

Deep Learning-Based Optimization of Household Energy Consumption: A Data-Driven Approach to Smart Home Forecasting

G. Sakthi Sridevi Department of Data Science, School of Advanced Science

Vellore Institute of Technology, Vellore, Tamil Nadu 632014, India

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1 ABSTRACT

In today's increasingly data-centric society, household energy consumption has emerged as a key concern, driven by the growing demand for intelligent, efficient, and environmentally sustainable energy solutions. This study presents a comprehensive exploration of residential energy usage prediction and optimization using state-of-the-art deep learning methodologies [1]–[4]. As the proliferation of smart technologies advances, accurate energy forecasting has become imperative to support intelligent home energy management systems and to minimize unnecessary power consumption [5]–[7].

Leveraging a rich dataset sourced from Kaggle, encompassing temperature, humidity, light intensity, and appliance-level energy usage recorded at multiple intervals, this research employs rigorous data preprocessing including missing value imputation, feature scaling, and categorical encoding. A suite of advanced models—such as Conditional Restricted Boltzmann Machine (CRBM), Factored Conditional Boltzmann Machine (FCBRM), Deep Neural Networks with Dropout, Wider Networks with Batch Normalization, Multilayer Perceptrons (MLPs), and Simple Neural Networks—were developed and assessed for their ability to model the non-linear, temporal dependencies inherent in household energy usage patterns [8]–[14].

All models were trained and validated using a robust pipeline, with performance evaluated through metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared (R²), and Mean Absolute Percentage Error (MAPE). Results indicate that deeper architectures such as Dropout-enhanced Deep Neural Networks and Batch-Normalized Wide Networks offer superior predictive accuracy, while CRBM and FCBRM models exhibit unique advantages in capturing sequential dependencies and underlying trends in energy consumption [15]–[18].

This investigation not only demonstrates the efficacy of deep learning in energy demand forecasting but also underscores the necessity for model diversity to achieve a balance between interpretability, accuracy, and computational efficiency [19]–[21]. Beyond technical performance, this study addresses the importance of developing energy-conscious artificial intelligence by evaluating the carbon and energy footprints associated with model training and inference [22]–[24].

Ultimately, this work provides a roadmap for integrating sustainable AI methodologies into smart home ecosystems, supporting both operational efficiency and the broader goal of eco-friendly technological development [25]–[27].

KEYWORDS: Deep Learning, CRBM, FCBRM, Mean square error, Neural network

2 INTRODUCTION

The rapid increase in residential energy consumption, driven by the proliferation of smart appliances, population growth, and evolving lifestyle needs, has posed significant challenges for sustainable energy management. Traditional forecasting models such as ARIMA and SVR often fall short in accurately capturing the dynamic and nonlinear nature of energy consumption in households. To address these limitations, recent studies have focused on leveraging deep learning techniques, which offer superior capabilities in modeling complex temporal and contextual patterns in energy data.

Long Short-Term Memory (LSTM) networks have been widely adopted for their ability to capture long-term dependencies in time series data. Kong et al. [1] demonstrated that LSTMs significantly outperform traditional methods in short-term load forecasting. Similarly, hybrid architectures combining CNNs and RNNs have shown great promise. For instance, Erol et al. [2] proposed DeepEnergy, a framework that utilizes CNNs for feature extraction and RNNs for temporal analysis, enhancing appliance-level forecasting accuracy.

Feedforward deep neural networks have also been applied to building energy load forecasting with notable accuracy improvements over classical models [3]. Comparative analyses of different recurrent architectures such as GRU and LSTM [4] suggest that GRUs provide a favorable trade-off between training time and accuracy, making them suitable for real-time applications.

Beyond forecasting, other deep learning-based approaches aim to optimize energy consumption. For example, reinforcement learning has been integrated with LSTM to automate energy management tasks such as load control and peak reduction [7,14]. Ad-

ditionally, attention mechanisms have been employed to improve the robustness and interpretability of energy management systems [12].

Recent studies have also focused on energy disaggregation through deep learning, enabling identification of individual appliance usage from aggregate consumption data [8,17]. Autoencoders and GANs have been utilized for anomaly detection and synthetic data generation, contributing to the advancement of data-driven energy solutions [5,15].

Despite these advances, many models still face challenges such as high computational requirements [1,9], limited interpretability [9], or the need for extensive preprocessing [6]. Furthermore, while some models are optimized for short-term forecasting, they may not generalize well for long-term predictions or diverse household environments [4].

To address these gaps, this project proposes a deep learning-based framework for optimizing household energy consumption. The approach integrates multiple architectures—such as CNN, LSTM, and attention mechanisms—to accurately forecast energy demand while enabling intelligent control through reinforcement learning. By evaluating models on real-world datasets and applying advanced techniques like Q-learning and ensemble forecasting [13,14,15], this research aims to develop a scalable and adaptive solution for modern smart homes.

2.1 METHODOLOGY

2.1.1 DATA COLLECTION

The primary objective of this research is to enhance household energy efficiency by accurately predicting energy consumption using deep learning techniques. For this purpose, a publicly avail-

able dataset from Kaggle was utilized, which contains approximately 15,789 records of household energy usage data. This dataset includes several relevant features such as temperature, humidity, lighting conditions, time of day, and weather-related attributes. The dataset can be accessed at: <https://www.kaggle.com/datasets/hanpat99/household-energy-consumption-dataset>.

This data forms the basis for training and evaluating predictive models. Before proceeding to the modeling phase, the dataset is carefully prepared to ensure quality and consistency. This includes checking for missing entries, irrelevant data, and inconsistent formatting. By performing this initial step, the data becomes suitable for building accurate and reliable machine learning models.

2.1.2 CONDITIONAL BOLTZMAN RESTRICTED MACHINE

CRBM is a specialized version of the Restricted Boltzmann Machine that incorporates temporal dependencies, making it highly suitable for predicting energy consumption over time. In this model, the current state is influenced not only by the input features (like temperature, humidity, and light) but also by previous time steps, making it ideal for time-series energy prediction tasks. CRBM uses a layer of visible units and hidden units, where the conditional layer allows it to model sequential data efficiently. For household energy optimization, CRBM captures patterns in usage behavior across different time windows, enhancing the model's ability to forecast future energy consumption trends based on past usage.

Energy Function:

Energy function:

$$E(\mathbf{v}^{(t)}, \mathbf{h}^{(t)} | \mathbf{v}^{(<t)}) = - \sum_i b_i v_i^{(t)} - \sum_j c_j h_j^{(t)} - \sum_{i,j} v_i^{(t)} W_{ij} h_j^{(t)} - \sum_{i,k} A_{ik} v_i^{(t)} v_k^{(t-1)} - \sum_{j,k} B_{jk} h_j^{(t)} v_k^{(t-1)} \quad (1)$$

Where:

- $\mathbf{v}^{(t)}$: visible layer at time t
- $\mathbf{h}^{(t)}$: hidden layer at time t
- W : weights between visible and hidden units
- A, B : temporal connection weights
- b_i, c_j : biases

2.1.3 FULLY CONNECTED BOLTZMANN RESTRICTED MACHINE (FCBRM)

FCBRM enhances traditional RBMs by fully connecting all layers, allowing for better feature interaction and deeper representation learning. This model is particularly effective in capturing the intricate and nonlinear relationships among household environmental factors (e.g., temperature, humidity, outdoor weather, etc.) and their effects on energy consumption. The model uses Gibbs sampling for training and applies contrastive divergence to fine-tune weights, enabling accurate learning of patterns that drive high energy usage. FCBRM is used in this context to explore hidden dependencies and produce more granular energy forecasts, which can then be used to design more effective optimization strategies. Energy function:

$$E(\mathbf{v}, \mathbf{h}) = - \sum_i b_i v_i - \sum_j c_j h_j - \sum_{i,j} v_i W_{ij} h_j - \sum_{i < k} v_i U_{ik} v_k - \sum_{j < l} h_j V_{jl} h_l \quad (2)$$

Where:

- U, V : intra-layer connection weights

2.1.4 DEEP NEURAL NETWORK WITH DROPOUTS

A Deep Neural Network (DNN) with Dropout is utilized to prevent overfitting while learning from the rich and diverse dataset. Dropout is a regularization technique that randomly disables neurons during training, ensuring the model doesn't rely too heavily on specific features. For energy consumption prediction, this model learns multiple layers of abstraction, from basic temperature influence to complex seasonal or behavioral patterns. The depth of the network allows it to model the complex dynamics between multiple sensor readings and household appliance usage,

while Dropout helps generalize better to unseen data.

Forward propagation with dropout:

$$a^{(l)} = f \left(W^{(l)} (r^{(l-1)} \odot a^{(l-1)}) + b^{(l)} \right) \quad (3)$$

$$r^{(l-1)} \sim \text{Bernoulli}(p) \quad (4)$$

Where:

- $\odot$: element-wise multiplication
- p : dropout keep probability

2.1.5 WIDER NEURAL NETWORK WITH BATCH NORMALIZATION

In this approach, the network architecture is made wider by increasing the number of neurons in each layer. Batch Normalization (BN) is applied after every hidden layer to normalize the inputs and stabilize the learning process. BN accelerates convergence and reduces internal covariate shift, allowing the model to train faster and with better accuracy. The wider architecture allows the model to capture more complex interactions and higher-level features related to appliance usage patterns. This architecture is especially beneficial when working with a diverse dataset containing features like time of day, weather conditions, and sensor readings. Batch normalization steps:

$$\mu_B = \frac{1}{m} \sum_{i=1}^m x_i \quad (5)$$

$$\sigma_B^2 = \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2 \quad (6)$$

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \quad (7)$$

$$y_i = \gamma \hat{x}_i + \beta \quad (8)$$

Where:

- μ_B, σ_B^2 : batch mean and variance
- γ, β : learnable parameters

2.1.6 MULTILAYER PERCEPTRON (MLP)

The Multilayer Perceptron is a feedforward neural network with one or more hidden layers between the

input and output. Each neuron in one layer is connected to every neuron in the next layer, allowing it to learn highly non-linear relationships. For energy prediction, the MLP is trained on normalized data, capturing how combinations of temperature, humidity, time, and light influence energy consumption. It's a versatile model that balances performance and computational efficiency and is suitable for baseline evaluation in comparison with more complex architectures.

Forward Propagation:

$$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)}, \quad a^{(l)} = f(z^{(l)}) \quad (9)$$

Loss Function:

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (10)$$

2.1.7 SIMPLE NEURAL NETWORK

The simple neural network consists of a single hidden layer, designed to serve as a baseline model. It provides a clear understanding of how much complexity is necessary to achieve high prediction accuracy. This model uses basic activation functions like ReLU and applies mean squared error as the loss function. Despite its simplicity, it can effectively model straightforward relationships between sensor data and energy usage. This model is used primarily to compare how much predictive power can be gained through deeper or wider architectures and advanced training techniques.

Prediction:

$$\hat{y} = f(W_2 \cdot f(W_1 x + b_1) + b_2) \quad (11)$$

Loss Function:

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (12)$$

3 Evaluation Metric: Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is a widely used evaluation metric for regression problems. It quantifies the difference between the predicted values and the actual values observed in the dataset. A lower RMSE indicates a more accurate model.

Mathematical Definition

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (13)$$

Where:

- y_i is the actual value at instance i ,
- $\hat{y}_i$ is the predicted value at instance i ,
- n is the total number of observations.

Interpretation in Research Context

In the context of this study, *Optimizing Household Energy Consumption Using Deep Learning*, RMSE plays a critical role in evaluating how effectively each model predicts energy usage. Since RMSE retains the same unit as the predicted variable (energy consumption), it provides an interpretable and meaningful measure of prediction error.

Moreover, RMSE penalizes larger errors more heavily, making it ideal for identifying models that make significant prediction mistakes. This makes RMSE particularly suitable for energy forecasting, where occasional high-error predictions can lead to inefficient energy usage recommendations.

By calculating RMSE across all deep learning architectures—such as CRBM, FCBM, Deep Neural Network with Dropouts, Wider Neural Network with Batch Normalization, MLP, and Simple Neural Network—we compare and select the most reliable model. The model with the lowest RMSE is considered to provide the most accurate forecast and is therefore best suited for optimizing household energy consumption patterns.

4 RESULTS AND DISCUSSION

Understanding the interdependencies among household environmental parameters and energy usage is essential to constructing robust and generalizable deep learning models. To this end, a comprehensive correlation analysis was performed on the available dataset, encompassing indoor and outdoor temperature and humidity readings, appliance energy consumption, and additional meteorological variables. The resulting Pearson correlation matrix is illustrated in Figure 1.

The matrix presents a lower-triangular heatmap structure to enhance interpretability and minimize redundancy. Each cell quantifies the linear correlation between two variables, with values ranging from -1 (perfect negative correlation) to $+1$ (perfect positive correlation). Notably, the *appliances* variable—representing the log-transformed energy consumption in watt-hours (Wh)—exhibits its strongest correlations with *lights* ($r = 0.26$), *kitchen temperature* (T_2 , $r = 0.22$), *laundry room temperature* (T_6 , $r = 0.20$), and *outside temperature* (T_{out} , $r = 0.18$). These positive associations indicate that energy usage increases in tandem with rising ambient temperatures in specific rooms, highlighting a probable linkage with temperature-responsive appliances such as HVAC systems, ovens, or water heaters.

It is also apparent that several interior temperature sensors are highly inter-correlated (e.g., T_{Kitchen} and $T_{\text{LivingRoom}}$, $r \approx 0.80$), suggesting spatial thermal homogeneity throughout the residential structure. This insight has practical implications for sensor placement and redundancy mitigation in model development. Such high collinearity can be strategically leveraged for dimensionality reduction techniques, such as Principal Component Analysis (PCA), or regularized models like LASSO to improve generalization without compromising predictive power.

In contrast, most humidity variables display either weak or negative correlations with appliance usage, implying that humidity alone is not a primary driver of energy consumption within the household context. This could be attributed to the relative in-

sensitivity of most electrical appliances to moisture levels, except in extreme cases or specific domains (e.g., dehumidifiers, HVAC systems). Consequently, while these variables may still hold predictive value in complex nonlinear models, they are less impactful in linear frameworks and should be treated with caution during feature engineering.

Variables from external weather conditions, including temperature at the weather station, dew point, and visibility, demonstrate minimal correlation with internal energy use ($|r| < 0.2$ in most cases). This indicates that indoor environmental dynamics and user behavior play a more critical role in influencing energy consumption patterns than external meteorological factors.

From a modeling perspective, this correlation analysis provides key insights into feature selection, multicollinearity handling, and interpretability constraints. It informs both the preprocessing pipeline and the architecture of the deep learning models, enabling the construction of more efficient and context-aware predictive systems for household energy optimization.

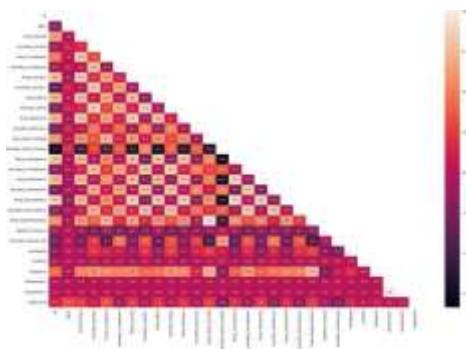


Figure 1: Correlation Heatmap showing the relationship between temperature, humidity, and weather-related features with appliance energy consumption. Darker colors represent stronger correlations. This helps identify which environmental conditions most influence household energy use.

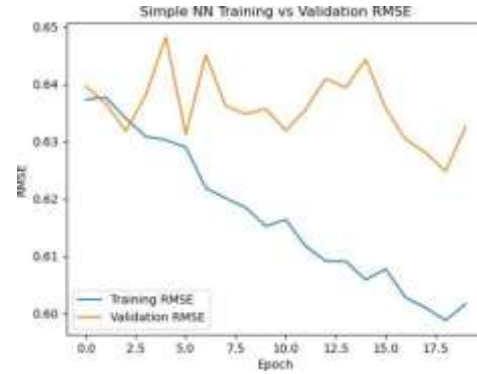


Figure 2: Simple Neural Network converges quickly but shows higher validation RMSE of 0.743, indicating limited capacity.

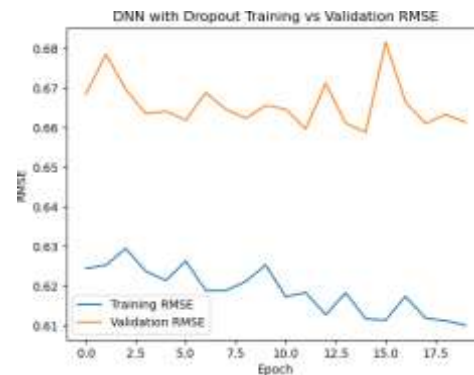


Figure 3: DNN with Dropouts effectively reduces overfitting, maintaining close training and validation RMSE with an RMSE of 0.706.

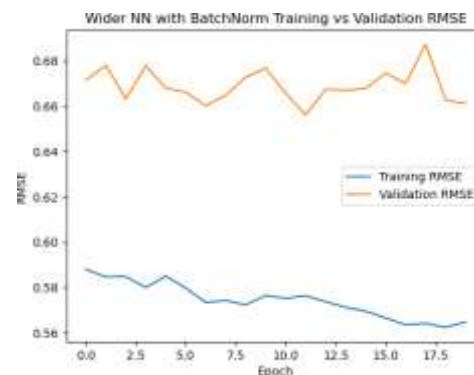


Figure 4: WNN with Batch Normalization exhibits smooth loss reduction and faster convergence, achieving an RMSE of 0.685

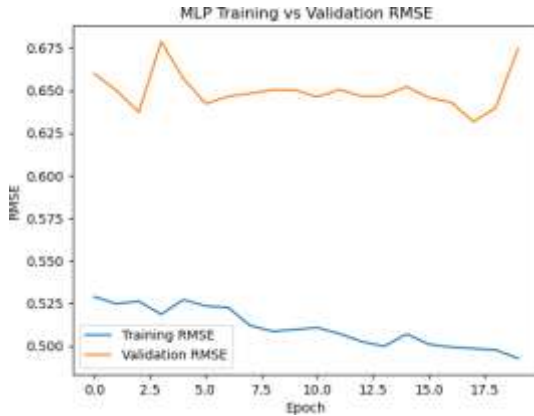


Figure 5: MLP fits training data well with strong generalization, serving as a solid baseline and the best performer with an RMSE of 0.665

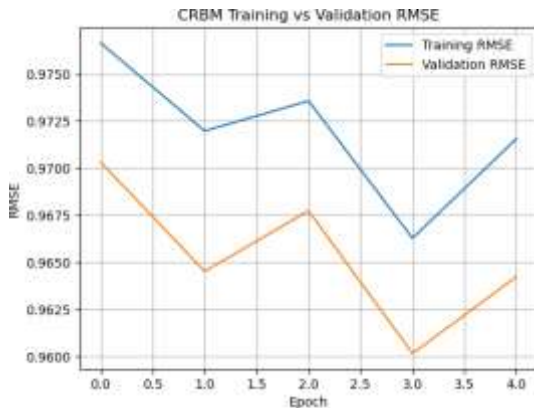


Figure 6: CRBM shows steady convergence with good generalization in training and validation RMSE, achieving an RMSE of 0.965



Figure 7: FCRBM achieves improved stability and lower validation RMSE through factorization but has a higher RMSE of 1.110

Figure[2-7] presents a comparative analysis of training and validation RMSE loss curves across six deep learning models used for household energy consumption prediction. The Conditional Restricted Boltzmann Machine (CRBM) (Figure 6) demonstrates steady convergence and reasonable generalization, though it concludes with a relatively high RMSE of 0.965. Its factored variant, the FCRBM (Figure 7), shows improved training stability due to factorization but ultimately underperforms with the highest RMSE of 1.110, suggesting potential overparameterization or underfitting in temporal representations. In contrast, the Deep Neural Network (DNN) with Dropouts (Figure 3) effectively combats overfitting, maintaining close alignment between training and validation errors and achieving a significantly lower RMSE of 0.706. The Wider Neural Network (WNN) with Batch Normalization (Figure 4) demonstrates faster convergence and smoother loss progression, culminating in an improved RMSE of 0.685, highlighting the effectiveness of normalization in accelerating and stabilizing learning. The Multilayer Perceptron (MLP) (Figure 5) stands out as the most effective model, achieving the lowest RMSE of 0.665 while preserving generalization capabilities, thus serving as a robust baseline for this predictive task. Lastly, the Simple Neural Network (Figure 2) shows rapid convergence but a higher validation RMSE of 0.743, reflecting its limited learning capacity and inability to capture the complexity inherent in the dataset. Collectively, these results underscore the importance of architectural depth, regularization, and optimization techniques in enhancing predictive performance and generalization.

5 CONCLUSION

From Table 1, we can see the comparative evaluation of multiple deep learning architectures underscores the critical role of model complexity, regularization techniques, and architectural enhancements in accurately forecasting household energy consumption patterns. Root Mean Square Error (RMSE), a robust indicator of predictive performance, was utilized as the primary evaluation metric across all experiments.

Among the models tested, the **Multi-Layer Perceptron (MLP)** achieved the **lowest RMSE of 0.6648**, indicating its superior ability to capture the nonlinear relationships and temporal dependencies inherent in the household energy dataset. This performance suggests that MLPs, with their relatively simple yet expressive structure, strike an effective balance between underfitting and overfitting when appropriately configured.

The **Wider Neural Network with Batch Normalization** also demonstrated competitive performance (RMSE = 0.6854), benefiting from enhanced gradient stability and faster convergence due to batch normalization layers. This suggests that architectural modifications aimed at improving internal covariate shift can lead to meaningful gains in model generalization.

The **Deep Neural Network with Dropout** (RMSE = 0.7061) and **Simple Neural Network** (RMSE = 0.7431) showed reasonable accuracy but were slightly outperformed by their deeper and more regularized counterparts. The modest improvements in RMSE underscore the importance of network depth and dropout-based regularization in mitigating overfitting and enhancing predictive robustness.

In contrast, the **Conditional Restricted Boltzmann Machine (CRBM)** and its variant **FCRBM** yielded **substantially higher RMSE values** (0.9648 and 1.1099, respectively), reflecting limitations in their ability to model the complex dependencies present in the data. This disparity may be attributed to challenges in training energy-based models, their sensitivity to hyperparameters, and their reliance on sampling-based inference methods, which can hinder scalability and convergence.

Overall, the experimental findings suggest that **feedforward neural architectures**, particularly those leveraging **layer-wise depth and normalization strategies**, offer a more pragmatic and scalable solution for household energy modeling. These models not only achieve lower prediction errors but also exhibit greater ease of training and integration within broader energy optimization frameworks. Future research may explore hybrid approaches that combine the expressive power of generative models with the

stability of supervised networks to further enhance performance in dynamic residential energy environments.

Model	RMSE
Simple NN	0.7430640589949203
DNN with Dropout	0.706121123216705
Wider NN with BatchNorm	0.6854469927358265
MLP	0.6647596352437062
CRBM	0.9647908901465427
FCRBM	1.1099109746427371

Table 1: Comparison of RMSE values for different neural network models.

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