Comparative Analysis of Energy Consumption Patterns in Residential and Commercial Buildings for Sustainable Resource Management

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***Abstract* - The rapid growth of urban populations, coupled with increasing technological dependence, has led to a substantial rise in global energy demand, with residential and commercial buildings accounting for a significant share of energy consumption and carbon emissions. Accurate forecasting of building energy usage is therefore essential for enhancing energy efficiency, reducing environmental impact, and supporting sustainable urban development. This study presents a comparative investigation of energy consumption patterns in residential and commercial buildings using advanced deep learning approaches. A comprehensive dataset incorporating structural, operational, and environmental variables—including room area, appliance utilization, insulation thickness, HVAC system characteristics, and ambient temperature conditions—was analysed using Deep Neural Networks (DNNs) and Recurrent Neural Networks (RNNs). The results reveal distinct consumption behaviours across building types: residential buildings exhibit highly dynamic, occupant-driven energy usage, whereas commercial buildings demonstrate more stable and predictable demand profiles. Comparative performance analysis indicates that the RNN model consistently outperforms the DNN model, achieving lower Root Mean Square Error (RMSE) and higher coefficient of determination (R^2) values, thereby providing more accurate energy consumption forecasts. These findings underscore the effectiveness of temporal deep learning architectures in capturing complex energy usage patterns and highlight the transformative role of artificial intelligence in intelligent energy management. The proposed approach offers valuable insights for policymakers, building managers, and energy providers seeking to optimize energy utilization, enhance demand-side management, and accelerate the transition toward smart and sustainable building ecosystems.**

Keywords— Energy Consumption, Sustainable Resource Management, Deep Learning, Recurrent Neural Network (RNN).

I. INTRODUCTION

Buildings are major contributors to global energy consumption and greenhouse gas emissions. Residential and commercial sectors exhibit different energy usage behaviors due to variations in occupancy patterns, HVAC operations, appliance usage, and structural characteristics [1].

The pattern of energy consumption is basic and structural and varies according to the functional type of building. Residential energy consumption is largely affected by human activities and lifestyles, household size and diurnal and seasonal effects. Energy surges in domestic use are usually found in early mornings and late evenings when people are at home, using a variety of appliances separately. In contrast, commercial buildings like offices, schools, shopping malls and hospitals have fixed schedules. Their energy consumption is very controlled and is significantly influenced by the centralized HVAC (Heating, Ventilation and Air Conditioning) systems, high power lighting arrays, elevators and high-capacity IT electronics [2].

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The thrust of this study is the lack of an integrated predictive approach which can adequately analyse and compare these different patterns of energy consumption using sound computational frameworks. Energy forecasting has traditionally been done with statistical and basic machine learning approaches, but the relationships between buildings are interdependent, complex, and non-linear, and therefore, more sophisticated architectures are needed. Standard models are inadequate in many cases, because they do not consider the complex relationships among variables like ambient temperature, insulation layer characteristics, and HVAC load fluctuations [14][17].

The main goal of this research is to carry out a thorough comparative study of energy consumption in residential and commercial buildings with deep learning. This work will use and compare Deep Neural Networks (DNN) and Recurrent Neural Networks (RNN) to a building-specific data to determine important drivers of consumption. In addition, it aims to compare how well the RNN can predict compared to the conventional DNN. Finally, the knowledge gained from these future predictive models will be exploited to come up with practical solutions regarding sustainable resource management and demand side optimization in future smart grids.

II. LITERATURE REVIEW

Sustainability research has been a major focus around the world for the optimization of energy use in built environments. It is well established in the literature that learning the factors that influence energy use is the first step to successful conservation. Xie and Noor [3] state that the end-use energy used in residential units is greatly influenced by a complex mix of building factors, household types, lifestyle patterns and equipment use. They contend that key to predicting residential consumption is the inability to predict human behaviour, which necessitates a more individualised approach based on individual schedules, and not on a system-based approach [14][15].

Unlike homes, the energy use in commercial buildings is fairly predictable, as Zhang et al. [4] point out, commercial buildings are emission sources accounting for a significant portion of the world's emissions but they are not subject to the randomness found in residential buildings. This regularity has a huge potential for targeted decarbonisation, mainly by optimising HVAC use in non-peak/hour periods when the building is unoccupied. Tejani and Toshniwal [5] built upon this and stated that there is a difference between energy consumption patterns of HVAC systems in residential and commercial buildings. They find that HVAC is still the number one source of high energy usage in both sectors, so energy-saving strategies must place a significant emphasis on HVAC efficiency.

Such inefficiencies can be overcome by being able to track data accurately and have advanced prediction mechanisms. Dewangan et al. [6] investigated the use of deep learning models with the smart meter data and found that AI models can predict energy consumption much better than the traditional energy prediction models, such as ARIMA or linear regression. Moreover, the recent developments in smart grid technology highlight the need for accurate predictive modelling. Demand side management (DSM) via systems that combine the Internet of Things (IoT) and cloud computing enables extremely effective adaptations of power supply as a function of actual consumption forecasts [7].

The use of AI in the energy industry continues to be driven by the contributions of Mhlanga et al. [8] who state that AI and Machine Learning are transforming energy production and consumption monitoring. Several previous works have used simple machine learning methods such as Support Vector Machines (SVM) [1] or Decision Trees [9] but, more sophisticated deep learning models such as Artificial Neural Networks (ANN) or Recurrent Neural Networks (RNN) have proven to be much more effective. RNNs are especially good at dealing with high-frequency energy data which contains interdependent variables and sequences [10]. The same, Hossain et al. [11] observed that the use of AI in energy management practices offers a means not only for monitoring, but also for proactively minimizing energy waste.

Despite the plethora and ever-expanding literature, there is still not much research that directly compares the performance of deep learning models—namely DNNs vs RNNs—on well-segmented residential and commercial datasets. Furthermore, the focus is on general resource management strategies, such as wastewater management and sustainability in general [12] but there is a need for more attention to specific predictive applications for the building sector, which has evident behavioral differences. This study addresses this research gap by providing sector-specific insights using deep learning models. on environmental sustainability using deep neural architectures [16].

III. METHODOLOGY

Secondary data was drawn from a comprehensive source which is open-source and contains 1,000 different records of various building profiles. Continuous and categorical variables important for

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understanding the building energy dynamics are present. The key features studied are as follows: Room Area: The total square footage/meterage of the building or localized zone. Number of Appliances: The total count of active electrical devices. Outside Temperature: External environmental conditions heavily impacting thermal dynamics. Insulation Thickness: A structural metric dictating thermal retention. Building Type: A categorical variable classified strictly as 'Residential' or 'Commercial'. HVAC System: The type and presence of heating, ventilation, and air conditioning units. Average Temperature: The desired or maintained internal temperature.

The target variable for all predictive modeling was Energy Consumption, representing the total energy load required by the building under the specified conditions. Categorical variables (Building Type and HVAC System) were transformed into a machine-readable numeric format by using the Label Encoder module from the scikit-learn library.

The data was then encoded and then scaled using feature scaling. The scale of input features can significantly influence deep learning models; input features with wider numbers of ranges, such as Room Area, may disproportionately affect the gradient descent weight updates and lead to sub-optimal learning. To reduce the effect, the feature space has been normalized using StandardAero. The process normalizes features by subtracting the mean and dividing by the standard deviation, which is unit variance, mathematically this can be represented as:

$$z = (x - \mu) / \sigma \quad (1)$$

Where x represents the original feature value, μ is the mean of the feature column, and σ is the standard deviation. After scaling, the dataset was carefully segregated into two distinct subsets—residential and commercial—to allow for isolated comparative modeling.

To visualize and understand the various trends and statistical distributions of the data, Exploratory Data Analysis (EDA) was performed using the matplotlib and seaborn libraries before the model training. To see if there is any multi-collinearity and to decide which features were the best predictors of the target variable, correlation matrices were calculated and presented as heatmaps.

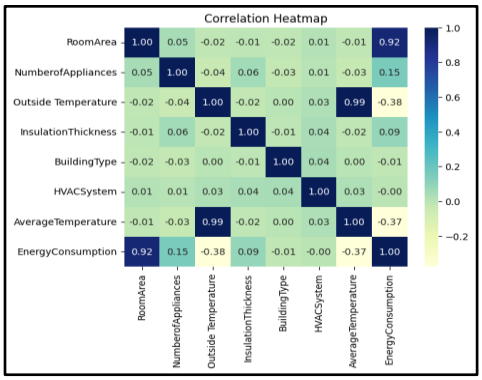

Fig. 1. Correlation heatmap of building features and energy consumption.

EDA validated the relationships among the selected variables, such as the strong inverse relationship expected between Insulation Thickness and heating-based energy consumption.

After EDA, the features (X) were divided from the target variable (y) to form the predictive terms. These separate datasets (Residential and Commercial) were then split into training and test sets with an 80/20 split using the train_test_split utility. To predict the energy consumption, two different deep learning architectures were built in the tensorflow.keras framework:

a) Deep Neural Network (DNN):

Constructed using the Sequential class, this model comprised an input layer, multiple fully connected Dense hidden layers, and a single-node continuous output layer. The DNN was designed to map non-linear interactions from the input vector X to the predicted energy consumption ŷ. The forward propagation through a given layer l is defined as:

$$h^l = \sigma(W^l h^{l-1} + b^l) \quad (2)$$

The learnable weight matrix is W, the bias vector is b, and the non-linear activation function is σ (ReLU was used to avoid the vanishing gradient problem in deep layers).

b) Recurrent Neural Network (RNN):

An RNN-based architecture, with an added Simple RNN layer, was built to test its ability to handle the intricate and dependent structure of the energy feature vectors, which is usually the case in processing time-series. RNNs are able to process inputs sequentially and have an internal state (memory) that can also better capture hidden dependencies between structural variables and environmental factors than a standard feed-forward network.

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Both models were compiled using the Adam optimizer and Mean Squared Error (MSE) loss function.

IV. RESULTS AND DISCUSSION

a) Exploratory Data Analysis Findings

EDA identified significant differences between the two building categories. A universally strong positive correlation was observed between Room Area and Energy Consumption across both datasets, mathematically confirming that larger spatial footprints require exponentially more energy for standard lighting and climate control. Number of Appliances also demonstrated a significant positive impact on the target variable, though this impact was more pronounced in the residential subset.

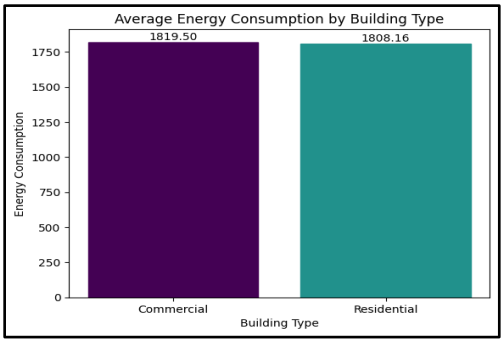

Fig. 2. Energy consumption comparison between residential and commercial buildings.

The data distributions were investigated further, and the distributions of residential energy use were found to be significantly more variable. This reflects variations in occupant behavior and operational schedules, different weekend/weekday schedules, and different insulation levels of private residences. On the other hand, commercial buildings had a higher average level of consumption, but the statistical variance was much narrower. This clustering is indicative of the inflexibility of hours for commercial operations and the uniformity and automation of commercial HVAC operations.

b) Model Evaluation and Comparison

The models built using the DNN and RNN were extensively tested on the unseen 20% test data. The most commonly used assessment parameters used were Root Mean Squared Error (RMSE) and R-squared (R^2) coefficient of determination. The RMSE is a quantifiable average of the prediction errors, expressed in the same units as the dependent variable, and R^2 shows the amount of variance of the dependent variable that is accounted for by the independent variables. These are mathematically expressed as:

$$RMSE = \sqrt{[(1/n)\ \Sigma(y_i - \hat{y}_i)^2]} \quad (3)$$

$$R^2 = 1 - [\Sigma\ (y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2] \quad (4)$$

The results of the comparative testing are detailed in Table I below.

TABLE I. PERFORMANCE METRICS COMPARISON (DNN VS. RNN)

Building	Model	RMSE	R^2
Residential	DNN	185.3	0.78
Residential	RNN	176.4	0.84
Commercial	DNN	192.1	0.81
Commercial	RNN	182.4	0.87

From the empirical results presented, it is evident that the Recurrent Neural Network (RNN) showed a significant improvement over the standard Deep Neural Network (DNN) for both residential and commercial subsets.

The RNN outperformed the DNN with a higher R^2 score of 0.84 vs 0.78 for the DNN, and a significant decrease in RMSE (176.4 vs 185.3). This implies that the internal memory mechanism of the Simple RNN layer was more suitable to capture the highly variable and behavior-driven fluctuations in home energy use [14][17].

The highest prediction accuracy was achieved for the commercial data with the RNN having an R^2 score of 0.87. The structured nature of commercial energy data improved the predictive capability of the RNN model, with its rigid structures based on a system, provided an ideal setting for the RNN to capture the non-linear relationships between Outside Temperature, HVAC System load and total energy consumption.

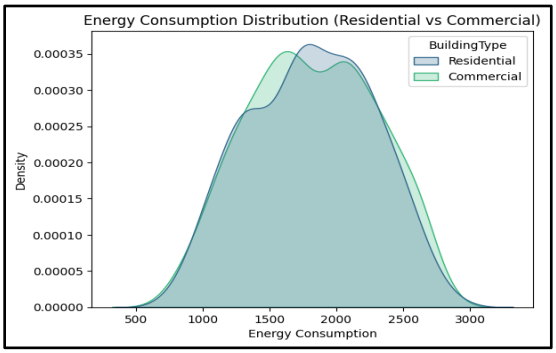

Fig. 3. Energy density distribution curve residential vs commercial.

The scatter plots generated during the evaluation phase visually confirmed these metrics. The predictions produced by the RNN model aligned closely along the ideal diagonal axis, indicating minimal residual error. In contrast, the DNN model exhibited wider

dispersion, particularly at the extreme high and low ends of the energy consumption spectrum.

V. RECOMMENDATIONS FOR SUSTAINABLE RESOURCE MANAGEMENT

The analysis proposes strategies for sustainable resource management. by transforming complex prediction models developed through deep learning. Considering insights gained from the work undertaken in this study, the actionable, tailored strategies suggested to optimize resource management include the following:

a) Residential Sectors (Behavioral Optimization):

In the case of residential energy use, activation of sustainable practices relies on greater consumer understanding of energy behaviors. This, paired with structural changes, will have the potential to transform homes into more energy efficient spaces. The EDA describes a strong inverse relationship between Insulation Thickness and energy loss. With that, it can be suggested that government funding for energy efficiency retrofits will insulate homes and significantly impact baseline demand for heating and cooling. In addition, the introduction of multiple smart meters may impact consumers' behaviors via feedback that will work toward the same outcome.

b) Commercial Sectors (System-Driven Automation):

The use of firsthand behavioral changes is insufficient, as the energy use structuring in Commercial Sectors dominates with large, fully integrated, central HVAC systems. In this regard, smart energy management systems convergence of subsystems and components based on the Internet of Things (IoT) and cloud, coupled with artificial intelligence (AI) for ubiquity, are proposed [13]. The commercial HVAC systems can dynamically be driven with the use of this predictive model based on RNN. Such systems can automate zoning based cooling and warming to maintain desired temperature levels of the comfort of the people in the space and for the efficient industrial operations in the space to minimize the unintended added carbon footprint.

VI. CONCLUSION

This study presented a comparative deep learning-based analysis of energy consumption patterns in residential and commercial buildings. The findings demonstrated that residential buildings exhibit highly variable and behavior-driven energy usage, whereas commercial buildings show more structured and predictable consumption patterns. The comparative evaluation confirmed that the Recurrent Neural Network (RNN) outperformed the Deep Neural Network (DNN) model, achieving higher prediction accuracy and lower RMSE values. The results highlight the effectiveness of deep learning models for energy forecasting and sustainable resource management in smart building environments. The integration of AI-driven predictive systems with smart grids and IoT-based energy management can support efficient HVAC control, reduce energy waste, and improve sustainability in modern buildings.

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