering is applied to all load profiles, we eliminated some redundant changepoints which are not satisfying certain validity constraints. Consider $P = \{P_n: n = 1{:}N\} \in R^N$ to be a vector of hourly power demand values for a daily load pattern and $\bar{P}_{seg}$ to be the average segment power. If:

1) Number of samples between two change points < 8, OR
2) $P_{max_{seg}} - P_{min_{seg}} \times \Delta t_{seg} \times 0.5 < \frac{2}{100} \times E$, ($E$ is the total energy of the load profile,
both change points are eliminated. Else if,

$$\left|\bar{P}(seg_{previous}) - \bar{P}(seg_{next})\right| > 0.2$$

Two corresponding changepoints (τ_k, τ_{k+1}) are replaced with a single change point located at $\tau_k + \frac{\Delta t_{seg}}{2}$ if Δt_{seg} is even, else it will be located at $\tau_k + \frac{\Delta t_{seg}+1}{2}$.

Algorithm.1. PELT:

Inputs: A load pattern $\boldsymbol{x} \in R^N$

An appropriate loss function $\mathcal{L}(.)$

An independent penalty constant α

A constant C such that satisfies the following inequality:

$\mathcal{L}(x_{(t_1+1:t_2)}) + \mathcal{L}(x_{(t_2+1:t_3)}) + C \leq \mathcal{L}(x_{(t_1+1:t_3)})\ \forall\ (t_1 < t_2 < t_3)$

Initializations: $\Xi(0) = -\alpha$, $\aleph_0 = NULL$

For $\tau^* = 1{:}\,N$

1. Calculate $\Xi(\tau^*) = \min\limits_{0 \leq \tau < \tau^*} \{\Xi(\tau) + \mathcal{L}(x_{(\tau+1:\tau^*)}) + \alpha\}$
2. Let $\acute{\tau} = arg(\min\limits_{0 \leq \tau < \tau^*} \{\Xi(\tau) + \mathcal{L}(x_{(\tau+1:\tau^*)}) + \alpha\})$
3. Set $\aleph_{\tau^*} = (\aleph_{\acute{\tau}}, \acute{\tau})$

Output: the set $\aleph_N$

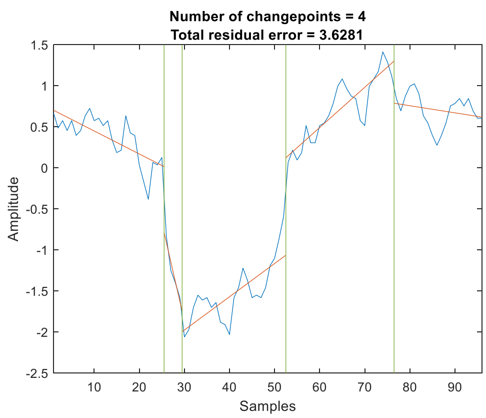

Fig. 3. Morphological filtering of a typical load pattern with $M = 4$ changepoints.

B. *Feature extraction*

Following the morphological segmentation step, in this work, the following set of energy-based features are extracted from each load segment. Consider $P = \{P_n: n = 1{:}\,N\} \in R^N$ to be the vector of hourly power demand values, for each load segment within two chasing changepoints we define:

1) load factor of the load profile (LF):

$$LF = \frac{\bar{P}}{P_{max}} \tag{4}$$

2) total energy of segment (E_{seg}):

$$E_{seg} = \sum_{t_k}^{t_{k+1}} P_k \tag{5}$$

3) segment time period (k):

$$\Delta t_{seg} = \tau_{k+1} - \tau_k \tag{6}$$

4) average power of segment (P_{seg}):

$$P_{seg} = \frac{E_{seg}}{\Delta t_{seg}} \tag{7}$$

C. *Hirarchical Clustering*

In PR, clustering is referred to any technique that tries to place similar data samples into the same group without any prior knowledge of groups specifications [27]. Based on the very own specifications of our approach, we implement a pre-clustering step where load patterns are initially assigned to a subgroup based on the number of changepoints they have within their support. In this study we considered the minimum and maximum number of valid changepoints to be 0 and 7, respectively. Consequently, we start with 8 subgroups. Obviously, the total number of possible features for a load pattern is equal to the number of segments, times the number of general extracted features, equal to 4 (as defined in section III.C). As such, a feature vector $f \in R^{(m\times 3)+1}, m = \{1{:}\,8\}$ is calculated and assigned to each load pattern (load factor is calculated over the whole load profile). In this way, for each load subgroup we have defined a multidimensional feature space and the goal of the clustering step is to marginalize this feature space to find the optimum number of load classes.

Regarding the enormous size of the data space we have (over 35000 load patterns), most of the sophisticated parametric clustering approaches are not adequately implementable. Moreover, some other methods, including the k-means family, would need a pre-knowledge on the maximum number of clusters which limits our flexibility in cluster number selection. Furthermore, our findings verify that the usual clustering evaluation criterions which are used to optimize the final number of clusters are widely ignoring the smaller-scale clusters and are biased toward the populated clusters. To avoid the associated drawbacks with these approaches we have used an elastic manual dendrogram cutting modification on hierarchical clustering approach that would result in the best overall performance.

The hierarchical clustering is a robust clustering technique that groups a set of data samples over various levels by generating a similarity graph widely known as the cluster-tree or dendrogram [23]. Dendrogram can be constructed agglomeratively, or divisively, where load samples are rather grouped or split to generate courser or finer clusters in a multilevel regime. Unlike, single scale colonized clustering algorithms such as k-means or GMM, it rather creates a multiscale hierarchy where clusters at neighbor levels can easily merge together. A sample of a dendrogram is presented in Fig.4.a. A major advantage of such a visualized clustered structure is the flexibility in constructing the final clusters by cutting the hierarchical cluster tree at a level that is most appropriate for a specific application.

D. *Cluster size elasticity issue and our solution*

The most important question in hierarchical clustering to answer is where and how to cut the dendrogram to extract the best possible clusters. In this regard, a variety of cluster evaluation metrics such as silhouette are available to estimate the optimal number of clusters. Consider a possible partition of clusters $c_1, \dots, c_p$, the Silhouette criterion is defined as the following average over all datums in each and every cluster c_j:

$$S = mean_{c_j}\left(mean \sum_{i=1}^{I_{c_j}} \frac{(b_i - a_i)}{max(a_i, b_i)}\right) for\ j = 1{:}\,p \tag{7}$$

where a_i is the average distance from the i^{th} datum to all other samples in the same cluster, and b_i is the smallest average distance from the i^{th} datum to all other samples in a different cluster, minimized over clusters. However, since these techniques are calculating the evaluation criteria using data samples in distinct clusters, the final value may vary if the number of cluster elements varies over a big range. In such a situation the evaluation metric would neglect the small size clusters and the algorithm will merge them with the closest large-size cluster. An alternative approach is to use the inconsistency coefficients which is a quantified indicator of the relative consistency of each link in a dendrogram. This value is defined as the ratio between the height of a link (the orange arrow in Fig.4.a) with respect to the average height of links below it. Consequently, a high inconsistency coefficient is calculated for those links that are joining into distinct clusters while those which are ending up with indistinct clusters would have a low inconsistency value. Whenever, there is a meaningful, visible, consistency gap in the tree we may cut the dendrogram horizontally and form the clusters accordingly.

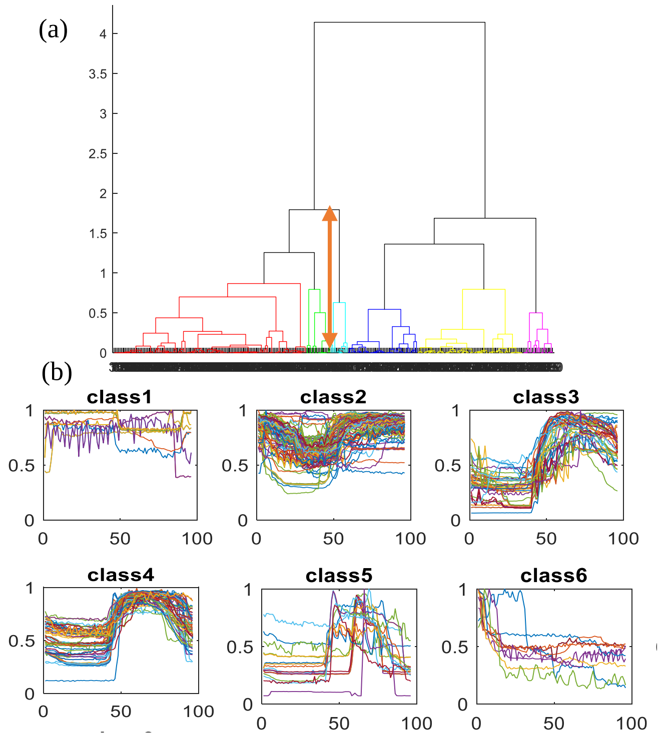

Figure 4.a) A manually cut dendrogram with 6 clusters using inconsistency threshold criterion for a partial dataset including 1000 loads with 2 changepoints along their support, b) Clustering results

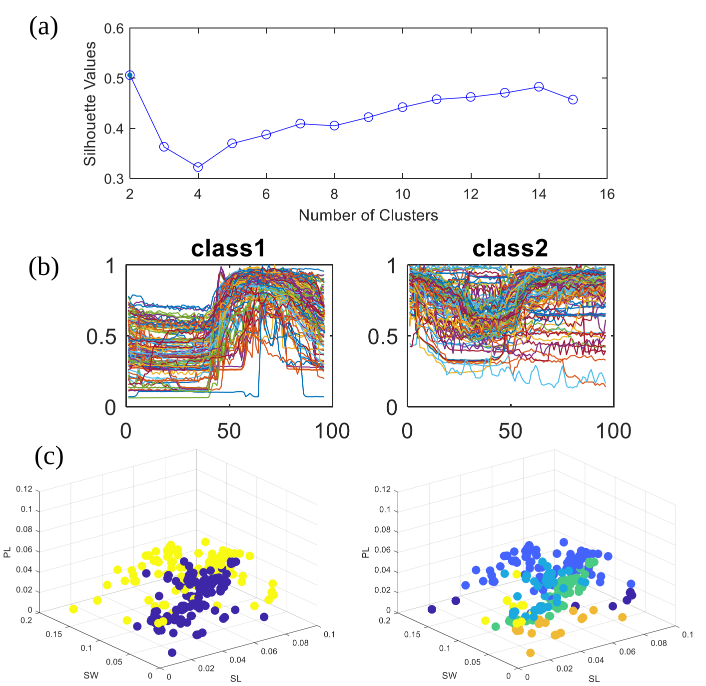

Figure 5.a) Silhouette criterion for a partial dataset including 1000 loads with 2 changepoints along their support, b) Clustering results, c) Clustered feature space based on Silhouette criterion (left), vs inconsistency criterion (right)

In Fig. 4.b and Fig. 5.b-c we compared the clustering performance of the hierarchical clustering, using the Silhouette vs direct usage of inconsistency coefficient. The inconsistency coefficient threshold has been set to 0.95. From Fig. 5.a we can see that the Silhouette criterion suggest the optimal number of clusters to be 2. However, a dendrogram with 6 cut clusters can reveal a much more appropriate illustration of the load samples distribution within the feature space. Obviously, there are 4 more load subclasses with distinctive characteristics in this typical dataset which are eliminated by Silhouette clustering metric, due to their small population (similar observations resulted from other cluster validation metrics). Fig.2 illustrates the detailed diagram of the proposed load clustering framework.

IV. Results, and Discussions

The proposed framework has been exploited to generate a comprehensive benchmark system for load profiles from the dataset which was introduced in Section II. As mentioned, following the morphological filtering step, the initial 35868 load samples are grouped, and associated features have been extracted. The inconsistency coefficient-based hierarchical clustering has been independently implemented on each subgroup of data samples. Table. I present the optimal number of clusters found for each subgroup. Consequently, a total number of 203 initial clusters have been formed for the whole dataset. Fig.6 illustrates a multiple set of load classes resulted from the clustering procedure, with 1-3 changepoints recognized along their supports.

Table. I

No-chgpnt	0	1	2	3	4	5	6	7
No-class	4	25	28	40	37	37	23	9

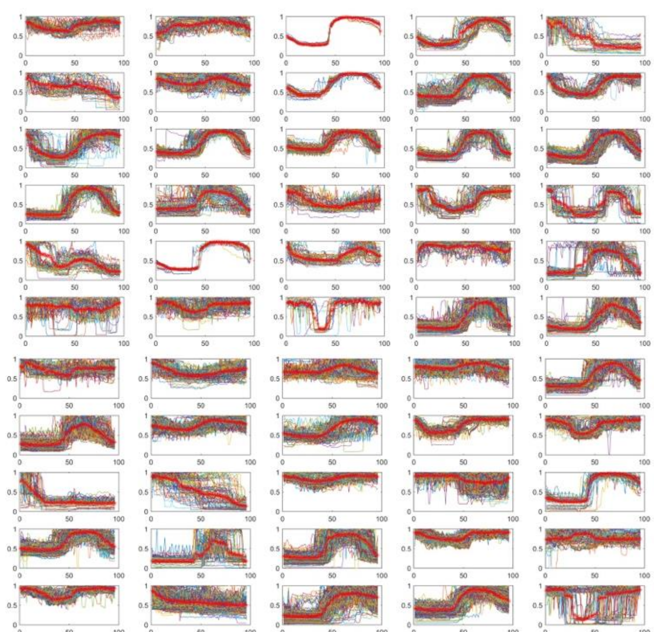

Figure.6. The clustering results over 28651 load samples with 1-3 changepoints along their support.

Although one may use all these clusters for further analysis, a level of similarity has been observed among some of the classes from different subgroups. As such a complementary merging mechanism has been developed to reduce the possible redundancy in the load classes. This approach has been summarized in Algorithm.2. Figure 7.a, and b, are representing the Grammian matrix formed by the correlation analysis among the average pattern of the 203 initial load classes, and the location of the most correlated classes with more than 95% of similarity level. Algorithm 2, reduces the total number of load categories to the 165 final classes.

Algorithm.2: Complementary Class Redundancy Elimination

1. The average load pattern of each initial load class is calculated
2. The N by N Grammian matrix (Fig.7.a) is formed by calculating the pairwise correlation coefficients among all average-class load patterns: N=203 is the number of initial classes.
3. During an iterative procedure:
   3.0 An appropriate correlation threshold (thr) would be selected
   3.1 For each average-load index a group of candidate loads satisfying the threshold criteria (pairwise) would be selected
   3.2 Due to pairwise checking, starting from each load index would result in a different set
   3.3 The set with the maximum sum of pairwise correlation among its members would be chosen
   3.4 Redundant class-index assignments are prohibited by removing the previously selected average-load indexes from the calculation in the future iterations
   3.5 L<N number of load classes after merging are formed: L= 115 for thr = 0.95
4. Each of these L new classes are checked among their members for energy flattening, and some classes are splitted into smaller sub-classes with similar energy level. Finally, L<M<N number of load classes are formed.
5. All load patterns associated with each average-load pattern index for each of the final M classes, are merged together and form the final classes: The final number of classes: M=165 for thr=0.95

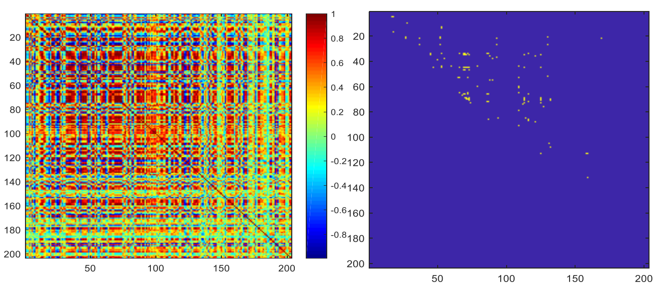

Figure 7.a. The Grammian matrix which reveals the similarity level among the average pattern of the 203 initial load classes, and b. the location of highly correlated class with more than 95% similarity in the correlation unit.

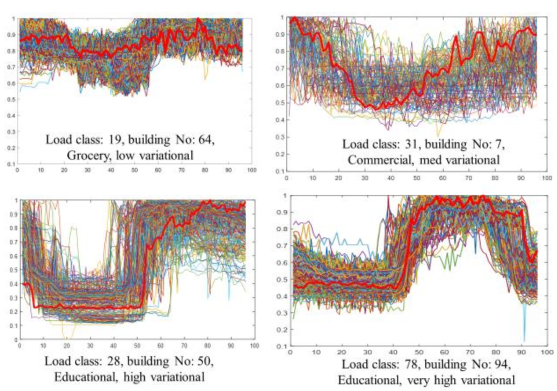

Figure.8. a-d: Examples from 4 different final load-classes assigned to different categories of buildings (red curves are specifying a sample pattern from each class).

Now we have all we needed to establish our final benchmark system. Figure 9.a, illustrates the distribution of load classes among each building. Building are ordered and numbered from 1 to 100 such that 1 to 25: commercial, 26 to 50: educational, 51 to 75: grocery and 76:100 industrial (building 76 and 84 are excluded). A natural and expected observation is that the variation of load classes in grocery stores is the least while is the most in industrial plants. Fig.9.b shows the other side of the coin, which is a histogram-type representation of the number of load classes vs building number.

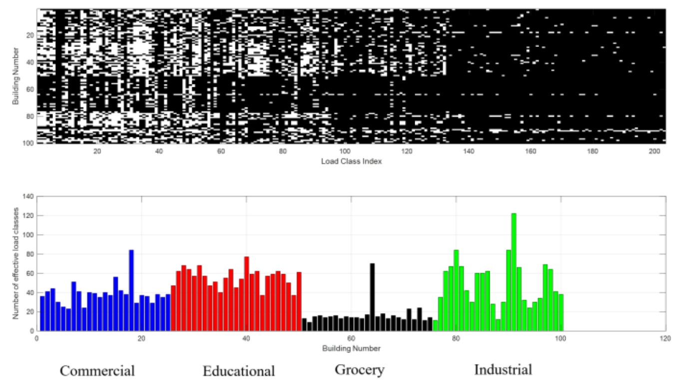

Figure 9.a, distribution of load classes among 100 buildings, b. total number of load classes contributing in each building load data.

At the final step of our analysis, each of our original 100 buildings, are classified into 4 levels of analysis difficulty based on the variation in their load-classes involvedness as mentioned in Table. III. Considering this criterion, the following chart is obtained for each building category (Table. II):

Table. II

	Low Variation	Medium Variation	High Variation	Enormous Variation
Commercial	0	23	1	1
Educational	0	10	15	0
Grocery	22	2	1	0
Industrial	1	11	8	3

Table. III

Low number of classes < 20
20 ≤ Medium number of classes≤40
41 ≤ High number of classes <64
64 ≤ enormous number of classes

Finally, Figure.10.a and b are representing the circular charts of the percentage of each building category in each analysis difficulty level based on the load-class variation and vice versa, respectively.

I. Conclusion Remarks

In this work, a reliable and comprehensive benchmark system for load profiles has been introduced which could play an important role in evaluating different building demand management frameworks. A large-scale dataset including the yearly load data from 100 commercial, educational, industrial and grocery buildings have been considered. Each daily pattern of each building was assumed as an individual load samples. Then, a morphological filtering procedure is used in to divide each of these load samples into a set of smaller segments after each considerable behavioral change in the pattern of load sample. Next, a set of energy-based features is extracted which forms a multidimensional feature space. An elastic hierarchical clustering algorithm is then utilized to divide this enormous feature space into an optimal number of classes. Finally, each building is assigned to a different categories based on the total number of load classes contributed in its sub dataset. Our designated benchmark system can easily be expanded by adding new buildings and forms a new powerful analysis toolbox that can be used further to validate any research in the area of demand response, building management and load classification.

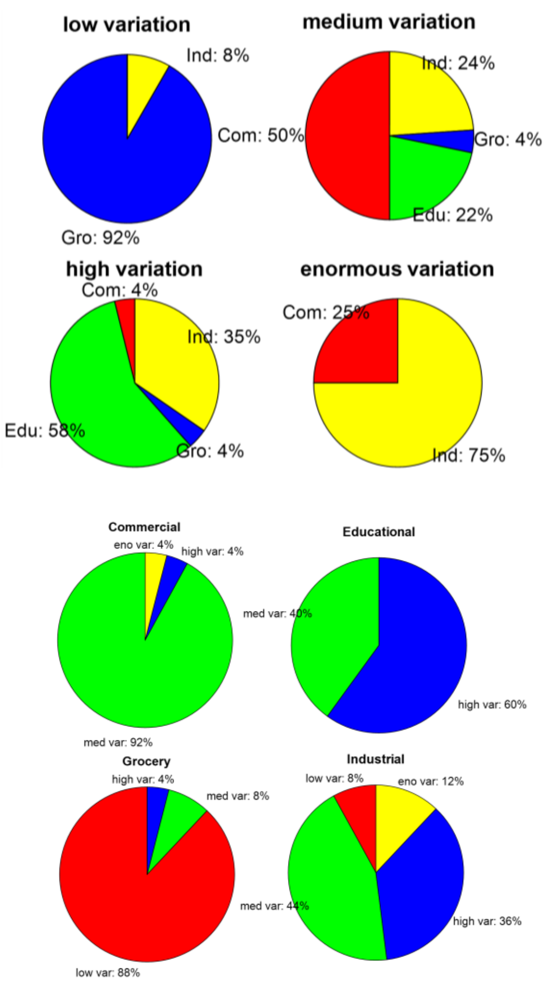

Figure.10.a and b The circular charts of the percentage of each building category with respect to load analysis difficulty level and vice versa, respectively.

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