Data Analysis of Building Sensors for Efficient Energy Management and Future Trends in the EU

Cletus Crasta
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology (TALTECH)
Tallinn, Estonia
clcras@taltech.ee

Hannes Agabus
Department of Electrical Power Engineering and Mechatronics
Tallinn University of Technology (TALTECH)
Tallinn, Estonia
hannes.agabus@taltech.ee

***Abstract*—Thermal comfort is an important aspect of home and office environments for maintaining proper human health and wellbeing. This paper presents the results of data analysis techniques employed on measured data of building sensors. The study underscores the importance of data pre-processing in data analysis. The data analysis reveals hidden characteristics of room temperature evolution which are influenced by different physical parameters recorded by sensors installed in a room. This influence is made clearer when seasonal data and different data pre-processing methods are considered. Space heating and cooling accounts for a significant portion of a building's energy consumption. Thus, deep analysis of room temperature data could prove a useful parameter to unlock sustainable energy efficiency measures using future-oriented technologies and solutions, such as Information and Communication Technology (ICT), Internet of Things (IoT), blockchain with smart contracts.**

Keywords—blockchain, building sensors, climate change, data analysis, energy consumption, energy efficiency, HVAC, ICT, IoT, room temperature, thermal comfort

I. INTRODUCTION

Today, the earth's climate is changing faster than any time in the history of human civilization, which is unequivocally the result of human activities [1], [2], particularly the emissions of greenhouse gases (GHG) when consuming energy in the form of fossil fuels. The negative impacts of climate change are being witnessed across the globe and in many sectors critical for the proper functioning of society – such as human health, agriculture, water supply, transportation, energy ecosystems, etc. The European Union (EU) is the third largest GHG emitter in the world after China and the US [3]. As a result, in 2009 the EU adopted a legislation to cut GHG emissions by 20% compared to 1990 levels and increase energy efficiency by 20% [4]. Later in 2014 under the Paris Agreement, the EU further built upon the 2009 legislation and targeted a 40% reduction in GHG by 2030 (compared to 1990 levels) and at least 27% increase in energy efficiency [5]. More recently in 2018, in the Clean Energy for all Europeans package, the energy efficiency target has been updated to 32.5% for 2030 [6]. As part of the package a revised Energy Performance of Buildings Directive (EPBD-2018/844/EU) entered into force. The directive aimed at accelerating the cost-effective renovating of existing buildings, with decarbonization in focus [7].

The building sector encompasses a diverse set of end-use activities, which have different energy implications. In an EU context, buildings are responsible for approximately 40% of energy consumption and 36% of CO_2 emissions [6], [7]. This is very unsurprising as we spend most of our lives in either at home or in an office with a controlled and comfortable environment. Globally on average, space heating and cooling accounts for a significant portion of a building's energy consumption, at about 42% [8]. While at the EU level, the energy consumed by space heating and cooling (space conditioning) forms a clear majority from the energy consumed by buildings, as it can be seen in Fig. 1 [9].

Over the past decade, various studies have addressed the influencing role of indoor temperature on the energy consumption due to the utilization of space conditioning systems. Research in [10] discusses waste of energy due to unnecessary space conditioning resulting from lack of real time information regarding the thermal comfort levels and occupancy. Another study [11] reports that building climate control in urbanized areas contributes 50–70% of the overall energy usage in residential and commercial buildings and proposes a predictive control model for building energy reduction and temperature regulation. To improve energy efficiency, the study in [12] is focused on forecasting the indoor room temperature through the functioning of the HVAC system for space conditioning which consumes large amounts of energy. Results of research in [13] report a 37% increase in energy efficiency achieved with better temperature control inside a room for a split AC system.

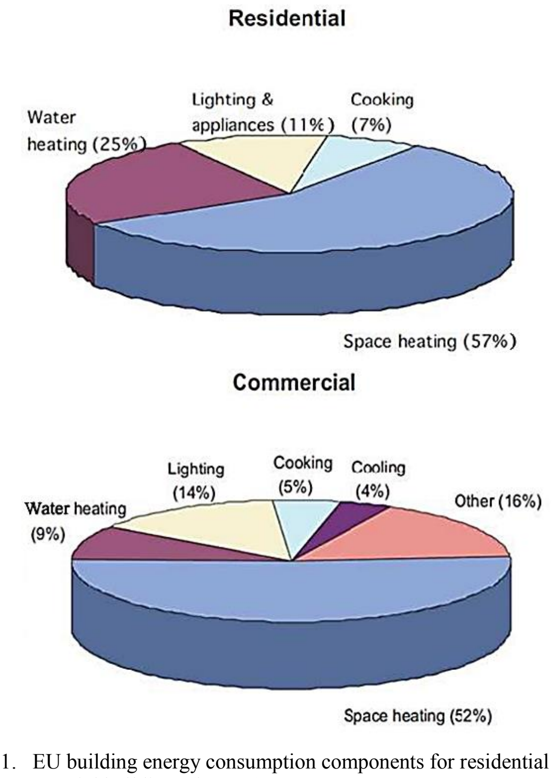

Fig. 1. EU building energy consumption components for residential (top) and commercial buildings (bottom).

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Thus, there is a direct relation between space conditioning and a building's energy consumption. The evolution of the indoor room temperature is influenced mainly by three factors: local weather conditions, human activities and the operation of the HVAC system. The purpose of our study is to analyze the information contained in these three factors by implementing data analysis techniques to unlock energy reduction potential at a reasonable cost and with a maturity compatible with international and regional commitments. This paper presents analysis of recorded data from different sensors present in a smart building.

The aim of this study is to achieve a better understanding of how the information contained by the various sensors influences the indoor room temperature. The results from the data analysis could be used to develop a better energy prediction model for buildings and explore possibilities of implementing IoT and blockchain based automated solutions to manage flexible building resources keeping thermal comfort and energy consumption in mind.

In the past decade, numerous future-oriented studies have been conducted, incorporating IoT and blockchain for energy efficient buildings. Researchers in [14] propose a model of a smart district, utilizing ICT, IoT and blockchain technology to achieve efficient energy management through home automation. The study [14] also suggests that smart homes and smart users will be fundamental elements in future cities. Other studies [15], [16] have presented case studies on the implementation of IoT and blockchain based solutions for smart homes analyzing data security, data flow and the implementation of smart contracts. Investigations in [15], [17], [18] have determined that presently data security, device security and privacy issues plague IoT mass adoption, especially in the building sector. They have concluded that blockchain based solutions for IoT device communication increases security and privacy. Thus, blockchain combined with IoT solutions for smart homes with smart contracts designed to ensure a balance between thermal comfort and energy consumption utilizing flexible resources proves to be a promising trend in the future. In pursuit of energy consumption efficiency, it is imperative to consider the needs of the occupants first, because buildings are constructed to serve people.

This paper also presents future insights in building energy management. It underscores the trend of more complete and precise data analytics, utilization of IoT and more recently blockchain technology for building energy management. In the EU, over 75% of the buildings are considered as energy inefficient [7]. Therefore, upgrading existing buildings with new technology solutions has the potential of reducing the EU's total energy consumption by 5–6% and lowering CO_2 emissions by about 5% [7], which will assist in conforming to the ambitious EU policy targets.

The paper is structured as follows. Section II discusses the general background of the presented work and gives a brief description of the experimental setup. Section III describes the approach and the data analysis methods used for the study. Section IV analyzes the results obtained from the data analysis. Section V presents the future trends regarding temperature measurement and room temperature control implementation in sustainable energy management along with blockchain and IoT based applications. Section VI presents key conclusions from our study. Section VII describes the future direction of the study and perspectives.

II. Background and Experimental Setup

As stated earlier in the paper, the building sector in the EU contributes a significant percentage of the energy consumption and CO_2 emissions [6], [7]. Over 50% of the energy consumed by the buildings is utilized for space conditioning (climate control) to satisfy human thermal comfort needs. Studies in [10]–[13] have analyzed the role indoor room temperature plays in the energy consumption and its link to space conditioning systems.

The study in [19] of building temperatures and Building Management Systems (BMS) states that a 1℃ increase in temperature set point results in a 8-10% increase in energy consumption; similarly, a 1℃ reduction in cooling results in a 4–5% increase in energy usage. A good space conditioning strategy can result in a 30% reduction in energy costs [19]. There are also relations between indoor room temperature and human productivity, as indicated in [20], [21]. Measures to improve indoor temperature control and increase ventilation rates would provide an annual economic benefit as high as $700 per person with benefits-cost ratio of 80 [21].

Building energy consumption is dominated by space conditioning, which is a function of room temperature. Understanding the evolution of the indoor temperature will give us greater insight into how we consume our energy. Using the information gained from the results of the data analysis along with future-oriented technologies like the Internet of Things (IoT) [22]–[24] and Blockchain [25], [26] could help us unlock energy reduction potential for buildings to meet our energy efficiency goals [27].

Our study was conducted in partnership with the 'Mesure de l'Efficacité Énergétique des Bâtiments et de leurs Systèmes' (Measurement of the Energy Efficiency of Buildings and their Systems) Department of CEREMA [28], which is a public sector company operating in France. In our analysis, we utilized the data (recorded from 2014-2017) of a smart building within CEREMA's facility located in Angers in the French mainland region of Pays de la Loire. Data here was obtained from the measurements recorded by a network of sensors located in an office room and a local weather station within CEREMA's facility in open space. Fig. 2 shows how some of the different sensors were installed in the room and Fig. 3 presents the local weather station.

Fig. 2. Installed room sensors.

Fig. 3. Local weather station.

The different sensors available in the selected room for our analysis were a temperature sensor, a light sensor, a presence sensor, a power consumption sensor, two window activity (opening or closing) sensors, the radiator and the HVAC power consumption sensors. The local weather station recorded information pertaining to the solar radiation, outdoor temperature, outdoor pressure and relative humidity experienced.

The key indicator in our analysis was the temperature observed in the room. According to numerous extensive studies, space conditioning as a significant contributor to a building's energy consumption.

III. Analytical Approach

Raw data from the various sensors used in our study were aggregated, pre-processed and synchronized to 15-minute periods to obtain useable time-series sensor data. Data pre-processing here entailed the removal of duplicates, missing data and overall smoothening of data, while synchronization meant that the recorded data from the sensors were stored at the same rate. By performing aggregation, pre-processing and synchronization, a database containing sensor data was created. R software was used in all our analyses, which was an ideal platform for handling large amounts of data and had a range of different numerical and statistical analysis tools. Data analysis of the sensor information was done using two main methods: Cluster analysis and ANOVA analysis.

Cluster Analysis – It is a data analysis method that groups similar objects together. Cluster analysis was performed on indoor temperature data. In our data analysis, days (referred to as objects) with similar indoor temperature profiles were grouped together. Cluster analysis consists of three important steps: data pre-processing, distance calculation and the clustering algorithm. We used three data pre-processing (normalization) methods: No Normalization, Mean Normalization and Mean and Standard Deviation Normalization; two distance methods: Euclidean distance and Dynamic Time Wrapping (DTW) distance method. Finally, two clustering algorithms: WARD.D2 and K-Means clustering algorithm were used.

As a result, 12 different clustering combinations ($3 * 2 * 2 = 12$) were utilized. The reason why we used 12 different clustering combinations was to extract as much information from the data as possible. This was an important aspect of our study. Information in the data can be hidden and by using different data pre-processing methods, distance methods and clustering algorithms, this concealed information could be unearthed from the data.

Variation of Information – From the 12 different clustering combinations, we narrowed down our selection based on the Variation of Information (VI) index [29]. The VI index is a unitless number that quantifies how much information is lost or gained when we move from one clustering combination to another. Using this function, we could determine which of the three steps of the cluster analysis (data pre-processing methods, distance methods or the clustering algorithms) contributes most to extract new information from the data.

ANOVA Analysis – ANOVA or Analysis Of Variance [30], [31] is a data analysis tool used in statistics to determine if there is a statistical influence on a data set. Results from the cluster analysis (performed using indoor temperature data) were used along with different sensor data to perform ANOVA analysis. This was done to determine whether a relationship exists between the indoor room temperature clusters (results obtained from cluster analysis) and the other sensors like outdoor temperature, humidity, presence sensor and so on. Using this statistical tool it enabled us to establish whether or not the formation of the indoor room temperature clusters were influenced by the different sensors.

This was determined using the 'p-value' or 'probability value' obtained which is the result of the ANOVA analysis for each sensor. The p-value (unitless number) was compared with the 'Significance level (α)'. In our case, we used an α of 0.05 (5%). So, if the p-value obtained is less than α, there is a 5% risk of concluding that an influence exists between the sensor information and the way the indoor temperature profiles are clustered when there is no actual influence between them. Similarly, the opposite case is true when the p-value is more than α. In simple terms, α is the probability of error that our conclusion (whether an influence exists or not) could be wrong.

Data visualization codes to express and interpret the results more clearly were also developed on R software. Various other functions and tools were used to complement the data analysis.

IV. Experimental Results

Cluster center plots for each of the three data pre-processing (normalization) methods were plotted using the DTW distance method and the WARD.D2 clustering algorithm, as shown in Figs. 4, 5, and 6. It can be concluded that the data pre-processing methods play a key role in the shape of the clustering results.

In Figs. 4, 5, and 6, each line is a cluster center for a particular cluster with the x-axis representing the duration of a day and the y-axis representing the temperature (°C). No Normalization cluster center plot (Fig. 4) shows that each of the cluster centers has a similar profile and is clearly layered according to the temperature. This suggests that all the objects, i.e. the daily indoor room temperatures, have a similar profile and are clustered according to the temperature.

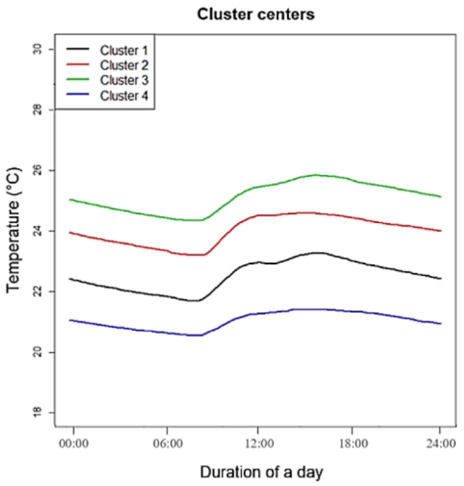

Fig. 4. No Normalization cluster centers.

However, the cluster center plots for both Mean Normalization in Fig. 5 and Mean and Standard Deviation Normalization in Fig. 6 show that the cluster centers have a unique profile. This can be strongly attributed to the data pre-processing method used. Thus, this demonstrates that the data pre-processing step of the cluster analysis has unearthed patterns (characteristics) of the temperature data that were otherwise hidden in No Normalization.

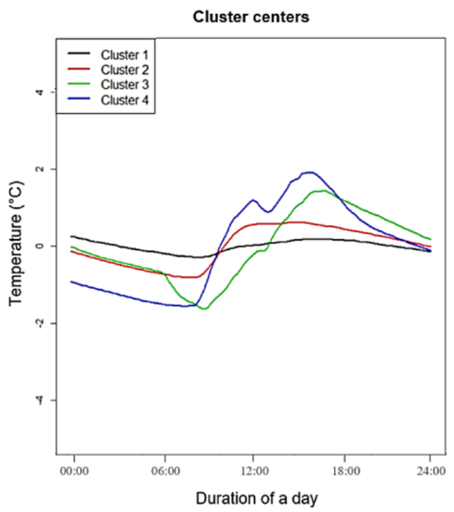

Fig. 5. Mean Normalization cluster centers.

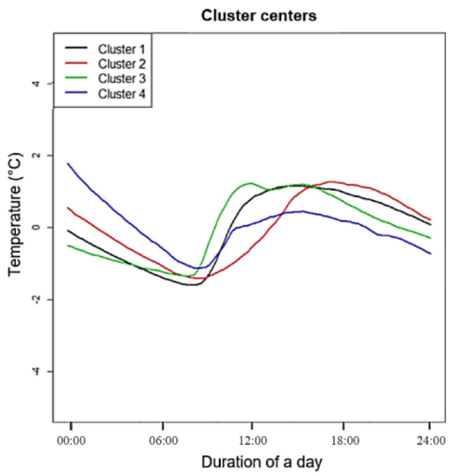

Fig. 6. Mean and Standard Deviation Normalization cluster centers.

Using the VI index function in R we quantified the change in information when we move from one clustering combination to another. The VI between the three different data pre-processing methods can be seen in Fig. 7, where 'N' is No Normalization, 'M' is Mean Normalization and 'M&SD' is Mean and Standard Deviation Normalization. While Fig. 8 shows the VI between the two different clustering algorithms and between the two different distance methods. Here 'E' and 'DTW' are the Euclidean distance and DTW distance methods, 'Kmeans' and 'HC' are the K-means and WARD.D2 clustering algorithms respectively.

From Fig. 7, we found that the average VI between the three different data pre-processing methods was 2.96. While analyzing Fig. 8 we found that the average VI between the two different clustering algorithms was lower at 0.9815. Lastly, the VI between the two different distance methods was 1.087. Thus, it is concluded that the different data pre-processing methods contribute most (almost 3 times) in extracting new information from the temperature data in our study (compared to distance methods or clustering algorithms).

With the results obtained from the cluster analysis and VI, we narrowed down the number of combinations to be used for ANOVA analysis. We kept all of the three data pre-processing methods because of their significance in extracting new information from the data. Since the VI between different distance methods and different clustering algorithms was less significant than that between the data pre-processing methods, we selected only one of each. Our selection was the DTW distance method because it is more compatible with time-series data over the Euclidean distance method and for the clustering algorithm, the WARD.D2 method over K-Means was selected. Thus, the number of clustering combinations was reduced from 12 to 3, ($3 * 1 * 1 = 3$).

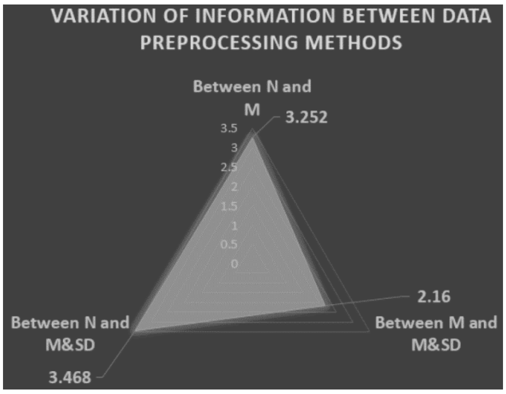

Fig. 7. VI between different data pre-processing methods.

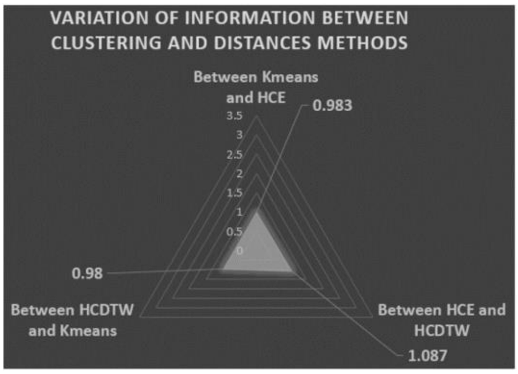

Fig. 8. VI between different distance methods and different clustering algorithms.

The reduced number of clustering combinations were implemented again for the cluster analysis on the indoor room temperature data. Combining the results obtained from the cluster analysis with the remaining sensor data (presence, solar radiation, different power consumptions, etc.), we conducted ANOVA analysis. From the results of the ANOVA analysis, we were able to determine the influence, if any, between the different sensors and the results obtained from the cluster analysis.

In the tables below, 'POWER' refers to the power consumed by the office, 'HEAT1' is the radiator power consumption, 'HEAT2' indicates the HVAC power consumption, 'OCCUPATION' refers to the presence sensor information, 'RHUMIDITY' is the relative humidity, 'SOLAR' is the solar radiation, 'PRESSURE' refers to the indoor pressure, 'OUTTEMP' is the outdoor temperature. Finally, 'WINDOW1' & 'WINDOW2' are the window activity sensors for the two windows of the room.

The 'Category' column indicates the type of data collected by the different sensors. For example, 'OCCUPATION', 'POWER', 'WINDOW1' & 'WINDOW2' sensors are attributed to the User's activity, while 'HEAT1' & 'HEAT2' are credited to the Building's operation. Lastly, the remaining sensors are a function of the prevailing weather and grouped in the Weather category.

The daily time-series data of each sensor was suitably transformed for ANOVA analysis as indicated by the 'Data Transformation Method' column. 'Daily sum' method translates that the numerical aggregate of the data recorded by the sensors for each day was considered. While 'Per day change' method was used for all power related data and meant the total power consumption for each day. That is, the change in the meter reading from the start to the end of the day. Finally, the 'Daily average' data transformation considered the numeric average of all the data recorded for each day. The number in brackets under each of the data pre-processing methods indicates the number of clusters used.

TABLE I. ANOVA ANALYSIS RESULTS FOR COMPLETE DATA OF THREE YEARS

ANOVA for Room 112 of 3 year data					
Catergories	Data transformation method	SENSOR	No Normalization (4)	Mean Normalization (2)	Mean and SD Normalization (2)
Building	Per day change	HEAT1	< 2*10^-6	0.000345	0.0356
	Per day change	HEAT2	< 2*10^-7	0.000432	0.145
User	Daily sum	OCCUPATION	0.00034	0.016	0.0175
	Per day change	POWER	0.773	0.464	0.839
	Daily sum	WINDOW1	1.38*10^-8	0.00607	0.694
	Daily sum	WINDOW2	< 2*10^-7	0.0128	0.158
Weather	Daily average	RHUMIDITY	< 2*10^-7	< 2*10^-7	1.26*10^-11
	Daily sum	SOLAR	< 2*10^-7	< 2*10^-7	4*10^-12
	Daily sum	PRESSURE	0.597	0.0155	0.23
	Daily average	OUTTEMP	< 2*10^-7	5.96*10^-13	0.000383

TABLE II. ANOVA ANALYSIS RESULTS WITH WINTER DATA OF THREE YEARS

ANOVA for the Winter days of room 112					
Catergories	Data transformation method	SENSOR	No Normalization (2)	Mean Normalization (2)	Mean and SD Normalization (2)
Building	Per day change	HEAT1	0.00382	0.66	0.0201
	Per day change	HEAT2	0.422	0.526	0.962
User	Daily sum	OCCUPATION	0.497	0.00186	0.332
	Per day change	POWER	Not enough information		
	Daily sum	WINDOW1	0.52	1.42*10^-9	0.221
	Daily sum	WINDOW2	0.251	1.08*10^-12	0.365
Weather	Daily average	RHUMIDITY	0.415	0.0903	0.00934
	Daily sum	SOLAR	0.159	0.163	0.0235
	Daily sum	PRESSURE	0.305	0.697	0.787
	Daily average	OUTTEMP	0.0024	0.254	0.00227

Table I shows the ANOVA analysis results when all the sensor data was used across the entire period of the analysis (3 years) and Table II gives the ANOVA analysis results when data from the winter months (December, January and February) was used across the period of the analysis. The tables are populated with p-values which were the results of the ANOVA analysis. The p-values were compared with an α of 0.05. The green tiles indicate that the sensor has influence (p-value $< \alpha$) on the temperature data while the red indicates that there is no influence (p-value $> \alpha$).

According to the data in Table I, we can conclude that all sensors (except power) have influence on the way the temperature data is clustered across the three data pre-processing methods. However, our analysis of the data presented in Table II shows that a more specific approach is required in the method of clustering to reveal the influence of the different sensors on the indoor temperature clusters. The influence of different sensor data on the temperature is sensitive to and is revealed when an appropriate data pre-processing method is applied for clustering, as seen in the results in Table II.

In Table II we see that HEAT2 sensor shows no influence on the temperature data. HEAT2 is the HVAC power consumption and should have an influence on the room temperature evolution. This can be attributed to the fact that the HEAT2 data is related to the functioning of the HVAC system for the entire building and not specifically to the room under our analysis. Thus, a concrete relationship between HEAT2 sensor and room temperature could not be established. Outdoor pressure naturally has very little influence on room temperature and this can be verified in the ANOVA results of Table II.

The main results obtained from our analysis can be summarized as follows:

1) Cluster analysis using different data pre-processing methods enabled us to reveal hidden characteristics of our temperature data as shown in Figs. 4, 5, and 6. These characteristics were the basis of the formation of the clusters.
2) Data pre-processing step of the cluster analysis contributed the most in extracting new information from our temperature data and was verified by the VI metric.
3) Distance methods and clustering algorithms fared approximately the same but less in extracting new information from the data when compared to the data pre-processing step using the VI metric.
4) ANOVA analysis results show that the influence exerted by sensors on room temperature were sensitive to seasonal data.
5) Depending on the data pre-processing method employed, hidden influences of the sensors were revealed on the temperature data using ANOVA analysis.
6) Using ANOVA analysis we identified which sensor data does not have a direct role in influencing the room temperature evolution, e.g., PRESSURE and HEAT2.

V. FUTURE TRENDS

As a result of economic growth, the trend of people moving to urban areas and the associated urbanization poses challenges to a city's services and resources [14], [32]. As a result, the concept of smart cities is developing extremely rapidly. Smart cities utilize the latest technologies to increase operation efficiency of the city and improve the quality of life of its citizens by integrating smart grid, services, buildings, houses and appliances. Smart urban technologies like IoT and blockchain have the potential to provide significant contributions to the sustainable development of smart cities [14].

There is an overwhelming trend of digitalization of buildings worldwide and more specifically in Europe digitalization is coupled with decarbonization. EU policy is driving the need for Nearly Zero Energy Buildings (NZEBs) incorporating Distributed Energy Resources (DERs), building automation and electronic monitoring of technical building systems [33], [34].

Buildings are being developed to be smarter by incorporating the latest technologies and deep analytics. Smart metering is to be a key element of future smart homes [35]. Smart meters allow monitoring not only the electricity consumption of end-user but also the gas, water and heating [36]. Accurate evaluation and analysis of data related to building operation is essential in order to improve energy efficiency and reduce overall energy consumption of buildings, as suggested in [37], [36].

Connected, interacting and online devices and sensors are increasingly becoming the norm of a modern building system. At the end of 2017 there were approximately 8.4 billion IoT devices deployed worldwide (across industries); this number will increase to 20.4 billion by 2020 [38]. IoT devices are increasingly being incorporated for remote monitoring and control of different building systems [39], [40]. They can be used to upgrade traditional systems like the HVAC to a more intelligent HVAC system, increasing its energy efficiency and performance [40]. IoT is a technology already used in most modern buildings and this trend is likely to increase as the security of IoT interacting devices increases.

Blockchain is a technology that is increasingly considered to compliment IoT in order to facilitate IoT mass adoption by solving the security and privacy issues associated with IoT, as stated previously. Blockchain and IoT will converge as blockchain will add immutability and integrity to IoT transactions. Another important aspect of blockchain is its scalability, meaning that as more devices are connected to the blockchain, the more secure it becomes. Analysis in [41] reports that in 2016 an average household held 7 connected devices every day and this number is likely to increase; thus, the convergence of blockchain and IoT is inevitable.

Peer-to-peer (P2P) energy trading is also a domain where blockchain technology is employed. Increasingly buildings today are producers of energy through distributed renewable energy generation can feed excess energy back to the grid. Blockchain and smart meters are used to track any traded energy along with the transaction, which is executed through smart contracts.

VI. Conclusions

The aim of our analysis was to study and understand how the behavior of the indoor room temperature is influenced by different sensor data. Indoor room temperature was considered as the basis of our study because space conditioning contributes significantly to the building energy consumption; thus, room temperature is a good parameter to consider in order to investigate energy reduction potential in buildings.

One of the key results from our analysis is that the data pre-processing methods contribute the most to extracting new information from the data, which was verified using the VI index function. From the different ANOVA analyses, we determined that different data pre-processing methods help to reveal the hidden influence different sensors exert on the indoor temperature. The influence of the different sensors was further enhanced when seasonal data was considered.

However, a limitation to our analysis is that some of the parameters affecting the indoor room temperature, e.g., the orientation of the room with respect to the sun, the irradiation experienced in the room that are valid influencers of indoor room temperature, were not considered. Missing or incomplete data is also an issue in our analysis. Different data preprocessing and data analysis tools specifically designed for time-series analysis and with a tolerance for missing data can be utilized to give more accurate information.

Another limitation is the accuracy of the sensors. Sometimes a sensor operates perfectly but does not register the ‘correct’ data, e.g., one ‘error’ observed in our analysis was in the case of the presence sensor. The role of the presence sensor is to register when the person is in the room, i.e., if the person is in the room it registers ‘1’, else ‘0’; but the presence sensor used for the analysis detects significant movements and interprets those as presence. In normal everyday working environments, people spend most of the time seated. So, the presence sensor will read large movements like moving in and out of the room, but, may not register the person sitting in the office as presence, which is inaccurate information.

Connected and online smart home IoT devices can record and store tamper-proof information onto a common blockchain. The use of blockchain by IoT devices eliminates data duplication, increases accuracy and transparency, increases home automation potential and execution speed through carefully coded smart contracts and provides greater resilience to the smart home system from a cybersecurity point of view. Increased performance in home automation translates to greater energy efficiency for buildings, thus reducing costs through reduced energy consumption for owners and reduction of GHG from the environment.

Apart from reduction in costs, there is also potential for additional income through P2P and building to grid energy trading which smart contracts can help facilitate. Additional income can also be generated using carbon certificates that can be sold on a blockchain.

VII. Future Direction and Perspectives

The next step of our study is to conduct further analysis on sensor data by weighing their influence exerted on the temperature evolution and to model a better and more complete energy prediction tool for buildings. Building on this, latest technologies like IoT and blockchain can be leveraged to make building energy reduction a more active and automated process.

There exists a significant potential of building energy reductions in the operation of energy hungry HVAC systems used in buildings. HVAC systems are ubiquitous in both residential and commercial buildings, and though they perform their task of conditioning the room space effectively, they do not necessarily always perform the task efficiently. Using the latest forward-looking technologies like IoT and blockchain technology, a traditional HVAC system can be converted into a Smart or an Intelligent HVAC system with an objective of ensuring energy efficiency without compromising the thermal comfort of the occupants. IoT devices can be used for monitoring data and interacting with each other while recording the information on a blockchain. Blockchains can utilize this information with smart contracts designed to maintain a balance between energy efficiency and thermal comfort. Smart contracts can be used to automate and drive the connected IoT devices. This will make significant strides towards the effective and efficient operation of NZEBs.

REFERENCES

[1] Buildings Performance Institute Europe (BPIE);Global Buildings Performance Network (GBPN);World Business Council for Sustainable Development (WBCSD); University of Cambridge Institute for Sustainability Leadership (CISL);European Climate Foundation (ECF), "Climate change: implications for buildings," 2014. [Online]. Available: http://bpie.eu/publication/climate-change-implications-for-buildings/. [Accessed 17 February 2019].

[2] U.S. Global Change Research Program, "Climate Change," [Online]. Available: https://www.globalchange.gov/climate-change. [Accessed 17 February 2019].

[3] European Parliament, "Climate change: EU measures to help reduce the impact," European Parliament, 7 August 2018. [Online]. Available: http://www.europarl.europa.eu/news/en/headlines/society/20180703STO07129/climate-change-eu-measures-to-help-reduce-the-impact. [Accessed 17 December 2019].

[4] European Commission, "2020 climate & energy package," 2009. [Online]. Available: https://ec.europa.eu/clima/policies/strategies/2020_nl. [Accessed 17 February 2019].

[5] European Commission, "2030 climate & energy framework," October 2014. [Online]. Available: https://ec.europa.eu/clima/policies/strategies/2030_nl. [Accessed 17 February 2019].

[6] M. A. Cañete, Interviewee, Post-COP24 High Level Debate. [Interview]. 22 January 2019.

[7] European Commission, "Buildings," European Commission, [Online]. Available: https://ec.europa.eu/energy/en/topics/energy-efficiency/buildings. [Accessed 17 February 2019].

[8] K. Syngellakis, S. Taylor, M. Draeck, F. Crick, et al., "Module 18: Energy efficiency in buildings," in Sustainable energy regulation and policymaking for Africa, 2009, p. 18.1.

[9] J. Goggins and M. Hajdukiewicz, "The influence of heat transfer and storage in structural precast building components on indoor environments," in Civil Engineering Research in Ireland Conference. CERI, Belfast, 2014.

[10] S. K. Gupta, K. Kar, S. Mishra, and J. T. Wen, "Incentive-based mechanism for truthful occupant comfort feedback in human-in-the-loop building thermal management," IEEE Systems Journal, vol. 12, no. 4, pp. 3725–3736, 2018.

[11] T. Zhang, M. P. Wan, B. F. Ng, and S. Yang, "Model predictive control for building energy reduction and temperature regulation," in IEEE Green Technologies Conference (GreenTech), Austin, 2018.

[12] F. Z. Martinez, P. Romeu, P. B. Rocamora, and J. Pardo, "Towards energy efficiency: Forecasting indoor temperature via multivariate analysis," Energies: Energy Efficient Building Design 2013, vol. 6, pp. 4639–4659, 2013.

[13] H. Nasution, A. A. Dahlan, A. A. Aziz, and A. M. Nasib, "Indoor temperature control and energy saving potential of split unit air conditioning system using fuzzy logic controller.," IAENG International Journal of Computer Science, vol. 43, no. 4, pp. 402–405, 2016.

[14] C. Lazaroiu and M. Roscia, "Smart district through IoT and blockchain," in IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA), San Diego, 2017.

[15] A. Dorri, S. S. Kanhere, R. Jurdak, and P. Gauravaram, "Blockchain for IoT security and privacy: The case study of a smart home," in IEEE PERCOM Workshop On Security Privacy And Trust In The Internet of Things, Kona, 2017.

[16] T. Tantidham and Y. N. Aung, "Review of ethereum: Smart home case study," in 2nd International Conference on Information Technology (INCIT), Nakhonpathom, 2017.

[17] M. Singh, A. Singh, and S. Kim, "Blockchain: A game changer for securing IoT data," in IEEE 4th World Forum on Internet of Things (WF-IoT), Singapore, 2018.

[18] D. Fakhri and K. Mutijarsa, "Secure IoT communication using blockchain technology," in International Symposium on Electronics and Smart Devices (ISESD), Bandung, 2018.

[19] The London School of Economics and Political Science, "Building temperatures and BMS," The London School of Economics and Political Science, [Online]. Available: https://info.lse.ac.uk/staff/divisions/estates-division/a-z-of-services/maintenance/building-temperatures-and-bms. [Accessed 17 February 2019].

[20] O. Seppanen, D. Faulkner, and W. J. Fisk, "Control of temperature for health and productivity in offices," ASHRAE Transactions, vol. 111, no. 2, pp. 476–484, 2004.

[21] O. Seppanen and W. J. Fisk, "Providing better indoor environmental quality brings economic benefits," in REHVA World Congress – CLIMA 2007, Helsinki, 2007.

[22] S. H. Shah and I. Yaqoob, "A survey: Internet of Things (IOT) technologies, applications and challenges," in IEEE Smart Energy Grid Engineering (SEGE), Oshawa, 2016.

[23] L. Tan and N. Wang, "Future internet: The Internet of Things," in 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE), Chengdu, 2010.

[24] G. M. Lee and J. Y. Kim, "The Internet of Things — A problem statement," in International Conference on Information and Communication Technology Convergence (ICTC), Jeju, 2010.

[25] Z. Zheng, S. Xie, X. Chen, H.-N. Dai, and H. Wang, "An overview of blockchain technology: Architecture, consensus, and future trends," in IEEE International Congress on Big Data (BigData Congress), Honolulu, 2017.

[26] J. Golosova and A. Romanovs, "The advantages and disadvantages of the blockchain technology," in IEEE 6th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), Vilnius, 2018.

[27] "Republic of Estonia Ministry of Economic Affairs and Communications: Energy Efficiency," [Online]. Available: https://www.mkm.ee/en/objectives-activities/energy-sector/energy-efficiency. [Accessed 4 February 2019].

[28] CEREMA, "Cerema, l'expertise publique pour le développement et la cohésion des territoires," CEREMA, [Online]. Available: https://www.cerema.fr/fr/cerema. [Accessed 19 February 2019].

[29] M. Meilă, "Comparing clusterings—an information based distance," Journal of Multivariate Analysis, vol. Volume 98, no. Issue 5, pp. 873–895, 2007.

[30] G. Millot, "Comparaison d'au moins deux moyennes observées," in Comprendre et réaliser statistiques à l'aide de R, 3ème édition, De Boeck Supérieur, 2018, pp. 446–458.

[31] M. Pasin, "Performing ANOVA test in R: Results and interpretation," Analytics for Fun, 23 June 2014. [Online]. Available: http://www.analyticsforfun.com/2014/06/performing-anova-test-in-r-results-and.html. [Accessed 10 April 2019].

[32] L. Horwitz, "How IoT devices lay the foundation for smart city infrastructure," Cisco, [Online]. Available: https://www.cisco.com/c/en/us/solutions/internet-of-things/smart-city-infrastructure-guide.html. [Accessed 20 February 2019].

[33] L. Martirano, E. Habib, A. Giuseppi, and A. Di Giorgio, "Nearly zero energy building model predictive control for efficient heating," in IEEE Industry Applications Society Annual Meeting (IAS), Portland, 2018.

[34] S. Kumar, "Towards net zero energy solar building, system, and concepts," in First International Conference on Sustainable Green Buildings and Communities (SGBC), Chennai, 2016.

[35] D. Alahakoon and X. Yu, "Smart electricity meter data intelligence for future energy systems: A survey," IEEE Transactions on Industrial Informatics, vol. 12, no. 1, pp. 425–436, 2015.

[36] E. Rodriguez-Diaz, E. J. Palacios-García, M. Savaghebi, J. C. Vasquez, J. M. Guerrero, and A. Moreno-Munoz, "Advanced smart metering infrastructure for future smart homes," in IEEE 5th International Conference on Consumer Electronics, Berlin, 2015.

[37] D. Schachinger, S. Gaida, W. Kastner, F. Petrushevski, C. Reinthaler, M. Sipetic, and G. Zucker, "An advanced data analytics framework for energy efficiency in buildings," in IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA), Berlin, 2016.

[38] Gartner, "Gartner Says 8.4 Billion Connected "Things" Will Be in Use in 2017, Up 31 Percent From 2016," Gartner, [Online]. Available: https://www.gartner.com/en/newsroom/press-releases/2017-02-07-gartner-says-8-billion-connected-things-will-be-in-use-in-2017-up-31-percent-from-2016. [Accessed 20 February 2019].

[39] D. Paul, T. Chakraborty, S. K. Datta, and D. Paul, "IoT and machine learning based prediction of smart building indoor temperature," in 4th International Conference on Computer and Information Sciences (ICCOINS), Kuala Lumpur, 2018.

[40] M.-i. Choi, K. Cho, J. Y. Hwang, L. W. Park, K. H. Jang, S. Park, and S. Park, "Design and implementation of IoT-based HVAC system for future zero energy building," in IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Kona, 2017.

[41] J. Maclean, Households Now Use an Average of Seven Connected Devices Every Day: Report. Cantech Communications, North Vancouver, 2016.

[42] D. Ürge-Vorsatz, L. F. Cabeza, S. Serrano, C. Barreneche, and K. Petrichenko, "Heating and cooling energy trends and drivers in buildings," Renewable and Sustainable Energy Reviews, vol. 41, pp. 85–98, 2015.

[43] G. Todesco, "Building energy use statistics," Low Energy Buildings, [Online]. Available: http://www.lowenergybuildings.com/energy-use-ghg-emissions-in-buildings. [Accessed 4 February 2019].