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Smart Home Energy Optimizer Utilizing Convolutional Neural Networks to Predict and Optimize Energy Usage in Intelligent Homes

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Abstract:

understanding energy consumption patterns is pivotal not only for Smart homes, equipped with advanced sensors and automation systems, offer significant potential for optimizing energy consumption and enhancing user comfort. In this study, we investigate the intricate relationship between weather patterns and energy consumption in smart homes. The dataset comprises 4.5 months of detailed information, including temperature and humidity data collected through ZigBee wireless sensor networks, as well as energy consumption records obtained from m-bus energy meters. Additionally, weather data from the nearby Chievres Airport in Belgium has been integrated with the experimental data, allowing us to analyse how external environmental factors impact energy usage within the home. In conventional energy management systems, energy consumption patterns are often based on historical data and predefined schedules, lacking the adaptability required to respond to changing weather conditions. This rigidity can lead to inefficient energy use, increased costs, and decreased environmental sustainability. Furthermore, these systems tend to overlook the dynamic nature of energy demand, which can be influenced by varying weather conditions. Therefore, there is a need for a more sophisticated approach that leverages advanced analytics to harness the relationship between weather patterns and energy consumption for improved efficiency. Our proposed system addresses the limitations of conventional energy management systems by utilizing regression analysis techniques to model the relationship between weather parameters and energy consumption in smart homes. Through the integration of the extensive dataset, we aim to develop predictive models that can forecast energy demand-based weather conditions. This approach will enable smart homes to dynamically adjust heating, cooling, and other energy- intensive systems in response to weather changes, ultimately optimizing energy usage and reducing costs. By exploring this novel machine learning methodology, we seek to contribute to the development of more energy-efficient and environmentally friendly smart home solutions, paving the way for a sustainable future in residential energy management..

***Keywords: Smart Homes, Energy Consumption, Weather Patterns, Sensors, Automation Systems, ZigBee Wireless Sensor Networks, m-bus energy meters, Adaptive Energy Management, Regression Analysis, Predictive Models, Machine Learning*.**

1.INTRODUCTION

The intersection of technology and sustainability has paved the way for innovations in smart home systems, revolutionizing the way we interact with our living spaces. In this era of smart homes,

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homeowners seeking efficient energy management but also for energy providers and policymakers striving for sustainable practices. The concept of smart homes has evolved significantly with the advent of the Internet of Things (IoT) and artificial intelligence. Today, smart homes are equipped with an array of sensors and devices that collect vast amounts of data, including temperature, humidity, occupancy, and energy usage.

Smart meters are used to accurately record the amount of electricity consumption at a very high frequency, dramatically changing the collection of electricity data and driving the household energy transition [1]. High frequency interval meter data, typically hourly and 15 min, provides important and rich information about household consumption patterns. Smart meter data can be used to cluster, classify, predict, and optimize electricity consumption patterns through a series of analytical methods and techniques [2]. The popularity of smart meters has grown rapidly over the past decade, from <2.5 million smart meters deployed globally in 2007 to ~729.1 million in 2019, an increase of 294 times, with the United States and China accounting for the highest percentage, 85.4% [3]. Smart meters provide utilities with detailed information and enable effective demand side management. Two-way AMI meters, which allow communication capability between electric utilities and customers, have been more prevalent after 2013 [4]. By providing real-time or near real-time electricity data, it supports smart consumption applications based on customer preferences and demand.

This data presents an unprecedented opportunity to analyse and understand the factors influencing energy consumption, particularly the impact of weather patterns. Weather variables such as temperature and humidity have long been known to affect energy demand, but the complexity of these interactions demands sophisticated data analysis methods. Traditional methods often fall short in capturing the nuanced relationships, necessitating the use of machine learning algorithms for precise predictions. This project delves deep into the intricate relationship between weather patterns and energy usage in smart homes.

2. LITERATURE SURVEY

High-frequency electricity data helps understand the electricity consumption patterns in different consumer groups at various time periods, and the changes in behaviours after the adoption of new technologies and demand-side management measures. Further, high- frequency data increases the accuracy of energy consumption forecasts due to the larger variation provided by the data. Applying high frequency electricity data during pandemic times, studies have analysed and examined the overall impact of COVID-19 on energy consumption and transition in pre- and post-pandemic. The world has seen a shift in people's habits and daily activities due to the pandemic. Therefore, electricity consumption patterns in both residential and commercial buildings have changed. Ku et al. [5] used individual hourly power consumption data within a machine learning framework to examine changes in electricity use patterns due to COVID-19 mandates in Arizona. Chinthavali et al. [6] examined changes in energy use patterns on weekdays and weekends before and after the COVID-19 pandemic. Raman and Peng [7] used residential electricity consumption data to reveal a strong positive correlation between pandemic progress and residential electricity consumption in Singapore. Li et al. analysed data from apartments in New York to examine the impact of the number of COVID-19 cases and the outdoor temperature on residential electricity usage [8].

Lou et al. found that the COVID-19 measures increased residential electricity consumption by 4– 5% and exacerbated energy insecurity using individual smart meter data from Arizona and Illinois [9]. Sánchez-López et al. explored the evolution of energy demands with hourly data among residential, commercial, and industrial demand during the first wave of COVID-19 [10]. Understanding how household hourly electricity demand changes after the pandemic, especially due to working from home, provides electricity system operators with valuable information in operation and management. Also, based on the changes in the spatial and temporal distributions of energy consumption, policymakers could make better decisions to increase the ratio of power supply from renewable energy sources.

The application of high frequency electricity data could help understand the electricity consumption patterns of specific consumer groups, especially families that have adopted new technologies [e.g., Photovoltaics (PV), batteries, and electric Vehicles (EV)]. Qiu et al. [11] applied a difference-in-differences approach to 1600 EV households' high frequency smart meter data and found that people increased EV charging in lower-priced off-peak hours

Al Khafaf et al. [12] compared the electricity consumption of consumers with PV and energy storage systems (ESS) against consumers without ESS using over 5,000 energy consumers' 30- min window smart meters recording. They found that on extremely hot days, installing batteries, to some extent, reduces peak power usage in the afternoon. Using household hourly electricity data in Arizona, in [13] Qiu et al. (2022b) found a high degree of heterogeneity in consumption patterns of PV consumers after adding battery storage. As to heat pump adoption, Liang et al. (2022a) provided empirical evidence from Arizona which suggested that heat pumps do not necessarily save energy [14]. Besides, combining electric vehicle charging profiles with residential electricity data helps study the impact of EVs on electricity distribution networks [15]. These patterns not only help residents explore the economic benefits of new technologies adoptions, but also answer whether and how those new technologies adoption has an impact on existing electric grid's capacity.

Forecast analysis relies on the data they're trained on, and high frequency smart meter data boosts the accuracy of the prediction model. High-resolution forecasting models with various data- driven algorithms need to be validated from high frequency data. Popularization of smart meters in recent years has created opportunities for improving household load forecasting. Accurate electricity load forecasting provides scientific theoretical support for the smart grid, like demand response, energy management, and infrastructure planning and investment.

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Sousa and Bernardo [16] compared the accuracy of multivariate adaptive regression splines, random forests, and artificial neural networks to predict the load of the next day with 5,567 households' half-hourly readings. Shaukat et al. [17] carried out short-term load forecasting by different models, such as artificial neural networks. Lin et al. [18] combined smart meters, telephone surveys, demographic information, and physical attributes of 83 houses in Oshawa; and identified that the backpropagation neural network model is the best in predicting the annual electricity and gas consumption among eight data-driven algorithms. Fekri et al. [19] proposed a load forecasting method that can continuously learn from new data and adapt to new patterns to test for load forecasting. Singh and Yassine [20] proposed unsupervised data clustering and frequent pattern mining analysis on three datasets, then did forecasting with Bayesian network and achieved energy consumption forecast accuracies of 81.89%. The data resolution of the high-frequency smart meter reached 6 s and 1 min, respectively.

3. PROPOSED METHODOLOGY

This research explores the intricate relationship between weather patterns and energy consumption in smart homes, employing sophisticated data analysis techniques and machine learning algorithms. In this endeavour, this work analyses a dataset containing information about weather variables such as temperature, humidity, and precipitation, alongside energy consumption data from smart homes.

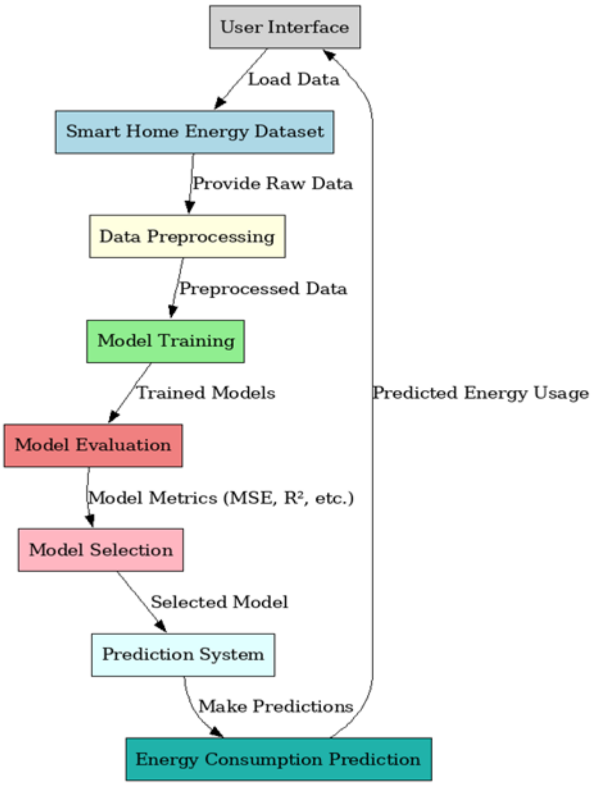

Figure 1: Proposed methodology of ML based energy consumption prediction in smart homes

The primary objective is to discern patterns and correlations within this data to understand how weather conditions impact energy usage.

- Data Analysis and Pre-processing: This initiates with data pre-processing, addressing missing values and ensuring data integrity. Basic statistical analyses and visualization tools are employed to gain a comprehensive understanding of the dataset. Exploratory data analysis techniques are utilized to visualize trends, histograms, and correlations among variables, providing valuable insights into the data's structure.
- Machine Learning Models: To uncover the intricate relationships hidden within the data, advanced machine learning models are implemented. The project employs

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two primary regression algorithms: Decision Tree Regressor and CNN Regressor. These algorithms are trained on the pre-processed data, utilizing historical weather and energy consumption patterns to make predictions. Decision trees offer interpretable insights into feature importance, while CNN s leverage multiple decision trees for enhanced accuracy and robustness.

- Analysis and Interpretation: The models' predictions are rigorously analysed, evaluating their accuracy and effectiveness in forecasting energy consumption based on weather patterns. Key performance metrics, such as R-squared scores, are calculated to quantify the models' predictive power. These metrics offer crucial insights into the models' ability to capture the complexities of energy usage dynamics in response to changing weather conditions.
- Significance and Implications: The findings have profound implications for various stakeholders. Homeowners can optimize their energy usage, reducing costs and environmental impact. Energy providers can enhance their demand forecasting, ensuring a stable energy supply. Policymakers gain valuable insights for crafting sustainable energy policies, aligning urban planning with energy efficiency goals. Moreover, the project showcases the potential of machine learning in addressing real-world challenges, underlining its significance in the realm of energy management and sustainability.
- Future Directions: Looking forward, this work lays the foundation for future research avenues. Refining machine learning models, integrating real-time data, exploring regional variations, and diversifying applications across sectors are promising directions. These advancements hold the potential to create even more accurate, responsive, and adaptable energy management systems, ushering in a future of sustainable and efficient energy usage.

Applications:

The Smart Home Energy Optimizer, powered by Convolutional Neural Networks (CNNs), has a broad range of applications, including:

- Smart Home Automation: Enhances energy efficiency by dynamically adjusting power consumption based on real- time weather conditions and usage patterns.
- Energy Management Systems: Helps homeowners and businesses optimize energy use by predicting peak consumption hours and adjusting device operations accordingly.
- Renewable Energy Integration: Assists in balancing energy consumption with renewable sources like solar and wind power by predicting energy demand fluctuations.
- Demand-Side Management: Provides utilities with insights into household energy consumption patterns, enabling demand-response programs and peak load reductions.
- Sustainability and Green Buildings: Supports the development of energy-efficient buildings by minimizing wasteful energy usage and reducing the overall carbon footprint.
- Smart Grid Optimization: Aids in balancing energy distribution in smart grids by forecasting household energy demand and adjusting supply accordingly.
- Industrial and Commercial Energy Efficiency: Can be applied in offices and industries to predict and optimize energy usage for HVAC systems, lighting, and machinery.

Advantages:

The Smart Home Energy Optimizer leverages Convolutional Neural Networks (CNNs) to predict and optimize energy consumption in intelligent homes. This deep learning approach provides several advantages over traditional methods, making it a highly effective solution for modern energy management:

- Optimized Energy Consumption: CNN-based predictions enable smart homes to dynamically adjust energy-intensive systems like heating, cooling, and lighting.
- Cost Savings: By optimizing energy consumption, homeowners can significantly lower electricity bills.
- Improved Forecasting Accuracy: CNNs outperform traditional statistical models by capturing complex, non- linear relationships between weather conditions and energy consumption.
- Automated Feature Extraction: Traditional machine learning models require manual feature engineering, where experts must define the most relevant input variables. CNNs automate this process, learning the most important energy consumption patterns without human intervention.
- High Accuracy: CNNs use multiple layers of neurons to extract meaningful patterns from raw data, leading to higher prediction accuracy.

- Robust to Variations: CNNs are highly resilient to variations in energy usage, which may be caused by changes in weather, occupant behaviour, or household appliances.
- Real-Time Control: The system can provide instantaneous recommendations based on CNN predictions, enabling smart appliances to react in real time. This ensures efficient energy distribution and avoids power wastage in fluctuating conditions.
- Scalability: CNNs efficiently process large datasets from multiple smart homes, making them suitable for city-wide energy optimization. The model can be extended to industrial and commercial buildings, further improving energy efficiency at a large scale.
- Environmental Benefits: Reducing unnecessary energy consumption helps lower carbon footprints and supports sustainability initiatives..
- User-Friendly Interface: It can be integrated with mobile apps and smart assistants, making energy management accessible and convenient.

4. EXPERIMENTAL ANALYSIS

Figure 2 displays a portion of the dataset used for predicting energy consumption in smart homes. It shows various features (columns) and their corresponding values. Figure 3 shows a histogram plot of the 'total load forecast' column. It provides insights into the distribution of total load forecasts in the dataset. Figure 4 displays a heatmap that visualizes the correlation between different features in the dataset. It helps to identify relationships and dependencies between variables. Figure 5 shows a scatter plot with a regression line. It visualizes the relationship between predicted and actual values generated by a Decision Tree Regressor model. This helps assess the model's performance.

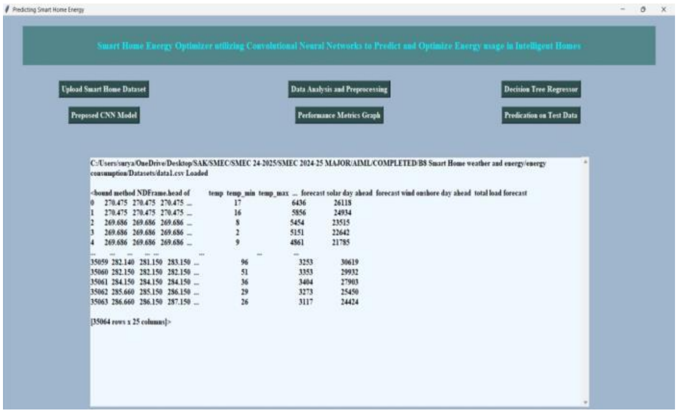

Figure 2: Upload of Energy Consumption Dataset Smart Homes GUI

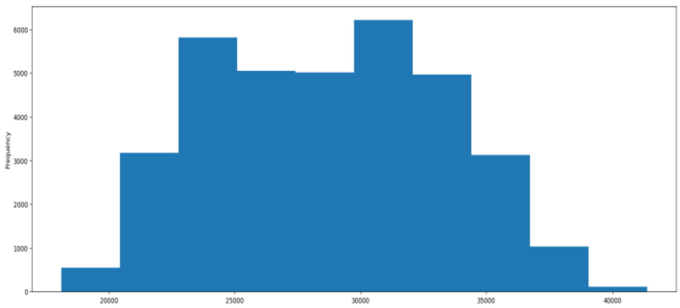

Figure 3: Histogram of 'total load forecast' column

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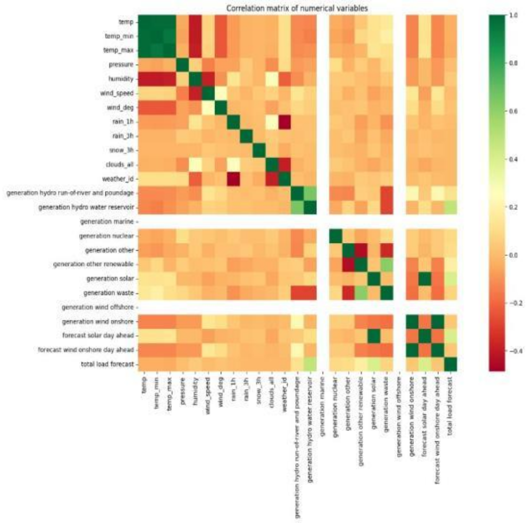

Figure 4: Heatmap of correlation of features of a dataset

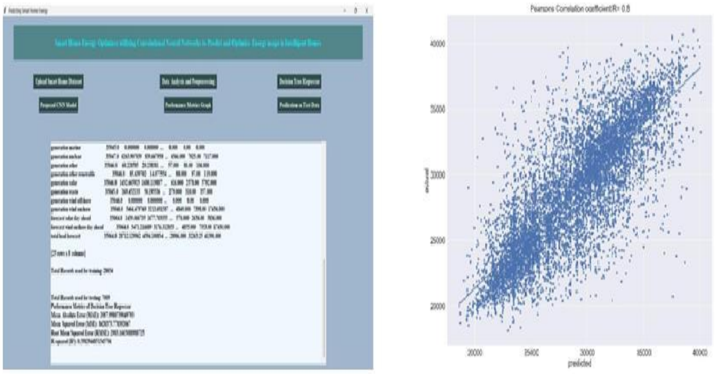

Figure 5: Scatter plot with a regression line to visualize the relationship between predicted and actual values of Decision Tree Regressor.

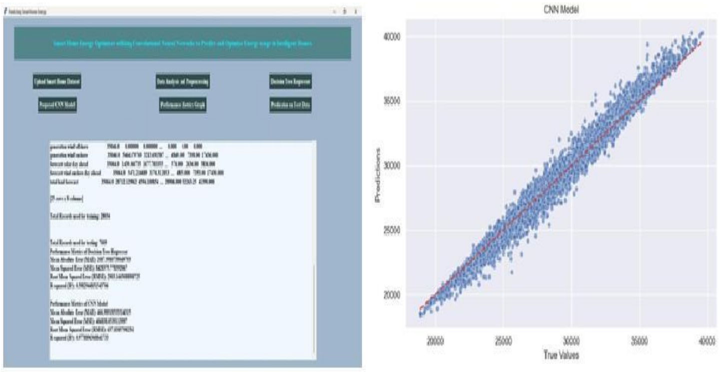

Figure 6: Scatter plot with a regression line to visualize the relationship between predicted and actual values of CNN

Figure 6 is similar to Figure 5, this figure displays a scatter plot with a regression line, but for a CNN model. It serves the same purpose of evaluating the model's performance. In summary, the CNN exhibited significantly better performance (as indicated by the higher R-squared score) in predicting energy consumption based on weather patterns when compared to the DTR in this particular analysis.

R-Squared (R^2) Score:

- The r2_score function calculates the R-Squared (R^2) Score, which is a widely used metric to measure the performance of a regression model.
- It compares the predicted values with the actual values and determines how well the independent variables explain the variability of the dependent variable.
- The result is a numerical value between -∞ and 1, where 1 indicates a perfect fit, 0 means the model performs as well as the mean of the data, and negative values suggest poor predictions that are worse than a simple average guess.

5. CONCLUSION

In conclusion, this research has successfully delved into the intricate relationship between weather patterns and energy consumption in smart homes, employing advanced regression analysis and machine learning techniques. Through meticulous data analysis, meaningful patterns have been extracted, shedding light on the impact of weather variables such as temperature, humidity, and precipitation on energy load. The developed regression models, particularly the decision tree and CNN algorithms, have showcased promising accuracy in predicting energy consumption under varying weather conditions. These findings hold substantial implications for homeowners, energy providers, and policymakers alike. For homeowners, this study provides actionable insights into optimizing energy usage based on weather forecasts. By understanding how weather influences energy consumption, homeowners can implement targeted strategies to reduce costs and enhance efficiency. Energy providers can benefit from these insights by improving demand forecasting and management, ensuring a stable and efficient energy supply. Policymakers can integrate these findings into energy policies, fostering sustainable practices and guiding urban planning initiatives. Furthermore, this work demonstrates the power of data analytics and machine learning in addressing real-world challenges, showcasing their potential in the realm of energy management and sustainability.

This analysis opens doors to several future avenues of research and application. Firstly, further refinement of machine learning models can enhance prediction accuracy. Exploring advanced algorithms such as deep learning neural networks might yield even more precise results, especially when dealing with vast and complex datasets from smart homes. Additionally, the integration of real-time data from IoT devices can transform these predictive models into dynamic systems. By incorporating live weather data and real-time energy consumption statistics, the models can adapt and provide instant recommendations, creating truly responsive and adaptive smart home environments.

REFERENCES

[1] U.S. Energy Information Administration (EIA) (2023). Available online at: https://www.eia.gov/index.php (accessed September 26, 2023)

[2] Ku, A. L., Qiu, Y., Lou, J., Nock, D., and Xing, B. (2022). Changes in hourly electricity consumption under COVID mandates: a glance to future hourly residential power consumption pattern with remote work in Arizona. Appl. Energy 310:118539. doi: 10.1016/j.apenergy.2022.118539

[3] Chinthavali, S., Tansakul, V., Lee, S., Whitehead, M., Tabassum, A., Bhandari, M., et al. (2022). COVID-19 pandemic ramifications on residential smart homes energy use load profiles. Energy Build. 259:111847. doi: 10.1016/j.enbuild.2022.111847

[4] Sánchez-López, M., Moreno, R., Alvarado, D., Suazo- Martínez, C., Negrete-Pincetic, M., Olivares, D., et al. (2022). The diverse impacts of COVID-19 on electricity demand: the case of Chile. Int. J. Electr. Power Energy Syst. 138:107883. doi: 10.1016/j.ijepes.2021.107883

[5] Al Khafaf, N., Rezaei, A. A., Moradi Amani, A., Jalili, M., McGrath, B., Meegahapola, L., et al. (2022). Impact of battery storage on residential energy consumption: an Australian case study based on smart meter data. Renew. Energy 182, 390–400. doi: 10.1016/j.renene.2021.10.005

[6] Qiu, Y. L., Wang, Y. D., Iseki, H., Shen, X., Xing, B., and Zhang, H. (2022a). Empirical grid impact of in-home electric vehicle charging differs from predictions. Resour. Energy Econ. 67:101275. doi: 10.1016/j.reseneeco.2021.101275

[7] Qiu, Y., Xing, B., Patwardhan, A., Hultman, N., and Zhang, H. (2022b). Heterogeneous changes in electricity consumption patterns of residential distributed solar consumers due to battery storage adoption. iScience 25:104352. doi: 10.1016/j.isci.2022.104352

[8] Liang, J., Qiu, Y., and Xing, B. (2022a). Impacts of

electric-driven heat pumps on residential electricity consumption: an empirical analysis from Arizona, USA. Clean. Responsible Consum. 4:100045. doi: 10.1016/j.clrc.2021.100045

[9] Liang, J., Qiu, Y., and Xing, B. (2022b). Impacts of the co-adoption of electric vehicles and solar panel systems: empirical evidence of changes in electricity demand and consumer behaviours from household smart meter data. Energy Econ. 112:106170. doi: 10.1016/j.eneco.2022.106170

[10]] Sousa, J. C., and Bernardo, H. (2022). Benchmarking of load forecasting methods using residential smart meter data. Appl. Sci. 12:9844. doi: 10.3390/app12199844

[11] Lin, Y., Liu, J., Gabriel, K., Yang, W., and Li, C.-Q. (2022). Data-driven based prediction of the energy consumption of residential buildings in Oshawa. Buildings 12:2039. doi: 10.3390/buildings12112039

[12] Sovacool, B. K., Hook, A., Sareen, S., and Geels, F. W. (2021). Global sustainability, innovation and governance dynamics of national smart electricity meter transitions. Glob.Environ. Change 68:102272.doi:10.1016/j.gloenvcha.2021.102272

[13] Raman, G., and Peng, J. C.-H. (2021). Electricity consumption of Singaporean households reveals proactive community response to COVID-19 progression. Proc. Natl. Acad. Sci. 118:e2026596118. doi: 10.1073/pnas.2026596118

[14] Li, L., Meinrenken, C. J., Modi, V., and Culligan, P. J. (2021). Impacts of COVID-19 related stay-at-home restrictions on residential electricity use and implications for future grid stability. Energy Build. 251:111330. doi: 10.1016/j.enbuild.2021.111330

[15] Lou, J., Qiu, Y., Ku, A. L., Nock, D., and Xing, B. (2021). Inequitable and heterogeneous impacts on electricity consumption from COVID-19 mitigation measures. iScience 24:103231. doi: 10.1016/j.isci.2021.103231

[16] Shaukat, M. A., Shaukat, H. R., Qadir, Z., Munawar, H. S., Kouzani, A. Z., and Mahmud,M. A. P. (2021). Cluster analysis and model comparison using smart meter data. Sensors 21:3157. doi: 10.3390/s21093157

[17] Fekri, M. N., Patel, H., Grolinger, K., and Sharma, V. (2021). Deep learning for load forecasting with smart meter data: online adaptive recurrent neural network. Appl.Energy,282:116177doi:10.1016/j.apenergy.2020.116177

[18] Ribeiro Serrenh, T, and Bertoldi, P. (2019). Smart Home and Appliances: State of the art.Luxembourg: Publications Office of the European Union. doi: 10.2760/453301

[19] Singh, S., and Yassine, A. (2018). Big data mining of energy time series for behavioural analytics and energy consumption forecasting. Energies 11:452. doi: 10.3390/en11020452

[20] Yildiz, B., Bilbao, J. I., Dore, J., and Sproul, A. B. (2017). Recent advances in the analysis of residential electricity consumption and applications of smart meter data. Appl. Energy 208, 402–427. doi: 10.1016/j.apenergy.2017.10.014