A Machine Learning Based Methodology for Load Profiles Clustering and Non-Residential Buildings Benchmarking

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***Abstract*—Buildings benchmarking based on their electric profiles is a fundamental step to identify, evaluate and then possibly implement energy efficiency oriented actions. Indeed, benchmarking enables comparison among peer buildings or industrial sites and the identification of reference cases, either efficient and inefficient ones. In this regard, temporal data clustering is an effective and widely applicable benchmarking tool. In this work, we propose a novel Machine Learning based methodology, taking advantage of two fundamental tools, namely a decomposition algorithm and a clustering one. Several clustering algorithms have been tested to identify k-Means as the most suitable one. The proposed methodology includes the evaluation of energy Key Performance Indicators for effective analysis and comparison of buildings. The proposed framework has been tested on a real-world case study including around 2000 non-residential buildings. The classification of buildings based on K-Means achieved an accuracy of 99.7% with respect to their usage category. Furthermore, reference Key Performance Indicator values for each cluster are obtained and discussed to understand buildings' energy behaviour and possible reasons for inefficiencies.**

***Index Terms*—Energy efficiency, non-residential buildings, clustering, machine learning, benchmarking.**

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I. INTRODUCTION

RETROFIT of existing buildings and efficient buildings operation are two of the key actions to be undertaken to enhance the transition towards energy sustainability [2]. In deeds, the buildings sector is the major responsible for energy usage and energy-related CO_2 emissions. Specifically, it accounted for 36% of global final energy consumption and was responsible for 37% of energy-related CO_2 emissions in 2020 [3], corresponding to 11.7 gigatons of CO_2. Despite carbon dioxide emissions associated with buildings decreased consistently after 2015, major challenges shall be addressed in the next decades to meet with the goal of keeping global temperature below 1.5°C with respect to pre-industrial levels [4]. The building stock is expected to increase dramatically, particularly in emerging countries. Furthermore, space cooling, which was responsible for 1 gigaton of CO_2 emissions and 5% of global energy consumption in 2020 [2], has doubled over the last two decades and it is expected to double once more by 2040. Besides, a number of energy intensive economic sectors are increasing dramatically their energy demand. This is the case, for example, of the Information and Communication Technology (ICT) branch. Pushed by the widespread of the Internet [5], ICT branch is experiencing an exponential growth of energy demand which increased by an annual rate of about 10% over the last decade [6]. The main contributor to this growth is the Telecommunication (TLC) sector, whose companies are in charge of the operation of the TLC network, including Central Offices (CO), Data Centres (DC), offices and many other buildings. TLC companies are responsible for about 7% of the global electrical demand [7]. DC and data transmission networks represent the two highest shares in the TLC sector energy demand, contributing to about 1% each of the worldwide total electrical demand in 2019 [8].

For these reasons, energy efficiency-oriented retrofit actions, as well as efficient management of buildings will be crucial challenges. This is witnessed by the actuality of the debate over energy efficiency at a political level, as well by the ongoing and growing economic investments and research efforts. The first aspect is certified by the centrality of the topic in the public and in the institutional debates and in the directives enacted by many political entities all around the world [3], [9]. At the same time, the global amount of investments for energy efficiency actions reached 180 billion dollars in 2020. Still, this amount is expected to burst over the next decades, as existing buildings shall be retrofitted with an annual rate equal to 3% to meet with the sustainability goals [2]. These investments are boosted by the economical benefit they produce, as they reduce costs and enhance economic competitiveness and sustainability [10].

Nevertheless, the pathway for an effective, broad and comprehensive energy transition struggles to gain a foothold. In many cases, this is due to a lack of awareness of the causes of inefficiency, or to inability to strategic planning of retrofit interventions. In this regard, the availability of data from large populations, capable of representing the conditions of the complex real-world buildings stock, is fundamental to derive strong evidence to support design of proper energy efficiency actions. Smart monitoring systems and the Internet-of-Things (IoT) paradigm represent the starting points to enhance awareness of energy behaviour of buildings [11]. Acquisition and investigation over huge amounts of data have become possible thanks to the widespread of systems for measurement, collection and data storage. By 2018, 100 million electricity smart meters had been installed in Europe [12]. Notwithstanding the impressive pace towards digitization, this represents just 34% of metering points around the Old Continent. In order to effectively process and exploit these data, new techniques and disciplines arose. These are generally addressed as data mining techniques. Particularly, Machine Learning (ML) emerged as the most promising discipline, thanks to its devotion to automation of the data investigation procedures and its numerous applications. Nowadays, ML is an effective and accurate approach to typical tasks such as pattern recognition, clustering, anomaly detection, regression and classification, and a powerful tool to take practical actions in support of a more energy efficient buildings management.

A key starting point for developing a strategic plan for energy efficiency of a building stock is identifying groups of buildings with similar characteristics and calculating energy performance indexes to allow comparison among peers. Eventually, reference buildings are selected within each group and retrofit analysis is undertaken. This approach, which is generally addressed as benchmarking, enables, for instance, the identification of priority refurbishments, ranking of peer buildings according to their efficiency and estimation of energy savings potential.

This paper proposes a novel ML-based methodology for benchmarking of buildings. Besides, the framework is intended to support the analysis of the characteristic Key Performance Indicators (KPI) of the buildings. With the perspective of providing the most effective and adequate clustering, smart meter measured electrical demand is employed. The proposed methodology includes *i)* the application of a time series (TS) decomposition model to obtain reference load components, and *ii)* a clustering algorithm to retrieve groups of homogeneous buildings. A real-world dataset has been employed to test the proposed framework. Specifically, a massive load profiles dataset regarding electrical demand from a heterogeneous stock of buildings from the largest TLC service provider in Italy. The data includes hourly aggregated load measures, measured from 1st January 2019 to 31st December 2019 for around 2000 buildings. It includes DC, CO, offices and mixed-use buildings. Moreover, this paper extends our previous work [1] by considering additional SoA clustering algorithms and additional temperature-at-use related KPIs.

The proposed work is organised as follows. Section II explores the literature efforts and discusses its gaps and presents the main contributions of this work. Section III describes the proposed methodology and the employed ML algorithms. Section IV includes the presentation of a tailored normalization tool for the investigated dataset and of the energy KPI. The outcomes from each step of the analysis are provided and discussed in Section V, including the clustering validation metrics to demonstrate the correctness of the obtained results. Final remarks and potential future developments are summarised in Section VI.

II. Literature Review

As data-driven approaches took over the sector of buildings performance analysis, a flourishing literature introduced and tested a number of new algorithms and applications of ML tools. Firstly, ML enabled benchmarking of buildings considering multiple factors related to buildings' energy performance [13]. To this purpose, the most broadly adopted algorithm was clustering, an unsupervised learning tool employed for a number of applications, including heating and cooling systems performance identification, energy usage pattern discovery, load profiling, classification, characterization, targeting, anomaly detection and energy management [14], [15]. Buildings benchmarking can be achieved by means of two different approaches: the first considers non-temporal parameters as inputs, the second deploys TS. Specifically, the first approach consists of considering some buildings parameters and performance indicators as input variables for the clustering model. For instance, Marrone et al. [16] group homogeneous schools and identify reference buildings for each cluster. These elements can be used to quantify the energy savings potential associated with a specific energy retrofit action to be undertaken for the whole set of buildings, hence supporting the administration in decision-making. A similar framework is employed by Geyer et al. [17], which make use of 50 different buildings' parameters. The authors underline that, to the aim of planning an efficiency-oriented renovation strategy, buildings shall be grouped according to their similarity in terms of reaction to retrofit measures, rather than in terms of descriptive and structural parameters. This can be achieved by incorporating appropriate performance indicators of the buildings as inputs of the model. Cecconi et al. [18] used k-Means to group homogeneous buildings and an Artificial Neural Network (ANN) to allow estimation of energy savings.

Contrary, given the availability of electrical load measurements, many researchers preferred to focus on time-domain inputs. These clustering models can be further divided into direct and indirect methods. The first are those making use of TS, or part of them, as they are. The second class of methodologies includes some data transformation step, which usually aims for dimensionality reduction of data. This is due to the issue of computational complexity of clustering long TS, for instance yearly load profiles (YLP) with hourly measurements. A couple of interesting examples of direct methods are described in [19],

[20]. The former is particularly noticeable for considering a massive dataset of about 3800 buildings, including both residential and non-residential ones, for a total number of over 2 million daily load profiles (DLP). These approaches include both an intra-building and an inter-buildings clustering steps. Yet, many authors adopted indirect methods, considering that some data-dimensionality technique may better preserve the meaningfulness and representativeness of TS and enhance computational cost reduction. For instance, Ryu et al. [21] encoded TS by means of a Convolutional Autoencoder. K-Means was then employed, resulting in dramatically lower computational time with respect to clustering of the original TS. Motlagh et al. [22] converted electrical load TS into signature objects by means of neural regression and subsequently performed clustering. Similarly did Westermann et al. [23]. The authors stress that temperature-at-use models, such as energy signatures, are more appropriate than those focusing solely on temporal patterns. Giordano et al. [24] instead identified homogeneous electricity customers by employing a spectral-based approach, which revealed itself as suitable for clustering TS featuring strong periodicity.

In this context, a number of clustering algorithms have been invented, tested and compared. The prevailing algorithm, by date, is k-Means, adopted in [16], [18], [19], [20], [21], [23], [25]. Hierarchical clustering has been adopted in [17], while Zarabie et al. [26] claim that Affinity Propagation Algorithm outperforms k-Means, k-Medoids and Spectral clustering for residential load profiles grouping. Damayanti et al. [27] achieved higher clustering performance by employing a k-Harmonic Means algorithm to cluster electrical load profiles with respect to k-Means and Fuzzy c-Means. Yang et al. [28] instead employed the k-Shape algorithm, introduced by Paparrizos et al. in [29], to analyse energy consumption patterns from academic buildings in Singapore. Li et al. proposed to use Gaussian Mixture Model and hierarchical clustering for intra-building and inter-buildings clustering respectively [30]. The search for novel clustering algorithms often dealt with the issue of shift, scaling and complexity invariance. For these same reasons, some authors focused their research on distance measures to be employed rather than traditional Euclidean ones. For instance, the Pearson Correlation Coefficient-based dissimilarity measure was employed in [31] and Dynamic Time Warping in [23].

Considering the urgency of pervasive energy efficiency measures regarding existing buildings, identification of groups of homogeneous buildings, construction of representative samples and investigation of representative case studies are key challenges to be addressed as soon as possible [3]. Both the buildings parameters and load profiles may be employed for clustering, which is a first necessary step of the aforementioned tasks. Nevertheless, thermal parameters are one of the sources of uncertainties in buildings' energy assessment [32]. These may be due to measurement errors as well as environmental conditions, such as moisture or age, which may modify the thermal properties of buildings. Furthermore, the collection of the necessary parameters for the whole existing buildings' stock is a tremendous challenge. On the contrary, smart meters penetration is expected to reach 92% of the electricity delivery points

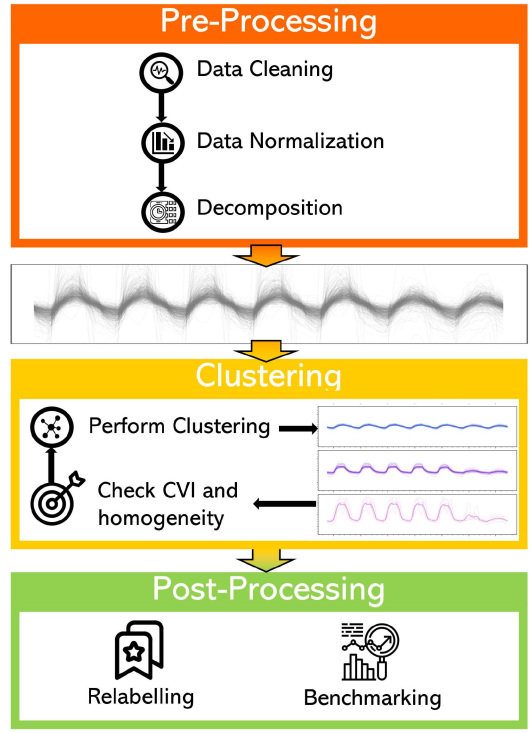

Fig. 1. Outlook of the proposed methodology.

in 2030 [12]. Hence, data regarding almost the whole number of existing buildings will be available in a few years. Proper algorithms will be needed to effectively and efficiently exploit these data. Furthermore, most of the research to date have dealt with small and not very diversified datasets. For these reasons, the present paper describes a new ML-based framework aimed at clustering buildings according to their energy behaviour. This is achieved by considering the hourly load measurements rather than the buildings' characteristics. The methodology features a decomposition tool to retrieve representative load components from the profiles. Hence, clustering of buildings is performed and validated through proper Clustering Validity Indexes (CVI). Finally, characterization of buildings is performed by means of specific Key Performance Indicators (KPI) and statistical analysis. The proposed framework was applied to a real-world dataset regarding a specially energy-intensive sector.

III. Methodology

In order to address the tasks outlined in the previous sections, here we present our novel methodology schematised in Fig. 1. The proposed approach provides an automated tool for buildings benchmarking. The framework relies on the exploitation of smart meter data. Specifically, hourly aggregated load profiles are considered. Besides the fundamental task of benchmarking, this work shall enhance detection and revision of wrong labels attached to buildings, in the perspective of supporting the facility management of the company. The methodology involves four parts, namely Data CollectionPre-processing, Clustering, and Post-Processing.

A. Data Collection

Electrical load measurements are obtained by smart meters. In this case study, these devices provide hourly aggregated energy consumption, that is mean total absorbed power. Raw data often include measurement errors, such as missing values, zeros or negative values, and values out of the plausible load range. Load profiles shall comprehend an adequate number of points and include measurements from any hour and season. Hence, load profiles shall contain measurements from one year or more.

B. Pre-Processing

Pre-processing, or pre-clustering phase, includes the steps necessary to handle raw input data. Specifically, pre-processing is intended to guarantee data reliability, comparability and exploitability. To this purpose, 3 steps are included in the pre-processing step: data cleaning, data normalization and decomposition.

Data Cleaning: Firstly, a data set cleaning step is carried out, to delete abnormal measurements and to reduce noise inside TS. Specifically, the abnormal values to deal with are measurement errors. To this purpose, load profiles are filtered by replacing values featuring gradients higher than three times the standard deviation calculated from the distribution of gradients from the TS itself. These values, as well as the missing ones, are replaced by means of linear interpolation. Besides, short TS, which are load profiles with less than one year of measurements or containing long-lasting abnormal measurements (i.e. whenever 48 consecutive values were considered abnormal), have been filtered out.

Data Normalization: Normalization of load profiles is applied to cluster buildings with similar characteristics but different size. This step is designed in accordance with the goal of clustering. For instance, in some cases buildings' size may be a criterion for grouping, hence a normalization step may not be included in the framework. More often, normalization is a step of the analysis to be tailored to the investigated dataset. In this case, base-load normalization is employed in accordance with the characteristic of the case study. This choice is described in depth in Section IV-A.

Decomposition: Identification of representative profiles is a crucial step of benchmarking. Previous works often focused on the identification of representative DLP by means of a intra-building clustering step [19], [20], [30]. Yet, it has been pointed out that the representativeness of DLP is questionable and that considering YLP is more adequate [21]. Nevertheless, exploiting YLP for clustering is hindered by the problem of dimensionality. Indeed, adequate load profiles often feature hourly resolution, which results in YLP in 8760 dimensions and may determine complexity and computational time issues. To deal with this obstacle, dimensionality reduction techniques may be adopted to preserve meaningful features of TS, while removing irrelevant or redundant attributes [33]. Dimensionality reduction techniques can be divided into feature extraction and feature selection, being the former the more suitable for TS. In fact, buildings are expected to depict particular load patterns, which may depend on a number of factors. For instance, outdoor temperature variations will affect electrical demand of those buildings equipped with air conditioning, typically determining seasonal and daily periodicity. Occupancy schedules will determine the load for lighting, and weekly patterns have to be expected for industrial, commercial and residential buildings. Assuming periodicity as a distinctive feature of buildings, the proposed methodology takes advantage of a decomposition algorithm in the attempt of isolating the fluctuations linked to sites' usage. This step is intended to preserve meaningfulness of YLP and to shorten computational time by reducing the dimensionality of the vectors which will be employed in the clustering phase. In order to identify the most significant periodical components, an auto-correlation analysis is carried out and Pearson's coefficients are calculated. Hence, the Loess decomposition model [34] has been applied to distinguish the base load, the seasonal and the periodic components of load profiles. This model consists of an additive decomposition tool, whereas TS are interpreted as follows:

$$E_{TOT} = l + t + p + n \tag{1}$$

where l is the level component, which is constant over the whole TS; t is the trend representing the tendency of the TS to grow or decrease over consecutive periods; p is the periodic component; and n are the residuals, or noise, which is the difference between the original TS and the sum of the previously mentioned components. Finally, the representative periodic component (RPC) has been isolated from the remaining part of the electrical demand and is used as an input for the clustering phase.

C. Clustering

Clustering is an automated and unsupervised ML algorithm designed to group elements according to their similarity. This phase of the analysis takes advantage of the comparison of several clustering algorithms and of proper CVIs to assess their performance.

Clustering Algorithms: Several clustering algorithms have been tested based on the related works presented in Section II. More in detail, k-Means, k-Shape, Partition Around Medoid (PAM) and hierarchical agglomerative algorithms were employed to group different TS considering their RPC. Euclidean distances were adopted as the distance measure of the above-mentioned algorithms. Since the best configuration can not be known a priori, each algorithm has been tested for a number of clusters between 2 and 10.

Clustering Validity Indexes (CVIs): A number of CVIs has been introduced to assess the performance of the algorithms [35]. These indexes essentially consider two aspects, which are intra-cluster similarity and inter-clusters separation. In this study four CVIs were considered, namely Within Cluster Sum of Square (WCSS), Silhouette Coefficient, Davies Bouldin Index (DBI) and Calinski-Harabasz Index (CHI). Yet, other factors shall be considered whereas clustering is employed to the specific purpose of benchmarking. In particular, a fundamental aspect is segregation of variables [36] in clusters. This aspect may be described considering the mean distance among the clusters mean values of the most significant KPIs. Moreover, since some usage labels were provided in the original dataset, homogeneity of usage classes within clusters was considered.

D. Post-Processing

The post-processing phase includes validation, exploitation and exploration of the results. In this study, these aspects are considered in accordance with two specific goals, which are relabelling and benchmarking.

Relabelling: Considering the clusters retrieved and the predominant usage categories labels within each single cluster, some buildings may result as discordant. In these cases, the TLC service provider energy managers have been asked to check if any change in the building usage or reduction/increase of the staff operating within those sites had occurred and had not been reported. Eventually, sites have been relabelled in accordance with their actual and current usage category.

Benchmarking: Finally, benchmarking of the building stock is performed, taking advantage of the definition of adequate KPIs for comparison. Hence, statistical analysis may be employed to determine reference elements from each cluster, rank buildings according to their efficiency and define KPIs intervals. At this stage the analysis may be easily deepened to understand energy and thermal behaviour of sites, to identify causes of inefficiencies of the sites and to determine priority retrofit interventions.

IV. Case Study, Dataset and KPIs

The methodology introduced in Section III is applied to a real-world dataset containing aggregated hourly electric load measurements for the whole year of 2019 regarding buildings managed by the largest TLC service provider in Italy. The vast majority of the buildings in the data set are COs, which are facilities containing telephone switches and other TLC hardware employed for the operation of the wired network, or similar ones, such as DC. Many of these buildings actually have promiscuous usage, featuring both areas devoted to TLC equipment and areas for offices. A few buildings predominantly occupied by offices are present as well. The geographical location, the Climatic Severity Index, the square footage of the areas devoted to offices and TLC equipment are included in the data set. With respect to most of the research efforts reported in Section II presenting applications on small datasets, this work deals with and relies on testing the proposed methodology on a dataset including almost 2000 buildings. Furthermore, the proposed application investigates a fast-growing and specially energy-intensive economical sector. For instance, the TLC industry in our country was responsible for 3.863 GWh of electrical demand in 2018 [37], which corresponds to 1.27% of the national consumption. Hopefully this work will represent a starting point for further investigation to provide effective solutions for energy efficiency in the buildings sector in general and in the TLC branch specifically. This Section is intended to provide a brief overview of the energy outlook of TLC buildings and of the proper KPIs which will be later discussed in Section V

A. Energy Outlook of TLC Buildings and Normalization

As the available data consists of aggregate electrical load profiles, it is worth noting that TLC sites' typical energy balance includes 4 fundamental contributions:

$$E_{TOT}(t) = E_{TLC}(t) + E_{DISS}(t) + E_{CLC}(t) + E_{AUX}(t) \tag{2}$$

where E_{TLC} represents the electrical demand from TLC equipment, E_{DISS} takes into account the energy conversion losses, E_{CLC} is the contribution from the cooling system and E_{AUX} includes the electrical loads from auxiliaries and lighting systems.

Since E_{TLC} and E_{DISS} may be assumed as constant values [38], their contribution well represents the TS base-load. Hence, the electrical load fluctuations are due to the cooling load, lighting and auxiliaries systems. It is worth pointing out that these load fluctuations depend on non-shiftable lighting or cooling demands. Hence, external variables which may affect normal electricity usage, such as its variable cost, shall not be considered.

Since no occupancy is expected to affect the electrical demand of the sites during nights, and since the weather conditions in Italy determine that the cooling system is not necessary during winter days' colder hours, the electrical load measured at these time steps is representative of the aforementioned base load. Notice that the size of TLC buildings is well-described by the constant electrical load of the TLC equipment. Accordingly, the normalization step, described in Section III-B, takes into account the base load. Nevertheless, the presence of measurement errors or anomalies may affect the calculation of the base load. Hence, the most suitable value for normalisation can be calculated as:

$$E_{min} \approx mean(min(E_i)_d),\ i \in [1,4],\ d \in winterdays \tag{3}$$

where E_i is the energy demand from the i_{th} hourly time step from winter day d. It is worth noting that the values obtained through the proposed normalisation method are analogous to the product of two of the most widely used efficiency metrics in the TLC branch, namely the Power Usage Effectiveness (PUE) and Utilization Factor (UF) [38]. In fact, these indexes are defined as:

$$PUE = E_{TOT}/E_{TLC} \tag{4}$$

$$UF = E_{TLC}/E_{MIN} \tag{5}$$

Hence:

$$E_{TOT}/E_{min} = PUE * UF = LI \tag{6}$$

where LI is the Load Index of a bulding. This index, as well as the PUE and UF, is generally calculated yearly.

PUE is generally used to assess the efficiency of DC and CO. One may easily guess that this value will rise as the contribution of the cooling load increases. On the other hand, promiscuous sites and predominant offices buildings are expected to have high PUE values due to the strong contribution of E_{AUX}. UF takes into account the energy conversion efficiency, which is generally constant and depends on the installed conversion devices.

B. Energy Key Performance Indicators

Besides LI, which was introduced in Section IV-A, a few other KPIs are considered for the analysis. The second one is *Specific Power* (SP), defined as the mean load by the building area. Other characteristic features of load profiles are the *mean fluctuations* ΔP, that is the mean difference between the peak and the trough daily loads. These KPIs are calculated separately for working days, Saturdays and Sundays and holidays, since the fluctuations determined by variations of E_{Aux} are heavily depending on the weekly occupancy schedule. Finally, since outdoor weather data were available for a subset of 75 buildings, additional features, which may be derived from Energy Signatures (ES) [39], are investigated. The first of these features is cooling *Balance Point* (BP), which is the maximum outdoor temperature determining a cooling load equal to zero. The second is the percentage rise, with respect to base load, in electrical demand determined by an increase of 1 °C, named β^{*}_{Temp}.

V. Results

Results from each step included in the proposed methodology are here discussed. To handle and analyse the dataset, we took advantage of Python programming language exploiting scikit-learn and Keras libraries.

A. Pre-Processing Results

In the data cleaning step, the dataset is reduced to 1328 buildings, corresponding to 73.22 % of the overall amount of sites, whose provided usage categories percentages are: *i)* CO: 96.84%; *ii)* DC: 0.08%; *iii)* Offices: 2.25%; *iv)* Radio Base Stations (RBS): 0.45% ;*v)* Unlabelled: 0.3%; *vi)* Others: 0.08%.

Subsequently, TS are rescaled accordingly to base load normalization. As a results, those sites devoted to the operation of TLC devices, depict low LI, while offices result in a higher average normalized load. Indeed, 75% of CO, RBS and DC feature a LI below 1.23, with a mean value of 1.20. Offices' average load demand instead is higher with respect to base-load, as 75% of the sites have LI over 1.24, with a mean value of 1.46.

Periodical components can be easily detected by means of autocorrelation analysis. Autocorrelation is described by means of Pearson's coefficients calculated within individual load profiles with respect to lagged values. The results, as shown in Fig. 2, clearly confirm the expectations expressed in Section III-B, that is the existence of daily and weekly periodicity. Indeed, local maxima are evident at lags 24, 48 and so on. This pattern corresponds to the daily periodic component, as values are strongly correlated to those at the same hour of previous days. Secondly, it may be observed that the value of peaks generally decreases as the lag increases. Still, the seventh and fourteenth peaks overcome other local maxima, enlightening the correlation of value from the same hour of the same day of the week. This witnesses the presence of weekly periodicity, whose relevancy is heavily depending on the buildings' usage. Indeed, in pure TLC buildings, electrical demand is strongly dependent on daily and seasonal outdoor temperature fluctuations, since the most important contribution to electrical demand variation is cooling load E_{CLC} [40]. On the contrary, offices load profiles are more strictly affected by E_{AUX}, which in turn heavily depends on the occupancy schedule. Hence, besides the daily periodic component, relevant periodicity is expected to be detected for lags equal to 168 hours, accordingly to the typically weekly occupancy schedules of offices. Notice that, since the dataset includes measurements from the sole year of 2019, the seasonal component is obtained through the trend component. Finally, we extracted RPC from TS taking advantage of Loess decomposition tool, as in the example in Fig. 3. Besides conveying meaningful information, handling the extracted 168-long RPC determines important computational time savings, with respect to the original entire load profiles. A few additional characteristics of TS become noticeable by observing different RPC. Firstly, peak and trough hours generally differ from TLC buildings and offices. Indeed, the maximum daily electrical demand for pure CO and DC is generally occurring during the afternoon, while many offices' buildings show a peak between noon and 2 p.m.. Again, this phenomenon looks reasonable accordingly to the relevancy of a specific load quota rather than another. Indeed, the impact of outdoor temperature, which generally reaches its maximum during the afternoon, is expected to be determinant in what concerns those buildings whose consumption is essentially

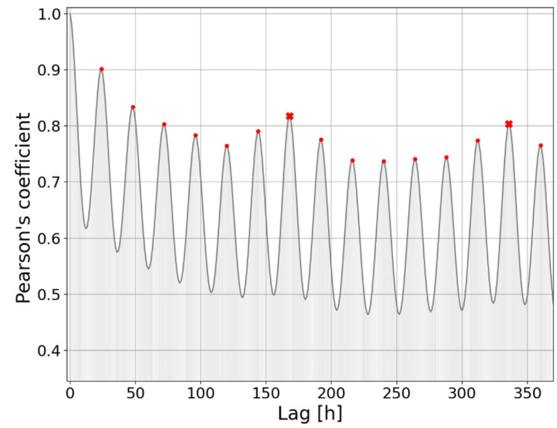

Fig. 2. Analysis of time serie auto-correlation, considering electrical measurements from a Central Office.

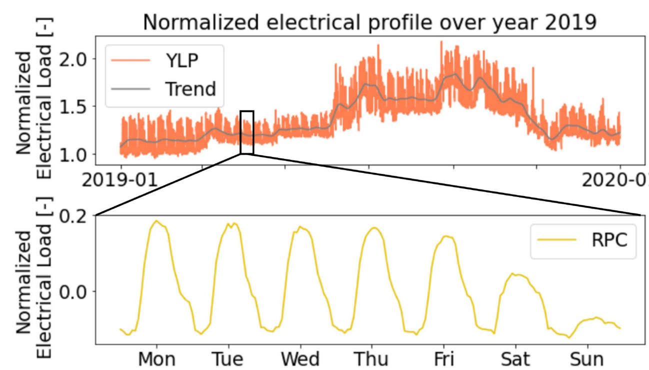

Fig. 3. Visualization of the original YLP, the trend and the 168 time steps long RPC obtained by additive decomposition.

TABLE I
F1 SCORE FROM THE 4 ALGORITHMS AND 9 CONFIGURATIONS

Algorithm	Number of Clusters								
	2	3	4	5	6	7	8	9	10
k-Means	0.73	0.71	0.73	0.71	0.71	0.75	075	0.75	0.74
k-Shape	0.67	0.67	0.67	0.67	0.67	0.67,	0.67	0.67	0.67
PAM	0.67	0.67	0.73	0.73	0.73	0.73	075	0.75	0.75
HA	0.71	0.71	0.71	0.71	0.71	0.71	0.73	0.74	0.74

TABLE II
MEAN LI OF THE ELEMENTS OF EACH CLUSTER, RETRIEVED BY EACH ALGORITHM FOR CONFIGURATION 7 CLUSTERS

Algorithm	Cluster ID							$d_{\mu,m}$
	I	II	III	IV	V	VI	VII	
k-Means	1.18	1.22	1.29	1.29	1.57	2.00	2.30	0.494
k-Shape	1.18	1.19	1.20	1.20	1.23	1.26	1.39	0.074
PAM	1.17	1.20	1.23	1.24	1.38	1.96	2.30	0.483
HA	1.18	1.23	1.23	1.29	1.46	2.00	2.30	0.488

TABLE III
STANDARD DEVIATION OF THE DISTRIBUTION OF LI, RETRIEVED BY EACH ALGORITHM FOR CONFIGURATION 7 CLUSTERS

Algorithm	Cluster ID							$\delta_{LI,m}$
	I	II	III	IV	V	VI	VII	
k-Means	0.07	0.07	0.59	0.12	0.16	0.24	-	0.208
k-Shape	0.19	0.06	0.08	0.07	0.13	0.20	0.39	0.162
PAM	0.08	0.07	0.07	0.07	0.16	0.23	-	0.115
HA	0.07	0.08	0.07	0.59	0.17	0.24	-	0.202

depending on cooling load, that is, in our case, CO and DC. Contrary, in offices peak electrical demand will likely occur in phase with peak occupancy within the buildings.

B. Clustering Results

Four State-of-Art unsupervised ML algorithms with nine different configurations each for a total of thirty-six different models are tested with the described case study. Each clustering configuration was performed considering the whole set of 1328 buildings resulting from the previous step, to enable fair performance comparison within the employed models. The results are described according to both variables segregation and CVIs. As a first aspect, it is convenient to investigate segregation of buildings usage categories in clusters. To this purpose, predominant usage categories in every single cluster are considered as predicted categories of the buildings within the cluster itself. Hence, precision, recall and F1 score can be calculated. The F1 score results are reported in Table I for the 36 clustering configurations tested. It may be easily seen that k-Shape algorithm has the lower performance for any number of clusters. The best configurations are from k-Means and PAM algorithms, respectively regarding configurations 7, 8, 9 and 8, 9, 10. To deepen the analysis of clustering algorithms' performance, another variable is considered, namely LI, which is the most important energy KPI of the buildings in our dataset. The results, shown for the exemplary case of 7 clusters, may be interpreted by means of Table II, reporting the mean value of LI within every single cluster, and Table III, reporting the standard deviations of the KPI. The former clearly depicts the good separation of clusters' mean values for k-Means, PAM and

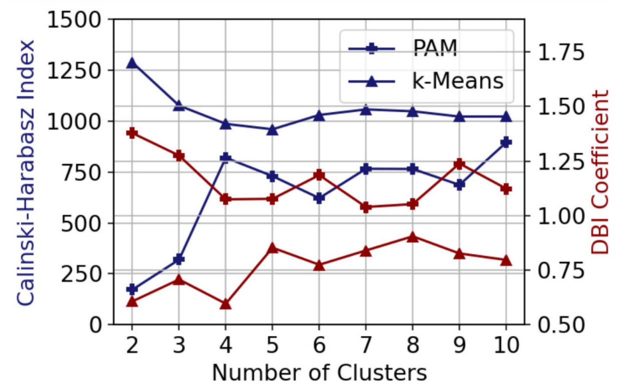

Fig. 4. CVIs comparison for the best performing algorithms, k-Means and PAM, according to different configurations.

Hierarchical Agglomerative (HA) algorithms. On the contrary, k-Shape clusters buildings in such a way that no segregation regarding LI exists. The righter column of Table II displays the mean value of distance among LI mean values. The higher the value, the better LI segregation. In this case, the Table witnesses the superior performance of k-Means. Besides of separation of values from one cluster to another, cohesion of values within clusters is a fundamental metric for variables' segregation. In Table III it may be easily noticed that PAM algorithm outperforms the remaining in terms of mean standard deviation of LI within clusters, as shown in the righter column. It is worth noticing that the poor performance of k-Shape, witnessed by the presented results, is likely due to the relevancy of the position of peaks discussed in Section V-A. Indeed, this algorithm was conceived to be phase and shift invariant. Furthermore, as we will discuss later, amplitude of fluctuations is a characteristic feature as well.

Hence, the two best performing algorithms, K-Means and PAM, are further investigated. To this purpose, four CVIs were considered, as introduced in Section III-C. The results are reported, for CHI and DBI, in Fig. 4. The plot clearly highlights the best performance of k-Means, which outperforms PAM in terms of both indexes for any configuration. The best CVIs result from k-Means configurations 2, 7 and 8 and 2, 3 and 4 for CHI and DBI respectively. Nevertheless, the WCSS index results in extremely high values for low numbers of clusters. This suggests not considering configurations 2, 3 and 4. Given the slightly superior performance of configuration 7 with respect to 8 concerning DBI (0.84, 0.91), CHI (1057, 1048) and Silhoutte Score (0.39 and 0.38), this configuration was finally selected as the most adequate. Finally, 7 clusters are obtained. The five most significant ones are reported in Fig. 5.

C. Post-Processing Results

1) Clustering-Based Identification of Usage Category and Labelling: Once the 7 clusters are obtained, clusters *III* and *VII* arouse suspicions about the reliability of these load profiles. Notice that these clusters only contained 3 and 1 buildings respectively. Further investigation of the RPC and original TS from

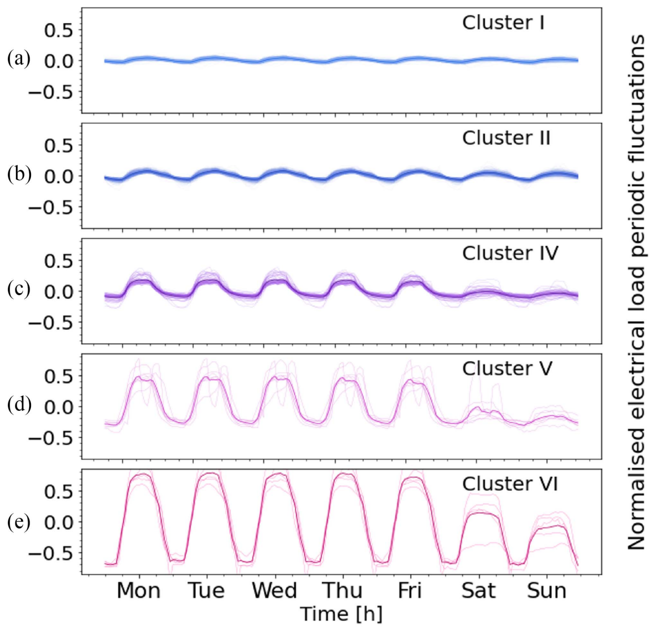

Fig. 5. Significant RPC clusters resulting from the best configuration.

TABLE IV
COMPOSITION OF THE MOST SIGNIFICANT CLUSTERS IN ACCORDANCE TO THE PROVIDED USAGE CATEGORY LABELS

Clusters	*I*	*II*	*IV*	*V*	*VI*
TLC	99.12%	98.66%	83.10%	37.50%	20.00%
Offices	0.50%	1.12%	15.49%	62.50%	80.00%
Unlabelled	0.38%	0.22%	1.41%	0.00%	0.00%

these buildings confirmed the existence of extreme anomalies in these load profiles. Hence they are filtered out. The remaining five clusters comprehend the vast majority of buildings, with a strong prevalence of TLC sites in clusters I and II (Fig. 5(a) and 5(b)), consisting of 803 and 447 buildings respectively. Offices are predominant in clusters V and VI (Fig. 5(d) and 5(e)), while cluster IV features a more heterogeneous composition (Fig. 5(c)). These three clusters include a minority of the original dataset, with cardinality 62, 8 and 5 for clusters IV, V and VI respectively. Fig. 5 highlights some peculiar features of clusters. Firstly, magnitude of fluctuations is a fundamental and distinguishing feature. This unfolds additional reasons for the poor performance of k-Shape algorithm, discussed in Section V-B. Furthermore, weekends load demand reduction is noticeable in clusters *IV*, *V* and *VI*. This confirms the existence of weekly patterns, which depend on the relative importance of occupancy in determining a building's energy demand. Besides, the last two plots, that is the clusters dominated by offices, depict differences in the RPC regarding Saturdays and Sundays. One may even notice a slight decrease in the daily load peak on Friday with respect to the other working days in Fig. 5(e).

The composition of clusters with respect to usage category is synthesized in Table IV. Assuming that most of the sites are correctly labelled, clusters I and II are assumed as representative of pure or predominant TLC buildings, clusters V and VI of offices and cluster IV is expected to contain promiscuous sites. A few sites' labels are hence detected as abnormal. Particularly, 3 sites labelled as CO (0.23% of the COs) and one as RBS (16.7% of the RBSs) are included in clusters representing offices. On the other hand, 9 sites with label office were identified in clusters dominated by TLC buildings. A field verification on these sites reported that the actual usage category of 9 out of 13 sites was correctly identified by the clustering algorithm. It is worth noting that most of the sites abnormally labelled were building containing both TLC equipment devoted areas and offices. Many of these occurred in a change of usage category due to an increase or reduction of employees within the site. Moreover, under the reasonable assumption that those sites whose label coincide with the usage category represented by a cluster are correctly labelled, the clustering algorithm achieves an accuracy of 99.7%.

2) Reference KPIs According to Cluster: The KPIs introduced in Section IV-B are calculated and statistical analysis is undertaken to identify reference buildings and ranges for each buildings' usage cluster. Notice that, for sake of brevity and to enhance better statistical description of groups, in this phase clusters *I* and *II* are merged to form the TLC buildings group, while *V* and *VI* clusters are combined into offices group. A quick overview of the different energy characterization of buildings is described by means of the radar charts in Fig. 6. Bold lines indicate each group's medoids. TLC facilities depict low LI, medium-high SP and low fluctuations regarding weekdays ($\Delta P^*_{weekdays}$) as well as Saturdays (ΔP^*_{sat}) and Sundays (ΔP^*_{sun}). The more noticeable difference between these buildings and promiscuous ones concerns SP and $\Delta P^*_{weekdays}$. The distribution of these KPIs may be better analysed by means of Figs. 7(a) and 9(a). Specifically, mean SP is 26.0 and 37.9 kWh/m^2 for promiscuous and TLC buildings respectively. TLC facilities in many cases depict SP values beyond 50 kWh/m^2, with a maximum of 65.0 kWh/m^2, due to the special energy intensity of these sites. Regarding load fluctuations, mean fluctuations from the vast majority of sites devoted to TLC equipment operation are below 19% with respect to base-load, regardless of the day of the week. The amplitude of fluctuations from holidays in promiscuous sites is pretty close to those from any day in the former category. This witnesses that, as soon as no occupancy affects electrical demand from the promiscuous site, their energy behaviour is analogous to the one from pure TLC buildings. Yet, slight differences may be observed within weekdays and holidays daily fluctuations for promiscuous buildings. Specifically, 90% of promiscuous sites have fluctuations in ranges from 20.5% to 49.4% during working days and from 4.2% to 23.1% during holidays. Nevertheless, Fig. 9(b) makes it evident the marked difference regarding LI as well, whose mean values are 1.19 and 1.26 for TLC and promiscuous buildings respectively. This aspect, along with the distribution of all the KPIs calculated, witnesses the accurate segregation of variables achieved by the proposed framework. Moreover, offices depict marked differences concerning all the KPIs, as it may be easily noticed in Fig. 6(c). More in detail, the 53.8% of offices depict mean working days fluctuations over 100% with respect to base load, and the whole set of sites have values beyond 70%. These fluctuations are significantly lower

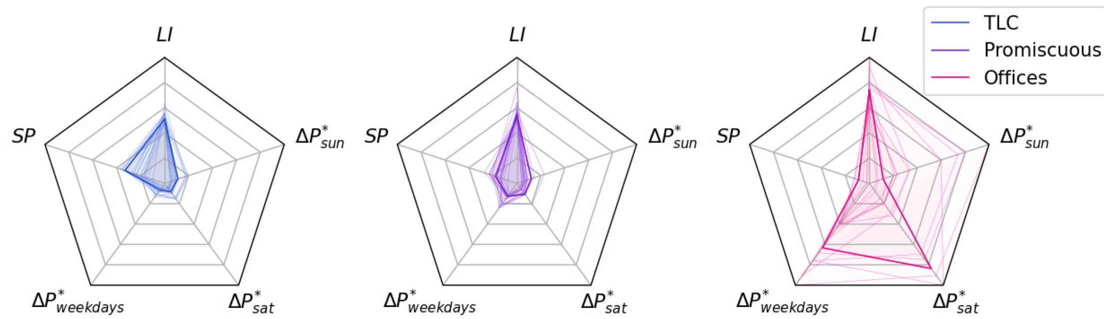

Fig. 6. Visualization of the energy KPIs characterizing buildings, according to their usage category cluster.

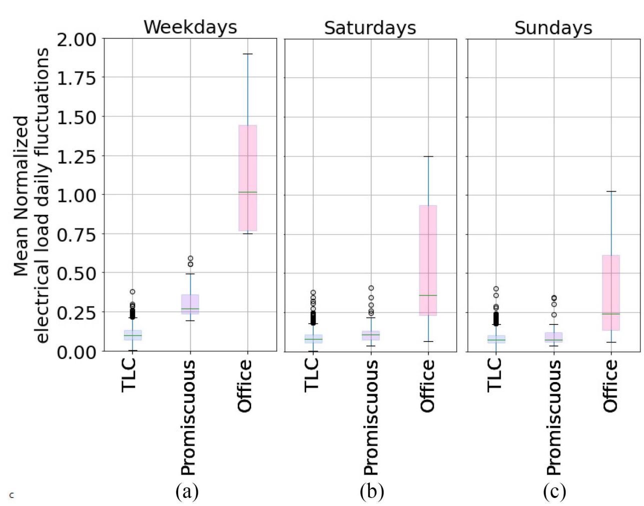

Fig. 7. Distribution of the mean daily fluctuations, according to day type and usage category cluster.

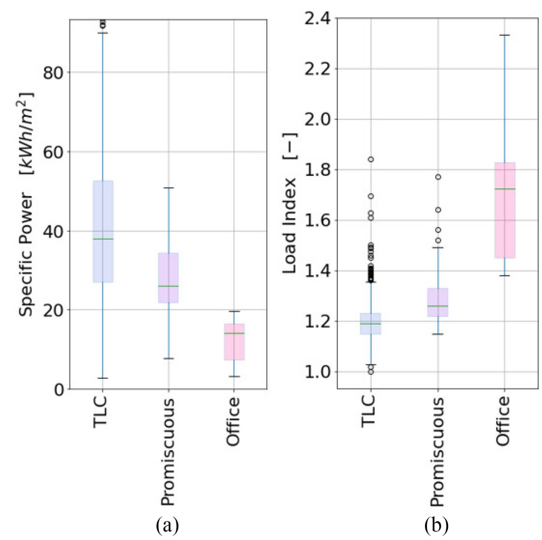

Fig. 9. Distribution of SP and LI, according to day type and usage category cluster.

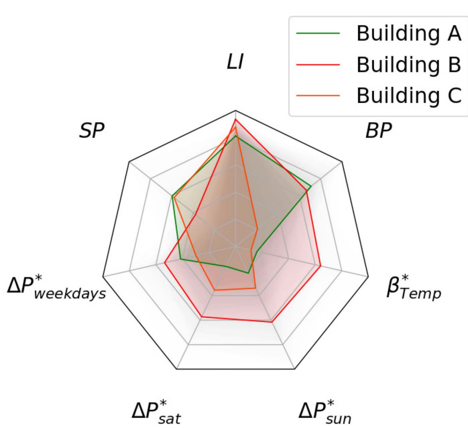

Fig. 8. Visualization of the energy KPIs characterizing efficient and bad performing TLC buildings.

during Saturdays and Sundays, whereas 90% of the sites are characterised by values in ranges from 8% to 118% and from 7 % and 91% respectively.

3) Reference Buildings and Possible Reasons of Inefficiencies: Finally, a subset of 75 buildings whose weather historical data are available is investigated more in detail. The summary of the two significant KPIs is reported in Table V. Promiscuous buildings look pretty similar to offices for what concerns BP, being both characterized by a mean value of around 17 °C, that is these buildings generally do not require space cooling until outdoor temperature overcomes this threshold. Differently, TLC buildings depict lower BP, in many cases even below 10 °C. This is likely due to the need for space cooling from the TLC equipment and to its high power density which corresponds to high heat generation density. Yet, marked differences among promiscuous buildings and offices are noticeable regarding β^*_{Temp}. This

TABLE V
ENERGY SIGNATURE DERIVED KPIS DISTRIBUTION ACCORDING TO USAGE CATEGORY CLUSTER

	Balance Point			β^*_{Temp}		
	Min	Mean	Max	Min	Mean	Max
Offices	15.6	17.6	19.9	7.07	9.69	25.81
Promiscuous	16.1	17.3	17.9	3.91	5.47	11.07
TLC	7.5	13.8	19.4	1.41	3.09	6.36

is explainable by considering the relevant differences in base load from the two categories of buildings.

As an example of the possible energy efficiency-oriented applications of benchmarking, we selected TLC buildings as a study case for comparison among peer buildings, with the perspective of analysing the possible reasons of inefficiencies. Firstly, buildings are ranked according to the efficiency KPI, that is, in our case, the LI. Afterward, we selected one building from the top performing ones as a reference building for what concerns energy efficiency. Similarly, the less efficient buildings were selected and compared to the reference one. The efficient building characteristic are summarized by the green line in Fig. 8, along with other two buildings, represented by the orange and the red lines. Notice that this radar chart presents a different scale with respect to the ones in Fig. 6, in order to make differences among the investigated buildings more evident. The radar chart clearly enlightens the reasons for the worst performance of each building. Regarding building *B*, one would easily guess that a major cause of inefficiency may be the extremely high value of β^*_{Temp}. Yet, strong differences may be noticed as well for load fluctuations, which are much higher, and SP, which is much lower than the one from the reference efficient building. All these aspects arise suspicion about the eventual presence of personnel within the worst performing building. This may be an additional contribution to electrical demand, which does not mean necessary it represents an energy inefficiency. Hence, rather than identifying this building as a priority retrofit intervention it may be advisable to investigate more in detail the occupancy of the site. On the contrary, building *C* has similar, or not so different, values to the reference building regarding most of the KPIs, with an important exception regarding the BP. This means that the cooling system intervenes, in the case of the worst performing building, for lower outdoor temperatures, even if the two buildings are similar in usage as well as in SP. This is likely to be due to differences in the indoor temperature set points or to issues regarding the building envelope. Hence, further investigation over these aspects is advisable with the perspective of understanding potential benefits of retrofit actions.

VI. Conclusion

Considering the existing challenges for buildings benchmarking and the opportunities disclosed by the imminent widespread of smart metering, a time-domain clustering algorithm is adopted in this paper to group buildings according to their usage category. Nevertheless, direct exploitation of load profiles may result in computational issue or in ineffective clustering. Hence, a decomposition tool is proposed as part of the pre-processing phase, with the aim of extracting representative periodic components from time series. The framework has been tested on a massive dataset containing hourly load profiles from different usage buildings. Several clustering algorithms are tested and clustering validity indexes, as well as variables segregation, have been employed to assess their performance. K-Means resulted as the best performing algorithm, and the model was able to reach an overall accuracy of 99.7%. Finally, energy KPI are calculated and discussed. Buildings are compared to more efficient ones belonging to the same cluster in the perspective of understanding possible sources of inefficiency.

Future work shall focus on extensive work regarding the temperature-at-use KPIs, since they may provide fundamental information on sources of inefficiencies. The methodology shall be tested as well on other datasets including non-residential buildings with different usage categories.

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References

[1] S. Eiraudo et al., “Load profiles clustering and knowledge extraction to assess actual usage of telecommunication sites,” in *Proc. IEEE Int. Conf. Environ. Elect. Eng., IEEE Ind. Commercial Power Syst. Euro.*, 2021, pp. 1–6.

[2] GlobalABC/IEA/UNEP, “GlobalABC roadmap for buildings and construction: Towards a zero-emission, efficient and resilient buildings and construction sector,” IEA: Paris, France, 2020. [Online]. Available: https://www.iea.org/reports/globalabc-roadmap-for-buildings-and-construction-2020-2050

[3] United Nations Environment Programme, “Global status report for buildings and construction 2021,” *United Nations Environment Programme*, 2021. [Online]. Available: https://globalabc.org/resources/publications/2021-global-status-report-buildings-and-construction

[4] IEA, “World energy outlook 2021: Part of the world energy outlook,” *Int. Energy Agency*, 2021. [Online]. Available: https://www.iea.org/reports/world-energy-outlook-2021

[5] ITU, “Global connectivity report 2022,” *Int. Telecommun. Union*, 2022. [Online]. Available: https://www.itu.int/itu-d/reports/statistics/global-connectivity-report-2022/

[6] S. Lambert, W. V. Heddeghem, W. Vereecken, B. Lannoo, D. Colle, and M. Pickavet, “Worldwide electricity consumption of communication networks,” *Opt. Exp.*, vol. 20, no. 26, pp. B513–B524, 2012.

[7] M. Avgerinou, P. Bertoldi, and L. Castellazzi, “Trends in data centre energy consumption under the European code of conduct for data centre energy efficiency,” *Energies*, vol. 10, no. 10, 2017, Art. no. 1470.

[8] IEA, “Data Centres and Data Transmission Networks,” *Int. Energy Agency*, 2022. [Online]. Available: https://www.iea.org/reports/data-centres-and-data-transmission-networks

[9] European Commission“Energy Efficiency Directive.” Accessed: May 24, 2021. [Online]. Available: https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficiency-targets-directive-and-rules/energy-efficiency-directive_en

[10] J. Malinauskaite, H. Jouhara, L. Ahmad, M. Milani, L. Montorsi, and M. Venturelli, “Energy efficiency in industry: EU and national policies in Italy and the UK,” *Energy*, vol. 172, pp. 255–269, 2019.

[11] R. Lee, D. Pinner, K. Somers, and S. Tunuguntla, “The case for committing to greener telecom networks,” *McKinsey Company*. Accessed: Nov. 11, 2020. [Online]. Available: https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/the-case-for-committing-to-greener-telecom-networks

[12] F. Tounquet and C. Alaton, “Benchmarking smart metering deployment in EU-28,” 2020. [Online]. Available: https://op.europa.eu/en/publication-detail/-/publication/b397ef73-698f-11ea-b735-01aa75ed71a1/language-en

[13] C. Deb and A. Schlueter, “Review of data-driven energy modelling techniques for building retrofit,” *Renewable Sustain. Energy Rev.*, vol. 144, 2021, Art. no. 110990, doi: 10.1016/j.rser.2021.110990.

[14] C. Fan, F. Xiao, Z. Li, and J. Wang, “Unsupervised data analytics in mining big building operational data for energy efficiency enhancement: A review,” *Energy Buildings*, vol. 159, pp. 296–308, 2018, doi: 10.1016/j.enbuild.2017.11.008.

[15] C. Miller, Z. Nagy, and A. Schlueter, “A review of unsupervised statistical learning and visual analytics techniques applied to performance analysis of non-residential buildings,” *Renewable Sustain. Energy Rev.*, vol. 81, pp. 1365–1377, 2018, doi: 10.1016/j.rser.2017.05.124.

[16] P. Marrone, P. Gori, F. Asdrubali, L. Evangelisti, L. Calcagnini, and G. Grazieschi, “Energy benchmarking in educational buildings through cluster analysis of energy retrofitting,” *Energies*, vol. 11, no. 3, Mar. 2018, Art. no. 649. [Online]. Available: https://www.mdpi.com/1996-1073/11/3/649/htmhttps://www.mdpi.com/1996-1073/11/3/649

[17] P. Geyer, A. Schlüter, and S. Cisar, "Application of clustering for the development of retrofit strategies for large building stocks," *Adv. Eng. Inform.*, vol. 31, pp. 32–47, 2017, doi: 10.1016/j.aei.2016.02.001.

[18] F. R. Cecconi, N. Moretti, and L. C. Tagliabue, "Application of artificial neutral network and geographic information system to evaluate retrofit potential in public school buildings," *Renewable Sustain. Energy Rev.*, vol. 110, 2018, pp. 266–277, 2019, doi: 10.1016/j.rser.2019.04.073.

[19] J. Y. Park, X. Yang, C. Miller, P. Arjunan, and Z. Nagy, "Apples or oranges? Identification of fundamental load shape profiles for benchmarking buildings using a large and diverse dataset," *Appl. Energy*, vol. 236, pp. 1280–1295, 2019, doi: 10.1016/j.apenergy.2018.12.025.

[20] S. Zhan, Z. Liu, A. Chong, and D. Yan, "Building categorization revisited: A clustering-based approach to using smart meter data for building energy benchmarking," *Appl. Energy*, vol. 269, 2020, Art. no. 114920, doi: 10.1016/j.apenergy.2020.114920.

[21] S. Ryu, H. Choi, H. Lee, and H. Kim, "Convolutional autoencoder based feature extraction and clustering for customer load analysis," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 1048–1060, Mar. 2020.

[22] O. Motlagh, A. Berry, and L. O'Neil, "Clustering of residential electricity customers using load time series," *Appl. Energy*, vol. 237, pp. 11–24, Mar. 2019.

[23] P. Westermann, C. Deb, A. Schlueter, and R. Evins, "Unsupervised learning of energy signatures to identify the heating system and building type using smart meter data," *Appl. Energy*, vol. 264, 2020, Art. no. 114715.

[24] F. Giordano, M. L. Rocca, and M. L. Parrella, "Clustering complex time-series databases by using periodic components," *Stat. Anal. Data Mining: ASA Data Sci. J.*, vol. 10, no. 2, pp. 89–106, 2017.

[25] M. S. Geraldi and E. Ghisi, "Data-driven framework towards realistic bottom-up energy benchmarking using an artificial neural network," *Appl. Energy*, vol. 306, 2022, Art. no. 117960, doi: 10.1016/j.apenergy.2021.117960.

[26] A. K. Zarabie, S. Lashkarbolooki, S. Das, K. Jhala, and A. Pahwa, "Load profile based electricity consumer clustering using affinity propagation," in *Proc. IEEE Comput. Soc.*, 2019, pp. 474–478.

[27] R. Damayanti, A. G. Abdullah, W. Purnama, and A. B. Nandiyanto, "Electrical load profile analysis using clustering techniques," *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 180, no. 1, 2017, Art. no. 012081. [Online]. Available: https://ui.adsabs.harvard.edu/abs/2017MS&E..180a2081D/abstract

[28] J. Yang et al., "k-Shape clustering algorithm for building energy usage patterns analysis and forecasting model accuracy improvement," *Energy Buildings*, vol. 146, pp. 27–37, 2017, doi: 10.1016/j.enbuild.2017.03.071.

[29] J. Paparrizos and L. Gravano, "κ-Shape: Efficient and accurate clustering of time series," in *Proc. ACM SIGMOD Int. Conf. Manage. Data*, 2015, pp. 1855–1870.

[30] K. Li, Z. Ma, D. Robinson, and J. Ma, "Identification of typical building daily electricity usage profiles using Gaussian mixture model-based clustering and hierarchical clustering," *Appl. Energy*, vol. 231, pp. 331–342, 2018, doi: 10.1016/j.apenergy.2018.09.050.

[31] Z. Ma, R. Yan, and N. Nord, "A variation focused cluster analysis strategy to identify typical daily heating load profiles of higher education buildings," *Energy*, vol. 134, pp. 90–102, 2017, doi: 10.1016/j.energy.2017.05.191.

[32] W. Tian et al., "A review of uncertainty analysis in building energy assessment," *Renewable Sustain. Energy Rev.*, vol. 93, pp. 285–301, 2018, doi: 10.1016/j.rser.2018.05.029.

[33] C. C. Aggarwal and C. K. Reddy, *Data Clustering - Algorithms Appl.*, Chapman & Hall / CRC, 2013.

[34] R. B. Cleveland, W. S. Cleveland, J. E. McRae, and I. Terpenning, "STL: A seasonal-trend decomposition," *J. Official Statist.*, vol. 6, no. 1, pp. 3–73, 1990.

[35] G. Chicco, "Overview and performance assessment of the clustering methods for electrical load pattern grouping," *Energy*, vol. 42, no. 1, pp. 68–80, 2012, doi: 10.1016/j.energy.2011.12.031.

[36] C. Deb and S. E. Lee, "Determining key variables influencing energy consumption in office buildings through cluster analysis of pre- and post-retrofit building data," *Energy Buildings*, vol. 159, pp. 228–245, 2018, doi: 10.1016/j.enbuild.2017.11.007.

[37] Terna S.p.A., "Pubblicazioni statistiche," Terna. Accessed: May 26, 2021. [Online]. Available: https://www.terna.it/it/sistema-elettrico/statistiche/pubblicazioni-statistich

[38] M. Sorrentino, M. Bruno, A. Trifirò, and G. Rizzo, "An innovative energy efficiency metric for data analytics and diagnostics in telecommunication applications," *Appl. Energy*, vol. 242, pp. 1539–1548, 2019, doi: 10.1016/j.apenergy.2019.03.173.

[39] S. Eiraudo, L. Barbierato, R. Giannantonio, E. Patti, L. Bottaccioli, and A. Lanzini, "A neural network-based methodology for non-intrusive energy audit of telecom sites," in *Proc. IEEE Int. Conf. Smart Energy Syst. Technol.*, 2022, pp. 1–6.

[40] S. Eiraudo, L. Barbierato, R. Giannantonio, E. Patti, A. Lanzini, and L. Bottaccioli, "Non-intrusive load disaggregation of industrial cooling demand with LSTM neural network," in *Proc. IEEE Int. Conf. Environ. Elect. Eng. IEEE Ind. Commercial Power Syst. Europe*, 2022, pp. 1–6.

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