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Exploratory Data Analysis for Building Energy Meters Using *Machine Learning*

Analisis Eksplorasi Data Meter Energi Bangunan Menggunakan *Machine Learning*

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Abstract

The purpose of this research was to apply exploratory data analysis techniques to building energy meters, such as electricity, cold, heat, and steam meters. A thorough understanding of energy usage patterns becomes increasingly vital in an era of growing awareness of energy management and sustainability. Trends, patterns, and anomalies can be identified in building energy meter data using meticulous data exploration approaches, which can give significant insights for increasing energy efficiency. Exploratory data analysis combined with machine learning approaches may be was used to reveal hidden patterns of energy usage and examine the links between relevant factors. The findings of this exploratory data analysis gave vital insights into building energy use trends. Some significant and hidden information that was crucial for understanding energy usage within a certain time frame in each building was discovered via the investigation of the data used in this study. Steam had the highest use, whereas electricity had the lowest. Utilities were more popular before 5 a.m., followed by healthcare, with daytime use hours beginning around 10 a.m., depending on the area. During the working day, the industry needs more energy. Places of worships use more energy on weekends. There was a significant relation between the number of floors and spaces per level of a building and the height meter reading between May and October. There is a significant association between the kind of buildings used for schools, workplaces and high energy use. This study significantly contributed to the management of the energy and sustainability domains. Using exploratory data analysis and machine learning approaches to building energy meters could optimize energy usage, minimize running costs, and enhance overall energy efficiency. This research is still very open to be continued using other methods, to obtain other hidden information.

Keywords: Building, Energy Meters, Machine Learning, Data Analysis.

Abstrak

Penelitian ini bertujuan untuk menerapkan analisis data eksploratif menggunakan teknik *machine learning* pada meter energi bangunan, termasuk meter listrik, dingin, panas, dan uap. Pads era peningkatan kesadaran tentang manajemen energi dan keberlanjutan, membuat pemahaman mendalam tentang pola-pola konsumsi energi menjadi semakin penting. Melalui penggunaan metode eksplorasi data yang cermat, kita dapat mengidentifikasi tren, pola, dan anomali dalam data meter energi bangunan. Hal ini pada gilirannya dapat memberikan wawasan berharga untuk meningkatkan efisiensi energi. Menggunakan teknik *machine learning* dengan analisis data eksploratif untuk mengungkap pola konsumsi energi yang tersembunyi dan mempelajari hubungan antara variabel-variabel yang berpengaruh. Hasil dari analisis data eksploratif ini memberikan wawasan penting tentang pola konsumsi energi dalam bangunan. Dari eksplorasi data yang telah dilakukan dalam penelitian ini, diperoleh beberapa informasi penting dan tersembunyi yang sangat diperlukan dalam pemakaian energi dalam rentang waktu tertentu di setiap bangunan. Uap memiliki konsumsi terbesar, sedangkan listrik memiliki konsumsi terendah. Utilitas tertinggi sebelum jam 5 pagi, diikuti oleh perawatan kesehatan dengan jam penggunaan siang hari setelah jam 10 pagi, tergantung wilayah. Industri akan membutuhkan lebih banyak energi selama hari kerja. Pada akhir pekan, tempat ibadah lebih banyak mengonsumsi energi. Pada jarak antara bulan Mei dan Oktober, terdapat hubungan yang cukup besar antara jumlah lantai dan ruang setiap tingkat bangunan dan pembacaan meteran tinggi. Terdapat hubungan substansial antara jenis bangunan yang digunakan untuk sekolah, kantor dan konsumsi meteran energi yang tinggi. Penelitian ini memberikan kontribusi penting dalam domain manajemen energi dan keberlanjutan. Dengan menerapkan analisis data eksploratif dan teknik *machine learning* pada meter energi bangunan, dapat mengoptimalkan penggunaan energi, mengurangi biaya operasional, dan meningkatkan efisiensi energi secara keseluruhan. Penelitian ini masih sangat terbuka untuk dapat dilanjutkan kembali dengan menggunakan metode lain, agar memperoleh informasi tersembunyi lainnya.

Kata kunci: Gedung, Meter Energi, Machine Learning, Analisis Data**.**

I. INTRODUCTION

Existing structures use around half of overall global energy consumption [1]. Since 2020, European building energy consumption laws require "structures that virtually match the NZEB (Net Zero Energy Building) requirements", particularly for new buildings [2], [3]. Smart meter infrastructure for urban structures is focused on properties and districts. While energy management for buildings is not yet accessible, measuring the energy consumed by property and structures attempts to recoup the money. To correctly spend money, we must, of course, consider energy, because the energy spent takes it straight to the end consumer [4]. Aside from expenses, energy emits carbon. A smart meter is a component of urban manufacturing and carbon impact regulation [5].

The meter is physically read once a month. Meters and data can only have an effect on one channel of transfer of energy. The smart meter analyzes energy use data in real-time and sends it to the utility remotely. They're useful for gathering data both locally and remotely, detecting long-term trends, and responding to real-time or short-term events or coordination mechanisms like management control. With modern smart meter technologies, two-way energy flow measurements are now achievable [6].

Data monitoring provides improved control over energy use as a result of networked renewable electricity, power storage, and electric cars. Because of the influence of distributed renewable power generation and battery storage, this will be crucial in future urban environments after CO2 emissions [7]. Customer perceptions of electric vehicles and trends in energy use. Over the past 25 years, in particular, in Canada and Germany, several solar system-related seasonal thermal storage test projects based on numerous collectors for the heating supply of some residential (or administrative) buildings in cold climates have been carried out [8], [9]. These projects show that this technology is possible but very expensive [10].

As a result, power electronics systems are a crucial enabler of technology for smart grids. Furthermore, smart meters serve as a link between green buildings and the energy grid. A two-way power conditioning module is necessary to achieve the interaction between the two systems [11]. Significant investments have been made in building efficiency to minimize costs and emissions. Success rates are determined by a variety of factors, including performance-based financing that pays building owners based on the difference between their current energy usage and their usage without retrofitting [12]. Improving energy adaptability can be crucial because there is no way to predict how much energy a building will use until it is repaired. So far, the counterfactual model is our best hope. Calculating savings from building renovations, energy usage reductions compared to pre-renovation building model values, and retrofitting older technology features. A more accurate model will help increase retail encouragement and enable cheaper loans.

Several more studies similar to this research that have been undertaken can give a broader view on the application of machine learning, data mining, and energy analytics in evaluating building energy meters. Deep learning ideas and techniques are thoroughly understood. This may be used to analyze building energy data with machine learning algorithms [13]. When analyzing building energy meters, it is critical to pick the appropriate data representation. This source provides information on numerous representational learning algorithms that may be used in energy data analysis [14]. A strong grasp of the processes and generalization features of deep learning models is required to generate accurate and trustworthy models when assessing building energy meters using machine learning [15]. This review paper delves into the use of machine learning algorithms to anticipate building energy usage. It analyzes numerous algorithms and their efficacy in forecasting energy use, which may be applied to the machine-learning analysis of building energy meters [16], [17]. The purpose of this survey article is to investigate smart meter data analytics in the context of smart networks. It covers a variety of data analytics topics, such as data pretreatment, feature extraction, and predictive modeling. This survey's findings may be beneficial for interpreting data from building energy meters [18]. This review study looks at how data mining techniques may be used to analyze building energy use. It covers subjects including estimating energy usage, detecting anomalies, and increasing energy efficiency. The review sheds light on data mining techniques that may be used to examine data from building energy meters [19], [20]. This study focuses on predicting electric load, which is crucial to electricity meter analysis. It gives an overview of load forecasting methods, such as statistical and machine learning techniques. This paper's findings can be used to better identify patterns and trends in power usage data [21]. With reference to these sources, this work intends to examine building energy meters using exploratory data analysis techniques and machine learning approaches. Deep learning, representational learning, and generalization ideas and techniques can be used to improve knowledge of energy use patterns and maximize energy efficiency.

The novelty of this research lies in the combination of exploratory data analysis and machine learning techniques in the context of building energy meters. While exploratory data analysis and machine learning have been used separately in energy research, this study presents an approach that comprehensively integrates both methods to uncover patterns and relationships related to building energy consumption. Combination of Exploratory Data Analysis and Machine Learning: This study combines the strengths of exploratory data analysis, which enables the identification of patterns and trends in data, with the power of machine learning, which can generate predictive models and identify complex relationships among influential variables. This approach enriches the understanding of building energy consumption and helps optimize energy usage. Application to Different Types of Building Energy Meters: This research focuses not only on electricity meters but also includes cold, hot, and steam meters. In many cases, energy consumption data for different types of meters are available separately. By integrating data analysis from different energy meters, this study provides a more comprehensive insight into energy consumption patterns in buildings.

The data collection contains three years of meter-per-hour readings from more than a thousand buildings in various locations around the world. Before addressing the issues of various current models and technologies, this study aims to provide a realistic understanding of energy demand using building energy meter data from cold water, electric, heated water, and steam demand. and Data are taken from over 1,000 structures over a three-year period. A realistic and careful knowledge and understanding of a building's energy needs can reveal a variety of critical and hidden information. Because the data is a historical journey on the actual use of energy meters in buildings. This critical hidden information helps determine the appropriate technology model to solve the problem. Therefore, if these energy-efficient contributions can be more accurately estimated, large investors and commercial associations will be more inclined to invest in this area to improve development efficiency. Data processing is done using the Python language because this language is commonly used in programming related to machine learning [22]. The existence of libraries, pandas, and matplotlib makes the Python programming language easy to use for matrix simulations, displays attractive visual graphs, and many others [23], [24].

II. RESEARCH METHOD

The 3 datasets (train_df, weather_train_df, and building_meta_df) used in the current research are processed and extracted in this part. The effective and efficient use of energy in a structure, including cold water, electricity, gas, hot water, and steam, depends on knowing specific data and extracting hidden information. In general, the methodologies used in this study were data gathering, extraction, analysis, feature engineering, and data correlation.

A. Load the Dataset

The data was obtained from Kaggle.com, from the existing data 3 files were used, as follows: The file training.csv (Figure 1) contains 20,216,100 lines of data and the following features: Building id is a foreign important for constructing metadata, code for each meter id, electricity (0), cold water (1), steam (2), water heating (3), measurement time, and meter reading for power electric expenditure (kWh).

```
train_df
```

	building_id	meter	timestamp	meter_reading
0	0	0	2016-01-01 00:00:00	0.000000
1	1	0	2016-01-01 00:00:00	0.000000
2	2	0	2016-01-01 00:00:00	0.000000
...	...	...	...	...
20216097	1446	0	2016-12-31 23:00:00	0.000000
20216098	1447	0	2016-12-31 23:00:00	159.574997
20216099	1448	0	2016-12-31 23:00:00	2.850000

20216100 rows × 4 columns

Figure 1. Train file

Weather data is gathered from the nearest meteorological station. The Weather.csv file (Figure 2) has 139,773 data lines and includes the following features: location identification (id-site), air temperature level for each place (Celsius), cloud conditions, humid temperature level (Celsius), rainfall depth per hour (mm), surface pressure conditions from the sea (milli-bar), wind direction (0-360), wind velocity (meters per second).

The file building meta.csv (Figure 3) has 1,449 lines of data and includes the following information: Identification of the place (id-site), foreign primary key connected with the weather state file, and building identity (id-building), foreign primary key for associated with the training file, main use indicates the main activity category indicators for the building, square feet represents the floor area of the building. Python libraries are used for developing.

```
weather_train_df
```

	site_id	timestamp	air_temperature	cloud_coverage	dew_temperature	precip_depth_1_hr	sea_level_pressure	wind_direction	wind_speed
0	0	2016-01-01 00:00:00	25.000000	6.0	20.000000	NaN	1019.5	0.0	0.000000
1	0	2016-01-01 01:00:00	24.406250	NaN	21.093750	-1.0	1020.0	70.0	1.500000
2	0	2016-01-01 02:00:00	22.796875	2.0	21.093750	0.0	1020.0	0.0	0.000000
...	...	...	...	...	...	...	...	...	...
139770	15	2016-12-31 21:00:00	2.800781	NaN	-7.199219	NaN	1007.5	180.0	5.101562
139771	15	2016-12-31 22:00:00	2.199219	NaN	-6.699219	NaN	1008.0	170.0	4.601562
139772	15	2016-12-31 23:00:00	1.700195	NaN	-5.601562	-1.0	1008.5	180.0	8.796875

139773 rows × 9 columns

Figure 2. Weather file

```
building_meta_df
```

	site_id	building_id	primary_use	square_feet	year_built	floor_count
0	0	0	Education	7432	2008.0	NaN
1	0	1	Education	2720	2004.0	NaN
2	0	2	Education	5376	1991.0	NaN
3	0	3	Education	23685	2002.0	NaN
4	0	4	Education	116607	1975.0	NaN
...	...	...	...	...	...	...
1444	15	1444	Entertainment/public assembly	19619	1914.0	NaN
1445	15	1445	Education	4298	NaN	NaN
1446	15	1446	Entertainment/public assembly	11265	1997.0	NaN
1447	15	1447	Lodging/residential	29775	2001.0	NaN
1448	15	1448	Office	92271	2001.0	NaN

1449 rows × 6 columns

Figure 3. Building_meta file

B. Exploratory Data Analysis (EDA)

Training, building, and weather datasets were merged to produce the following analysis. We attempted to combine the training and test sets, however, the processing time for the subsequent EDA was so sluggish that it would repeat whatever cleanup/feature engineering was done on the train to the test set [25]. The total number of rows and columns in the combined data frame (combine train) is now 20,216,100. Feature Engineering expands over time as we develop new features, including month of the year, day of week timestamp, and hour of day.

C. Missing Data

The missing data is described below. Weather observations and missing structures should be checked throughout the report. To visualize the distribution of meter readings without outliers, dividing the outliers using the formula (1.5 x IQR) turns out to produce a very skewed target variable, even for these observations within the outlier limits. After performing several transformations on meter_reading for modeling purposes, we obtain the distribution of meter data (Figure 4).

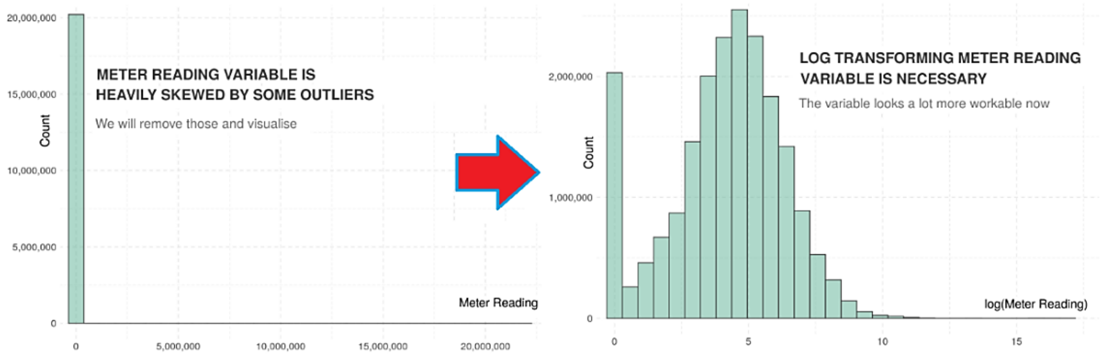

Figure 4. Log transforming meter reading variable is necessary

D. Kind of meter and several sorts of meters

The ggplot package included with the Python programming language may be used to show several sorts of meter readings. For meter reading and meter types, there are four different types of meters that are shown in coded form, namely: Electricity (0), Coldwater (1), Steam (2), and Hot water (3). As we can see, these types of steam meters tend to have higher meter readings, while electricity tends to have the lowest energy readings (Figure 5). For Weekday and Meter readings, we take that to be expected, Sundays tend to have lower readings, but there isn't a big difference between the days (Figure 6).

```
combine_train %>%
  ggplot(aes(x= log(meter_reading + 1), fill = as.character(meter))) +
  geom_density(alpha = 0.5, adjust = 2) +
  scale_fill_manual(values = col_pal) +
  ggtitle("THE STEAM METER TYPE IS THE LEAST EFFICIENT, ELECTRICITY\nTHE MOST EFFICIENT",
          subtitle = "Meter readings of 0 have been excluded") +
  labs(x= "log(Meter Reading)") +
  theme(axis.title.y = density, legend.position = "top")
```

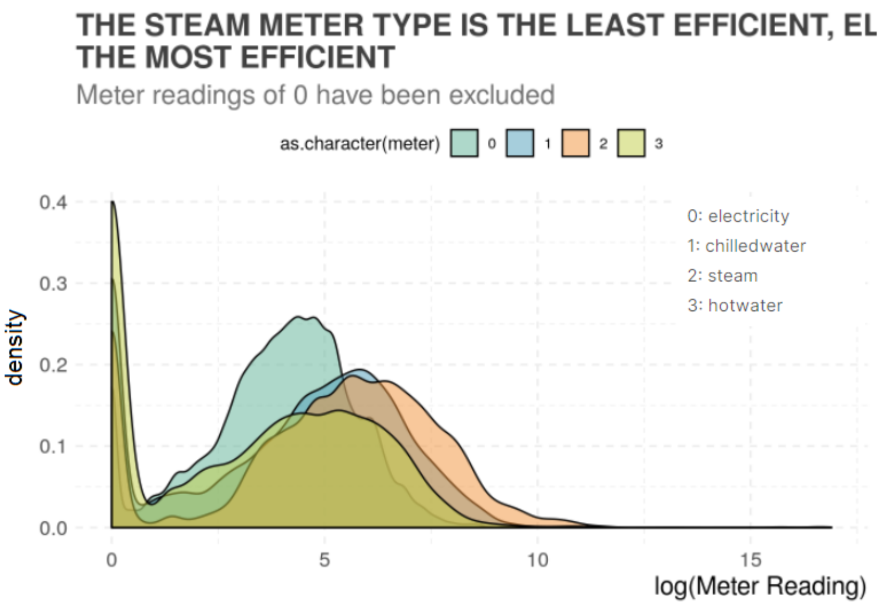

Figure 5. Readings from four types of meters' density logs

Figure 6. Weekly readings from a daily density log

The time of day and meter readings are significantly higher during traditional business hours and this is to be expected. Time of day is likely to be a significant predictor in future models. There are many variations of meter readings for each type of building. Meter readings for maintenance buildings (more than 225) with peak usage time during the day (15:00). For housing, the peak is around 80, with the peak usage time at night at 19:00. Manufacturing with meter readings of over 150 occurred around 5 am. Meanwhile, the lowest meter use only reaches 6 around 10:00 for places of worship. The highest usage meter for utility locations with usage before 5 am reaches 350 (Figure 7). For prime usage and meter readings, we can see that Utilities and Healthcare establishments tend to have the highest readings, while Religious Places of Worship the fewest - no doubt they are visited less often than high energy users (Figure 8).

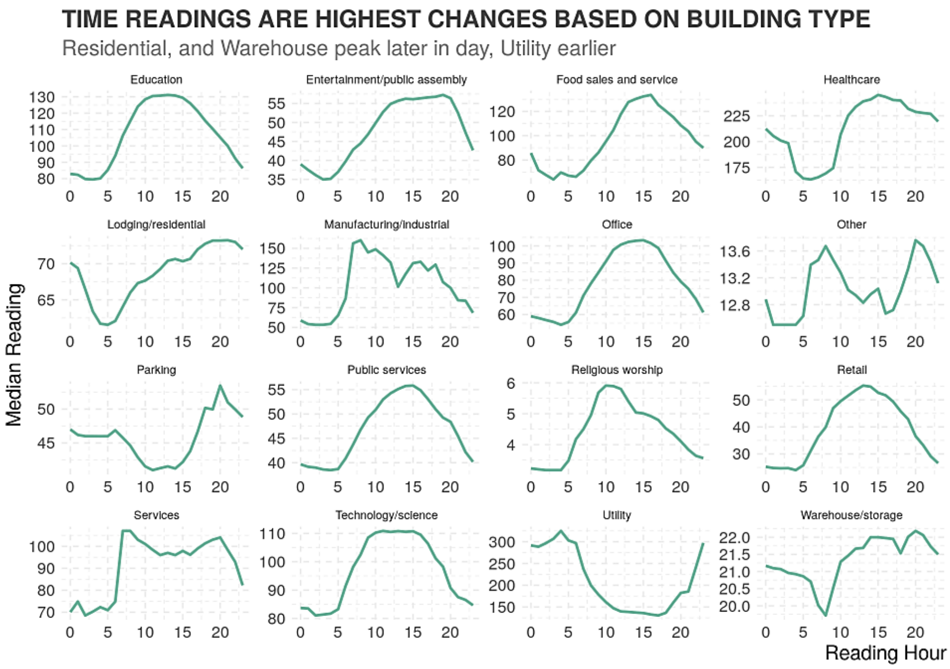

Figure 7. Hourly meter readings per day for all types of buildings.

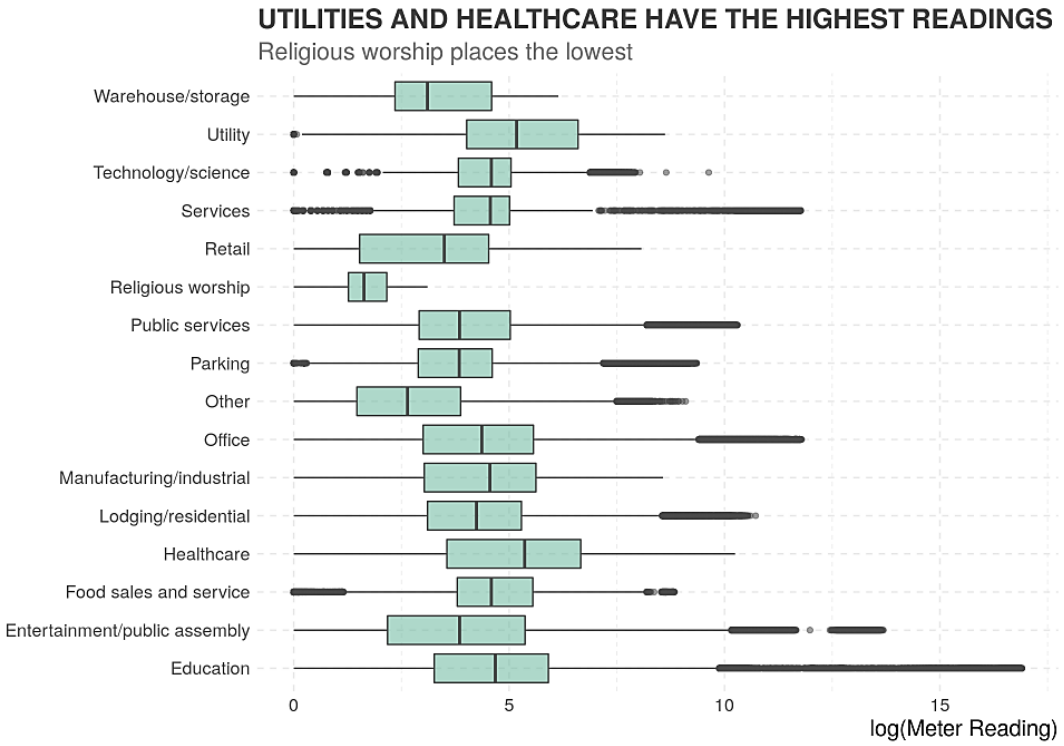

Figure 8. Log meter readings for some building utilities

It's important to note that different building types use energy differently on different days. For example, religious facilities typically use more energy on weekends than on weekdays, while industrial (commercial) facilities typically use more energy on weekdays (Figure.9). Intriguingly, the average meters reading per reading began to rise in May and peaked between July and October 2016 in terms of meters readings over time (Figure 10). With a few exceptions, this tendency is true for the most of building types. Manufacturing decreased during the peak times mentioned above, but Services, Technology, Utilities, and Warehouses stayed largely stable throughout the year (Figure 11).

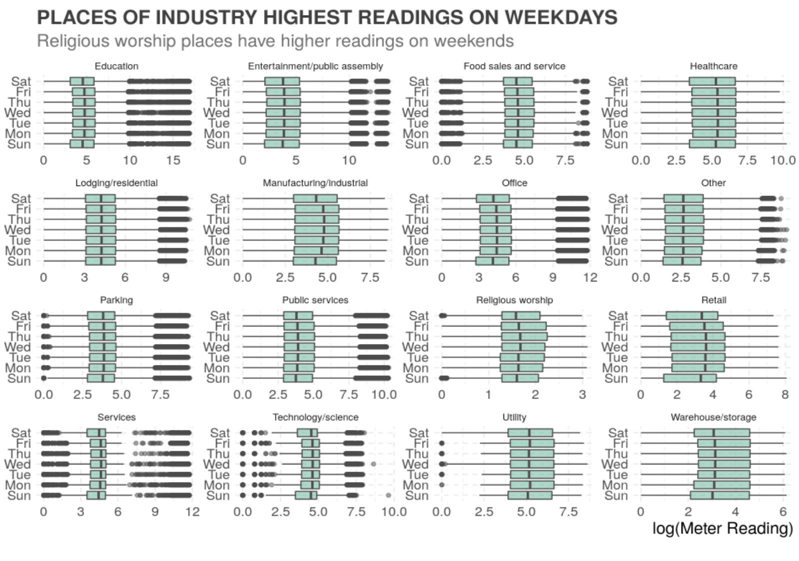

Figure 9. For each building's utility, record readings within a week.

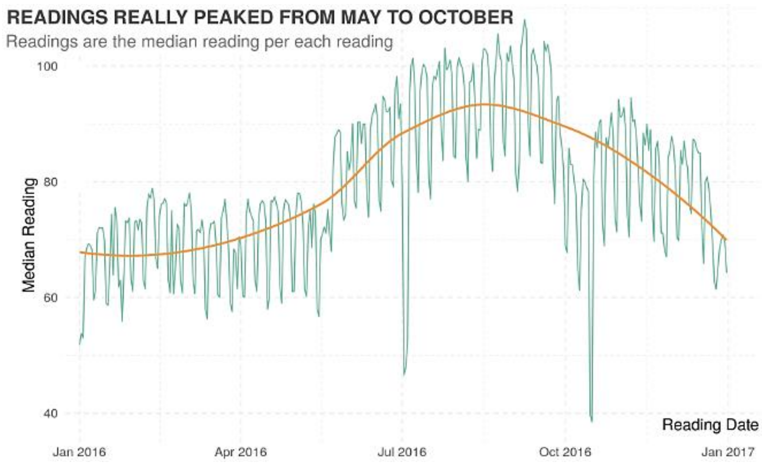

Figure 10. Median meter readings between January 2016 and January 2017

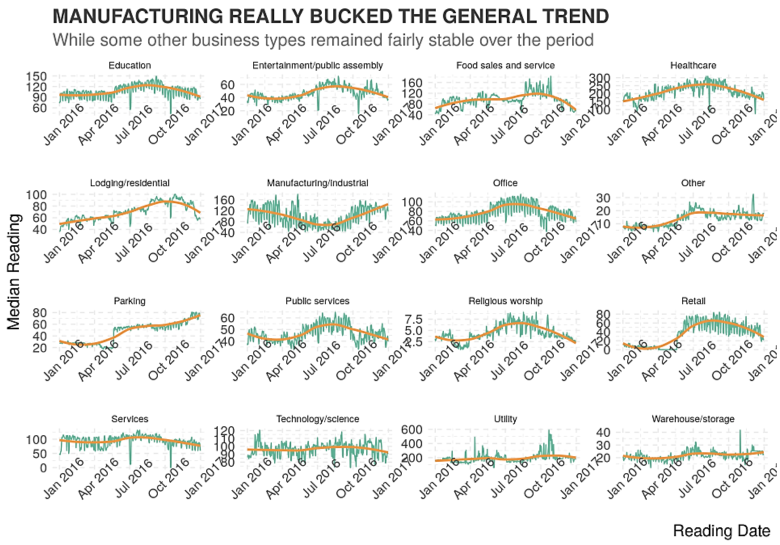

Figure 11. For each utility building, the median meter readings from January 2016 to January 2017

E. Correlation

The amount of storeys and the size of the structure both have a strong Pearson correlation with meter readings, implying that the larger the structure, the greater the reading. The year of construction also has a substantial positive link - older structures may have higher values. Any model created with extremely weak negative Pearson correlations may need wind speed, air temperature, and cloudy weather (Figure 12).

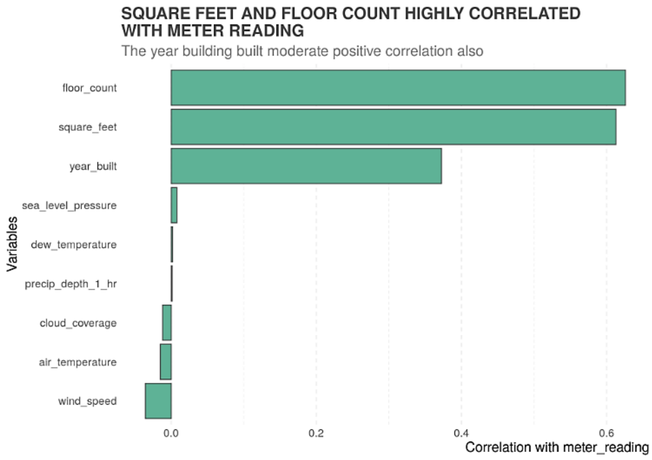

Figure 12. Pearson Correlations

Analyzing these variables will also assist us in determining how they are distributed and whether or not there are any problems with the data (missing variables, skewness, extreme outliers, etc.). There are no missing records in the primary usage variable. The educational building type is by far the most read, followed by the office building type, which is somewhat less read but still more than twice the third most read Entertainment building type. The tail is fairly long, with 11 underparts that are slightly lower (Figure 13).

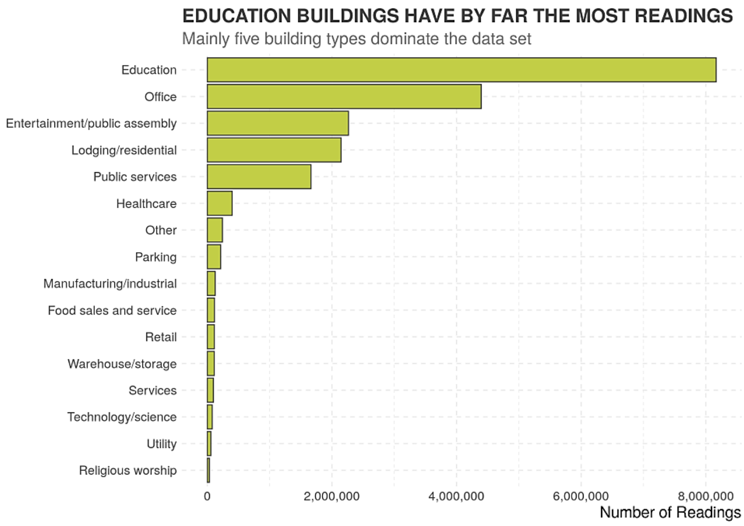

Figure 13. Data distribution by building

The square feet variable has 0 missing values. With a median of 72,709 feet and a mean of 107,783 square feet, the square foot distribution is favorably skewed (Figure 14). The meter variable has 0 missing records.

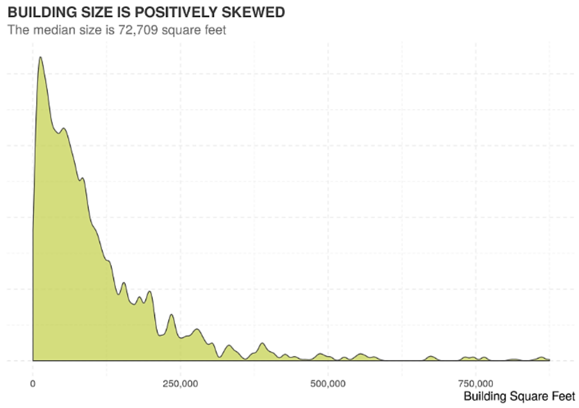

Figure 14. Skewed data distribution

We can see that electricity was the most often read, with a record of almost 12m, while hot water had a record of 1.26m (Figure 15).

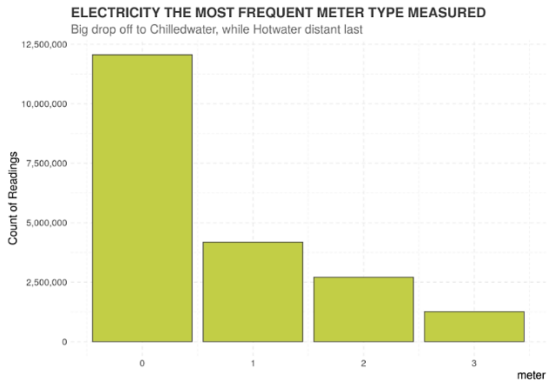

Figure 15. Histogram of the amount of data for each type of meter

The year built variable has 12,127,645 missing records. These years are depicted below. 11 of the 16 distinct types of service buildings had no year built at all, while 11 of the 16 different types were missing by more than half (Figure 16). With 55 structures completed, 1976 was the most often constructed year in recorded history (Figure 17). The floor count variable has 16,709,167 missing records. 1094 of the 1449 distinct building IDs do not have a floor count. This number indicates that there aren't many buildings with more than ten levels, whereas the average number of floors is three (Figure 18).

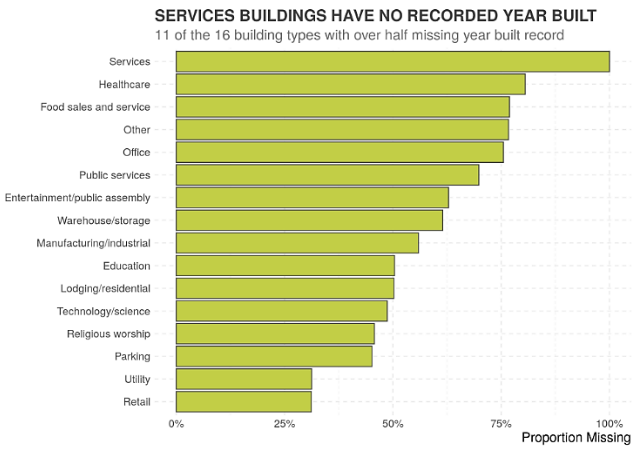

Figure 16. Services building have no recorded year built

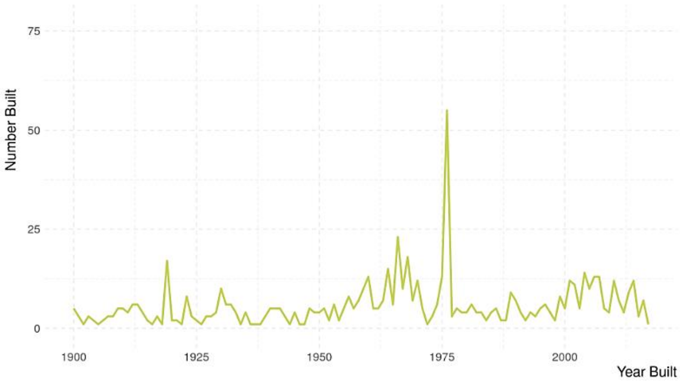

Figure 17. The number of buildings built each year

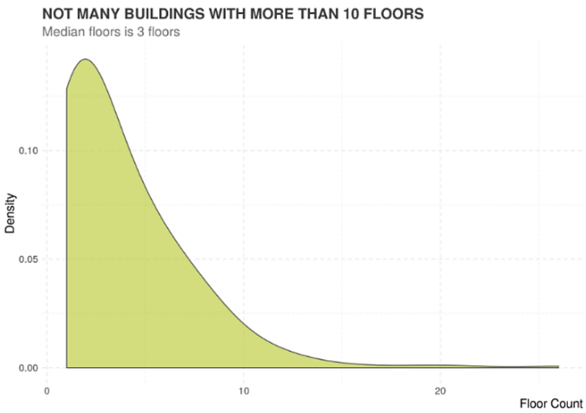

Figure 18. Density number of floors

Air Temperature. There are 96,658 missing air_temperature records in our combined training set, however as helpfully pointed out by PC Jimmy in the comments section, there are only 55 missing air temp records in the weather_train data set. I will create a function to fill these missing values.

Filling these missing values will not be a simple mean/median imputation, but rather a two step process:

a. Take the air_temperature value for the last timestamp as the next timestamps value
b. If the previous timestamp is also NA, then take the average of that day's temperature for that particular site_id

Following this process results in no further NAs in the air temperature variable.

Conveniently, the function can also be applied to dew temperature.

Plotting the variable shows the variable to be fairly normally distributed, with the majority of recordings being between ~13 and 25 degrees (Figure 19). Dew Temperature, in our combined training set, there are over 100,000 missing dew temperature data. The function created above can be applied to fill these missing values (Figure 20).

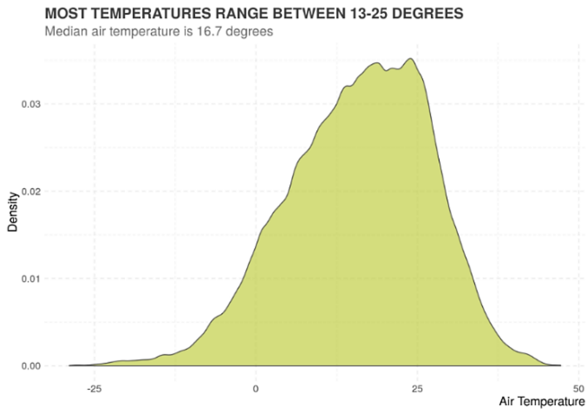

Figure 19. Air temperature density

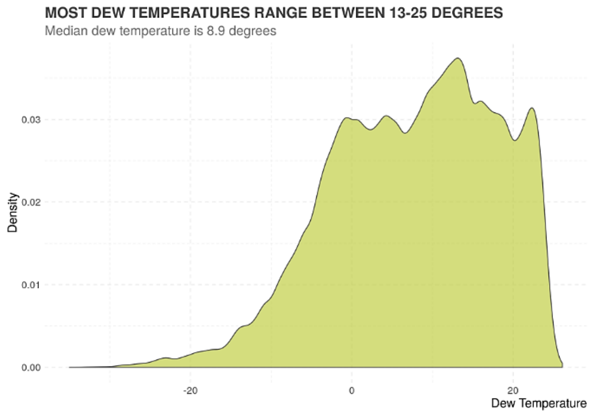

Figure 20. Dew temperature density

III. CONCLUSION

Energy efficiency must be the ultimate objective in order to achieve sustainable development goals. Because of the differences in height based on location and time, the management of energy consumption looks to be quite difficult. The study's conclusions are based on relevant data analysis, which demonstrates that various factors must be addressed for the management of energy management in a building in order to make it more efficient. The experiment's findings can be summed up as follows:

a. According to the meter reading, steam has the largest consumption, while electricity has the lowest.
b. Utility is highest before 5 a.m., followed by healthcare with daytime utilization hours after 10 a.m., depending on region.
c. The industry will need more energy during working days.
d. On weekends, places of worship consume more energy.
e. Between the months of May and October, there is a considerable association between the number of storeys and the space of each level of the building and high meter readings.
f. There is a substantial association between the kind of building used for school and offices and high energy meter consumption.

Generating wiser and more knowledgeable decisions can be aided by the insights obtained from the EDA process. While improving productivity and process efficiency might present challenges and opportunities, doing so ultimately benefits the organisation. In the future, these insights will be used to sophisticated data analytics modeling of energy consumption and resource usage in data centers for energy efficiency management.

AUTHOR CONTRIBUTION

Conceptualization Rudy Yulianto. and Meika Syahbana Rusli.; methodology, Sukardi and Faqihudin.; software, Adhitio Satyo Bayangkari Karno. and Widi Hastomo; writing-original draft, Rudy Yulianto.; visualization, Nia Yuningsih. and Nada Kamilia.

REFERENCES

[1] D. Kolokotsa, D. Rovas, E. Kosmatopoulos, and K. Kalaitzakis, "A roadmap towards intelligent net zero- and positive-energy buildings," *Sol. Energy*, vol. 85, no. 12, pp. 3067–3084, 2011, doi: https://doi.org/10.1016/j.solener.2010.09.001.

[2] Y. Lu, S. Wang, Y. Zhao, and C. Yan, "Renewable energy system optimization of low/zero energy buildings using single-objective and multi-objective optimization methods," *Energy Build.*, vol. 89, pp. 61–75, 2015, doi: https://doi.org/10.1016/j.enbuild.2014.12.032.

[3] K. Kashyap, U. Iyer-Raniga, and M. M. Andamon, "Highlighting the Design and Performance Gaps: Case Studies of University Buildings," in *Nearly Zero Energy Building (NZEB)*, D. Bienvenido-Huertas, Ed. Rijeka: IntechOpen, 2022. doi: 10.5772/intechopen.102779.

[4] A. Haning and M. Anda, "The Post Carbon City and Smart Metering," in *Smart Metering Technology and Services*, M. Eissa, Ed. Rijeka: IntechOpen, 2016. doi: 10.5772/64082.

[5] M. Anda and J. Temmen, "Smart metering for residential energy efficiency: The use of community based social marketing for behavioural change and smart grid introduction," *Renew. Energy*, vol. 67, pp. 119–127, 2014, doi: https://doi.org/10.1016/j.renene.2013.11.020.

[6] K. Sharma and L. Mohan Saini, "Performance analysis of smart metering for smart grid: An overview," *Renew. Sustain. Energy Rev.*, vol. 49, pp. 720–735, 2015, doi: https://doi.org/10.1016/j.rser.2015.04.170.

[7] M. Anda, M. Brueckner, and Y. Haigh, "Transitions to a Post-carbon Society: Scenarios for Western Australia," in *Renewable Energy in the Service of Mankind Vol II: Selected Topics from the World Renewable Energy Congress WREC 2014*, A. Sayigh, Ed. Cham: Springer International Publishing, 2016, pp. 147–162. doi: 10.1007/978-3-319-18215-5_13.

[8] A. V Novo, J. R. Bayon, D. Castro-Fresno, and J. Rodriguez-Hernandez, "Review of seasonal heat storage in large basins: Water tanks and gravel–water pits," *Appl. Energy*, vol. 87, no. 2, pp. 390–397, 2010, doi: https://doi.org/10.1016/j.apenergy.2009.06.033.

[9] F. M. Rad and A. S. Fung, "Solar community heating and cooling system with borehole thermal energy storage – Review of systems," *Renew. Sustain. Energy Rev.*, vol. 60, pp. 1550–1561, 2016, doi: https://doi.org/10.1016/j.rser.2016.03.025.

[10] L. E. Juanicó, "Holistic and Affordable Approach to Supporting the Sustainability of Family Houses in Cold Climates by Using Many Vacuum-Tube Solar Collectors and Small Water Tank to Provide the Sanitary Hot Water, Space Heating, Greenhouse, and Swimming Poole Heating De," in *Nearly Zero Energy Building (NZEB)*, D. Bienvenido-Huertas, Ed. Rijeka: IntechOpen, 2022. doi: 10.5772/intechopen.103110.

[11] M. Amin, *Power Electronics Platforms for Grid-Tied Smart Buildings.* Smart Metering Technology and Services-Inspirations for Energy Utilities., 2016.

[12] Sivagami, A., & Kandavalli, M. A., and B. Yakkala, *Design and Evaluation of an Automated Monitoring and Control System for Greenhouse Crop Production. In Next-Generation Greenhouses for Food Security*. IntechOpen, 2021.

[13] A. Goodfellow, I., Bengio, Y., & Courville, *Deep learning*. MIT press, 2016.

[14] Y. Bengio, A. Courville, and P. Vincent, "Representation Learning: A Review and New Perspectives," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1798–1828, 2013, doi: 10.1109/TPAMI.2013.50.

[15] Y. Ji, X. Zhang, S. Ji, X. Luo, and T. Wang, "Model-Reuse Attacks on Deep Learning Systems," in *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, 2018, pp. 349–363. doi: 10.1145/3243734.3243757.

[16] R. Olu-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, and S. Ajayi, "Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques," *J. Build. Eng.*, vol. 45, p. 103406, 2022, doi: https://doi.org/10.1016/j.jobe.2021.103406.

[17] H. Olu-Ajayi, R., & Alaka, "Building energy consumption prediction using deep learning," *Environ. Des. Manag. Conf.*, vol. 202, p. 1, 2021.

[18] F. Liu, C. Liang, and Q. He, "Remote Malfunctional Smart Meter Detection in Edge Computing Environment," *IEEE Access*, vol. 8, pp. 67436–67443, 2020, doi: 10.1109/ACCESS.2020.2985725.

[19] Y. Wei *et al.*, "A review of data-driven approaches for prediction and classification of building energy consumption," *Renew. Sustain. Energy Rev.*, vol. 82, pp. 1027–1047, 2018, doi: https://doi.org/10.1016/j.rser.2017.09.108.

[20] K. Amasyali and N. M. El-Gohary, "A review of data-driven building energy consumption prediction studies," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1192–1205, 2018, doi: https://doi.org/10.1016/j.rser.2017.04.095.

[21] A. Azeem, I. Ismail, S. M. Jameel, and V. R. Harindran, "Electrical Load Forecasting Models for Different Generation Modalities: A Review," *IEEE Access*, vol. 9, pp. 142239–142263, 2021, doi: 10.1109/ACCESS.2021.3120731.

[22] E. S. Karno, A. S. B., Arif, D., Wardhana, I. S. K., & Moreta, "Deteksi Covid-19 Image Chest X-Ray Dengan Convolution Neural Network Efficient Net-B7," *Pros. SeNTIK*, vol. 5, no. 1, pp. 23–28, 2021.

[23] W. Hastomo, A. S. Bayangkari Karno, N. Kalbuana, A. Meiriki, and Sutarno, "Characteristic Parameters of Epoch Deep Learning to Predict Covid-19 Data in Indonesia," *J. Phys. Conf. Ser.*, vol. 1933, no. 1, 2021, doi: 10.1088/1742-6596/1933/1/012050.

[24] L. Hastomo, Widi Karno, Adhitio Satyo Bayangkari Kalbuana, Nawang Nisfiani, Ervina ETP, "Optimasi Deep Learning untuk Prediksi Saham di Masa Pandemi Covid-19," *JEPIN (Jurnal Edukasi dan Penelit. Inform.*, vol. 7, no. 2, pp. 133–140, 2021, [Online]. Available: https://jurnal.untan.ac.id/index.php/jepin/article/view/47411

[25] E. S. Hastomo, W., Karno, A. S. B., Sudjiran, S., Arif, D., & Moreta, "Exploratory Data Analysis Untuk Analisa Data Belanja Pelanggan dan Pendapatan Bisnis Retail Fashion Dengan Bahasa Python," *Infotekmesin*, vol. 13, no. 2, 2022, [Online]. Available: https://www.ejournal.pnc.ac.id/index.php/infotekmesin/article/view/1319