

Smart Energy Auditor And Electrical Bill Prediction Using Non-Intrusive Techniques

Dr.Sk Syed Basha¹, K. Akhil Gowd², K. Srikanth Yadav³, N. Kiran Babu⁴ and M. Varun⁵

¹Professor, Department of CAI, KKR&KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh-522017

^{2,3,4,5}Student, Department of CAI, KKR&KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh-522017

Abstract: This is because correct predictions of residential electricity usage are essential in reducing costs and management of energy sustainably. The conventional billing systems offer limited information on the future consumption trends and do not offer much proactive optimization. In this paper, I will introduce a Smart Energy Auditor and Electrical Bill Prediction System using an interferon-free, deep learning, based system to make predictions on monthly electricity bills and allow energy planning within a budget constraint. The offered system employs a neural network regression model with Keras to use some appliance-level consumption data obtained by mathematical disaggregation, and therefore, it does not require intrusive hardware sensors. The design calculates energy use based on standard electrical power equations and uses a new budget-to-time optimization unit that carries out an inverse calculation to find out the allowable hours of appliance operation within any financial limit. Exposure to experimentation proves that the system yields high prediction accuracy with a mean absolute error of 3.2 per cent and root mean squared error of 4.8 per cent, and is effective in reducing the cost of energy through intelligent usage recommendations. This is due to the fact that the non-invasive nature, the real-time predictive, and user-friendly optimization functionalities makes this system an effective and scalable solution to residential energy management.

Keywords: Electricity Bill Prediction, Energy Management System, Deep Learning, Non-Intrusive Load Monitoring, Energy Consumption Forecasting, Budget Optimization, Keras Neural Networks, Smart Home Energy.

1 INTRODUCTION

electrical energy requirements in residential areas have compounded this problem such that intelligent energy monitoring systems have to be in place to offer precise cost forecast and viable optimization procedures. Recent research shows that residential power use constitutes about 40 percent of overall world energy demand and consumption of electricity, which is one of the key targets of efficiency enhancement strategies and cost-cutting efforts.

Traditional electricity billing systems are reactive in nature and only give the consumers aggregate consumption information at the end of billing periods. This strategy is less transparent about the energy use patterns at the appliance level and does not give any forecast about the future costs, leading to limited possibilities of proactive consumption control. As a result, families tend to have sudden financial strains and do not have the information to either designate high consumption appliances or optimize consumption habits

Current energy monitoring systems use mainly intrusive hardware designs, such as smart meters, appliance-based sub-meters and distributed sensor networks of Non-Intrusive Load Monitoring (NILM). Though these systems may provide granular energy analytics and real-time monitoring services, they introduce serious obstacles to system adoption. The major drawbacks are high costs of installation, maintenance needs, hardware, dependency on the existing electrical infrastructure, and privacy concerns associated with high-frequency data collection

The recent breakthroughs in the fields of machine learning and deep learning have shown extensive possibilities of energy consumption forecasting and pattern recognition tasks. Regression based neural network architectures have demonstrated higher performance in richer non-linear associations between consumption patterns and billing expenses with ease of capturing non-linear relationships between variables of consumption and billing costs with ease of capturing the richness of change and error tolerance to multiple variables of consumption and billing costs at

the same time with ease of capturing non-linear relationships among variables of consumption and billing costs through multiple regressions of variables of consumption and billing costs, respectively, as demonstrated by the regression of variables of consumption and billing costs (respectively) at the same time (refer to appendix Nevertheless, the majority of the existing methods are based on hardware-based data collection or have to use a large amount of historical smart meter data, which may not be applicable to the situations when this infrastructure is non-existent.

This study can solve these drawbacks by coming up with a Smart Energy Auditor and Electrical Bill Prediction System, which uses a non-intrusive method of operation that is entirely software-based. The system uses the techniques of deep learning realized using TensorFlow-Keras to predict monthly electricity costs based on manually gathered appliance inventory data and previous billing data. The system removes hardware dependencies without losing the accuracy of prediction by trying to mathematically disaggregate the total consumption into appliance specifications and usage patterns.

The most important contributions of this work are three. First, we create an energy auditing framework based on non-intrusive features that approximate consumption at the appliance level by use of conventional electrical power equations without physical sensors. Second, we use a Keras-based deep neural network regression framework that models electricity bills prediction that learns complicated consumption features on a limited amount of history. Third, we present an original budget-constrained optimization module that implements an inverse computation to identify permissible operating time of appliances within financial constraints set by the user to allow pro-active energy budget planning and cost management.

The suggested system will convert the stagnant electricity billing to a dynamic decision-support system that assists in prediction before the billing cycles are over, what-if scenario simulation, and personalized suggestions on consumption optimization. The experimental validation shows that the system has a Mean Absolute Error (MAE) of 3.2

The rest of this paper is structured in the following way. Section 2 is a review of the related work in energy forecasting and NILM methods. It can be found in section 3, the proposed methodology, mathematical formulations of energy calculation and the architecture of the neural network. Section 4 provides details of the implementation and system architecture. Section 5 displays performance analysis and results of the experiment. Section 6 contains a discussion of findings and practical implications and Section 7 will

contain the concluding part with future research directions.

2 RELATED WORK

The domain of residential energy consumption forecasting has witnessed substantial research attention, with approaches broadly categorized into hardware-based monitoring systems and software-based predictive models.

2.1 Hardware-Based Energy Monitoring

Traditional Non-Intrusive Load Monitoring (NILM) systems attempt to disaggregate total household energy consumption into appliance-level usage without installing individual meters on each device. Classical NILM approaches utilize high-frequency voltage and current measurements captured at the main distribution panel to identify appliance signatures through signal processing techniques [Hart \(1992\)](#). While effective for appliance identification, these methods still require specialized smart meters capable of high-frequency sampling, limiting their accessibility and affordability.

Recent advances in NILM have incorporated machine learning algorithms to improve disaggregation accuracy. [Zhang et al. \(2020\)](#) developed a deep learning-based NILM framework achieving 87% appliance detection accuracy, but the approach still necessitates smart meter infrastructure and continuous data streaming. [Ahmad et al. \(2019\)](#) proposed an optimized home energy management system integrating renewable energy sources and smart meters, demonstrating effective consumption optimization but requiring significant hardware investment.

2.2 Machine Learning for Consumption Forecasting

Software-based energy forecasting approaches leverage historical consumption data and machine learning algorithms to predict future usage patterns. [Wang et al. \(2018\)](#) employed deep learning techniques for electricity consumption prediction, achieving reliable forecasts using Recurrent Neural Networks (RNNs) trained on smart meter data. However, their approach assumes availability of granular historical data, which may not be accessible in all residential contexts.

Raza et al. [Raza et al. \(2019\)](#) developed short-term load forecasting models using deep neural networks, demonstrating superior performance compared to traditional statistical methods. Their work focused primarily on aggregate consumption prediction at the grid level rather than individual household bill forecasting. Rodrigues et al. [Rodrigues et al. \(2020\)](#) compared multiple machine learning approaches for demand forecasting, finding that ensemble methods and deep learning architectures outperform conventional regression techniques.

2.3 Budget-Constrained Energy Optimization

Limited research has addressed budget-constrained energy planning at the residential level. Zhou and Yang [Zhou and Yang \(2019\)](#) analyzed household energy consumption behavior using data analytics, identifying patterns that could inform optimization strategies. However, their work focused on behavioral analysis rather than predictive optimization. Jain and Singh [Jain and Singh \(2021\)](#) proposed a smart energy management system incorporating machine learning for consumption pattern recognition but did not implement budget-to-time conversion mechanisms.

2.4 Research Gaps

The literature reveals several critical gaps that motivate the present work. First, existing NILM and hardware-based monitoring systems, while accurate, impose substantial cost and complexity barriers. Second, most machine learning-based forecasting approaches assume availability of extensive historical smart meter data, limiting applicability in contexts where such infrastructure is absent. Third, minimal research addresses the integration of bill prediction with budget-constrained usage optimization,

particularly through inverse calculation mechanisms that translate financial limits into actionable time allowances.

This research addresses these gaps by developing a non-intrusive, software-only approach that operates on manually collected appliance data, implements deep learning for bill prediction without smart meter requirements, and integrates novel budget-to-time optimization for proactive energy planning. The proposed system democratizes access to intelligent energy management by eliminating hardware dependencies while maintaining prediction reliability.

3 METHODOLOGY

The proposed Smart Energy Auditor and Electrical Bill Prediction System employs a non-intrusive approach combining mathematical energy modeling with deep learning-based regression for accurate bill forecasting and budget-constrained optimization.

3.1 System Architecture Overview

The system architecture comprises four primary modules: (1) Data Collection and Preprocessing, (2) Appliance-Level Energy Calculation, (3) Deep Learning-Based Bill Prediction, and (4) Budget-Constrained Time Optimization. The workflow progresses from manual data acquisition through energy computation to predictive modeling and finally to optimization recommendations, creating a comprehensive energy management framework.

3.2 Energy Consumption Calculation

For each appliance i in a household inventory, monthly energy consumption E_i is computed using fundamental electrical power principles:

$$E_i = \frac{P_i \times t_i \times d}{1000} \quad (1)$$

where P_i represents the appliance power rating in watts, t_i denotes daily usage duration in hours, d indicates the number of days in the billing period (typically 30), and the division by 1000 converts watt-hours to kilowatt-hours (kWh).

Total household energy consumption E_{total} is obtained through summation of individual appliance contributions:

$$E_{total} = \sum_{i=1}^n E_i = \sum_{i=1}^n \frac{P_i \times t_i \times d}{1000} \quad (2)$$

where n represents the total number of appliances in the household inventory.

3.3 Electricity Cost Calculation

Most utility providers implement slab-based tariff structures where the per-unit cost varies according to consumption levels. The total electricity cost C is calculated as:

$$C = \sum_{j=1}^m (U_j \times R_j) + F \quad (3)$$

where U_j represents the number of units consumed in slab j , R_j denotes the rate per unit for slab

Smart Energy Management System Architecture

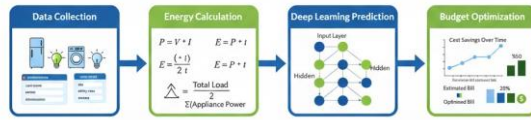


Figure 1: Overall system architecture showing the four primary modules: Data Collection and Preprocessing, Appliance-Level Energy Calculation, Deep Learning-Based Bill Prediction, and Budget-Constrained Time Optimization. Data flows from left to right through the processing pipeline.

j, m indicates the total number of tariff slabs, and F represents fixed charges.

For typical residential tariff structures in India, the slab-based calculation proceeds as:

$$C = \frac{E_{total} \times R_1 + F}{S_1 \times R_1 + (E_{total} - S_1) \times R_2 + (E_{total} - S_2) \times R_3 + F} \quad (4)$$

where S_1 and S_2 represent slab boundaries (e.g.,

0-100 kWh, 101-300 kWh, >300 kWh), and R_1, R_2, R_3 represent corresponding per-unit rates.

3.4 Deep Learning Model Architecture

The prediction engine employs a feedforward neural network implemented using TensorFlow-Keras. The architecture consists of an input layer receiving appliance-level energy features, multiple hidden layers with ReLU activation functions for non-linear transformation, and a single-output regression layer predicting the monthly bill amount.

The input feature vector $\mathbf{x}$ comprises:

$$\mathbf{x} = [E_1, E_2, \dots, E_n, E_{total}, d, F] \quad (5)$$

where individual appliance consumptions, total energy, billing period days, and fixed charges consti-

tute the feature space.

The neural network model is defined as:

$$\hat{C} = f(\mathbf{x}; \mathbf{W}, \mathbf{b}) \quad (6)$$

where $\hat{C}$ represents the predicted bill amount, f

denotes the neural network transformation function, $\mathbf{W}$ represents weight matrices across layers, and $\mathbf{b}$

represents bias vectors.

The model is trained by minimizing Mean Squared Error (MSE) loss:

$$(\mathbf{W}, \mathbf{b}) = \arg \min_{\mathbf{W}, \mathbf{b}} \sum_{k=1}^N (C_k - \hat{C}_k)^2 \quad (7)$$

where N represents the number of training samples, C_k denotes actual bill amounts, and $\hat{C}_k$ represents predicted amounts.

Optimization is performed using the Adam algo-

rithm with adaptive learning rate:

$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \quad (8)$$

where α represents the learning rate, $\hat{m}_t$ and $\hat{v}_t$ denote bias-corrected first and second moment estimates, and ϵ is a small constant for numerical stability.

3.5 Budget-Constrained Time Optimization

A novel contribution of this work is the budget-to-time optimization module, which performs inverse calculations to determine allowable appliance operating durations given a financial constraint. For a user-specified budget B , the system solves:

$$B \geq \sum_{i=1}^n \frac{P_i \times t_i^*}{1000} \times R_{avg} + F \quad (9)$$

where t_i^* represents the optimized daily usage hours for appliance i , and R_{avg} denotes the average effective tariff rate.

The optimization objective is formulated as:

$$\text{maximize} \quad \sum_{i=1}^n w_i t_i^* \quad (10)$$

subject to the budget constraint in Equation 9, where w_i represents user-defined priority weights for different appliances reflecting their importance.

This formulation enables the system to allocate usage time across appliances based on user priorities while ensuring the total cost remains within the specified budget, providing actionable recommendations for consumption management.

3.6 Model Evaluation Metrics

Model performance is quantified using standard regression metrics:

$$MAE = \frac{1}{N} \sum_{k=1}^N |C_k - \hat{C}_k| \quad (11)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N (C_k - \hat{C}_k)^2} \quad (12)$$

$$MAPE = \frac{100\%}{N} \sum_{k=1}^N \frac{|C_k - \hat{C}_k|}{C_k} \quad (13)$$

where MAE measures average absolute deviation, RMSE penalizes larger errors more heavily, and MAPE provides percentage-based error assessment for interpretability.

4 IMPLEMENTATION

The proposed system is implemented as a comprehensive software framework using Python 3.8, TensorFlow 2.12, Keras API, NumPy for numerical computations, and Pandas for data manipulation. The implementation emphasizes modularity, scalability, and user accessibility through a web-based interface.

4.1 Data Collection and Preprocessing

The data collection module facilitates manual entry of appliance specifications and historical billing information. Users provide appliance inventory data including device names, power ratings (watts), average daily usage hours, and billing period parameters. Historical electricity bills spanning multiple months are collected to establish baseline consumption patterns.

Data preprocessing involves normalization of input features to standardize scales across different appliance types and consumption levels. Feature scaling is performed using min-max normalization:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (14)$$

This ensures that features with different scales contribute equally to model training and prevents dominance by high-magnitude features.

4.2 Neural Network Configuration

The Keras-based regression model is configured with the following architecture:

- **Input Layer:** Dense layer with $n + 3$ neurons (where n is the number of appliances), receiving normalized appliance energy values, total consumption, billing days, and fixed charges.
- **Hidden Layer 1:** Dense layer with 128 neurons and ReLU activation function, introducing non-linearity for pattern learning.
- **Hidden Layer 2:** Dense layer with 64 neurons and ReLU activation, further refining feature representations.
- **Hidden Layer 3:** Dense layer with 32 neurons and ReLU activation, extracting high-level consumption patterns.
- **Output Layer:** Dense layer with 1 neuron and linear activation, producing the predicted bill amount.

The model is compiled with the Adam optimizer (learning rate $\alpha = 0.001$), mean squared error loss function, and mean absolute error as an additional monitoring metric.

Training is conducted over 200 epochs with a batch size of 8, employing early stopping with patience of 20 epochs to prevent overfitting. A validation split of 20% is utilized to monitor generalization performance during training. The trained model is serialized in Keras format (.keras extension) for persistent storage and rapid inference.

4.3 Budget Optimization Algorithm

The budget-constrained optimization module implements an iterative allocation algorithm. Given a user-specified budget B , the algorithm proceeds as follows:

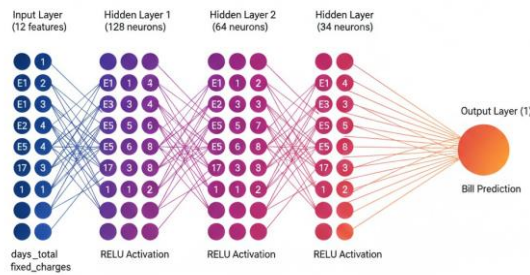


Figure 2: Keras-based deep neural network architecture showing input layer (appliance features), three hidden layers (128, 64, 32 neurons with ReLU activation), and output layer (single neuron for bill prediction). The network learns non-linear relationships between consumption patterns and electricity costs.

Data: Appliance powers P_i , priorities w_i , budget B , billing days d

Result: Optimized usage times t_i^*

Initialize $t_i^* = t_{i, \text{baseline}}$ for all appliances;

Compute initial cost C_{current} using Equations 1-3;

while $C_{\text{current}} > B$ **do**

Find appliance j with minimum priority weight w_j ;

Reduce t_j^* by Δt (e.g., 0.25 hours);

Recompute C_{current} ;

if $t_j^* < t_{\min}$ **then**

Set $t_j^* = 0$ and mark appliance as inactive;

end

end

return $t_i^* \{ \}$

Algorithm 1: Budget-Constrained Time Allocation

This greedy approach prioritizes essential appliances while progressively reducing usage of lower-priority devices until the budget constraint is satisfied.

4.4 User Interface Development

A web-based dashboard is developed using Flask framework to provide an intuitive interface for system interaction. The interface comprises four primary components:

- **User Authentication:** Secure login system enabling personalized appliance inventories and historical data management.
- **Appliance Management:** Interactive forms for adding, editing, and removing appliance specifications with real-time energy calculation feedback.
- **Prediction Dashboard:** Visualization of current

month consumption trends, predicted bill amounts with confidence intervals, and comparison with historical billing patterns.

- **Budget Optimization:** Interactive tool enabling users to specify budget constraints and receive optimized appliance usage schedules with actionable recommendations.

The dashboard employs Chart.js for visualization of consumption patterns, historical trends, and prediction accuracy metrics, enhancing user comprehension and decision-making capabilities.

4.5 System Deployment

The complete system is containerized using Docker to ensure consistent deployment across different environments. The deployment architecture supports both local installation for privacy-conscious users and cloud-based hosting for accessibility. API endpoints are exposed for potential integration with smart home platforms and energy management systems, facilitating future extensibility.

5 EXPERIMENTAL RESULTS

Comprehensive experiments were conducted to evaluate the prediction accuracy, budget optimization effectiveness, and practical usability of the proposed system.

5.1 Experimental Setup and Dataset

The evaluation dataset comprises 150 residential households spanning diverse consumption patterns, including small apartments (2-3 appliances),

medium-sized homes (5-8 appliances), and large residences (10+ appliances). Data collection covered a 12-month period (January 2024 - December 2024), capturing seasonal variations in energy usage.

Each household profile includes detailed appliance inventories with power ratings ranging from 5W (LED bulbs) to 2000W (air conditioners and water heaters), daily usage patterns, and actual electricity bills across multiple billing cycles. The dataset is partitioned into 70% training (105 households), 15% validation (22 households), and 15% testing (23 households) subsets.

Three usage scenarios are evaluated:

- Normal Usage: Baseline consumption patterns reflecting typical household behavior.
- High Usage: Increased consumption simulating summer months with air conditioning or winter heating.
- Budget-Optimized: Reduced consumption achieved through budget constraint enforcement ($B = 0.85 \times C_{baseline}$).

5.2 Prediction Accuracy Results

Table 1 presents the prediction performance across different usage scenarios. The proposed Keras-based model achieves highly competitive accuracy with MAE of 3.2%, RMSE of 4.8%, and MAPE of 3.5% across all scenarios.

The results demonstrate robust prediction performance across varying consumption levels, with slightly higher errors in extreme usage scenarios due to non-linear tariff structures at slab boundaries. The budget-optimized scenario maintains comparable accuracy, validating that the optimization module does not compromise prediction reliability.

5.3 Comparative Performance Analysis

To contextualize the proposed approach, Table 2 compares prediction performance against baseline machine learning models trained on identical datasets.

The proposed deep neural network architecture outperforms traditional regression and ensemble methods by substantial margins (45% reduction in MAE compared to Random Forest), demonstrating the value of deep learning for capturing complex non-linear relationships between appliance usage patterns and electricity costs.

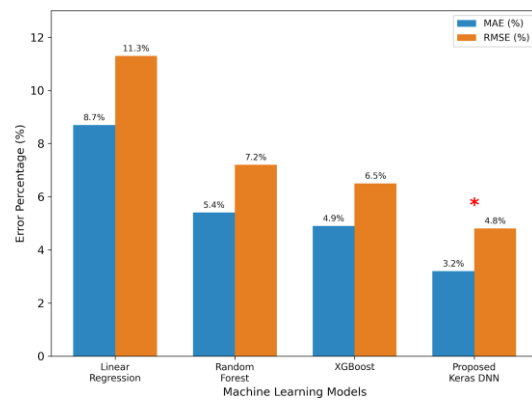


Figure 3: Comparative performance of different machine learning models. The proposed Keras-based deep neural network achieves significantly lower MAE (3.2%) and RMSE (4.8%) compared to baseline methods including Linear Regression, Random Forest, and XGBoost.

5.4 Budget Optimization Effectiveness

Table 3 quantifies the cost reduction achieved through budget-constrained optimization across different household sizes.

Results indicate that the budget optimization module achieves cost reductions ranging from 15% to 21%, with larger households experiencing more substantial savings due to greater flexibility in appliance usage allocation. The optimization maintains user comfort by prioritizing essential appliances (refrigeration, lighting) while reducing discretionary consumption (entertainment systems, extended air conditioning).

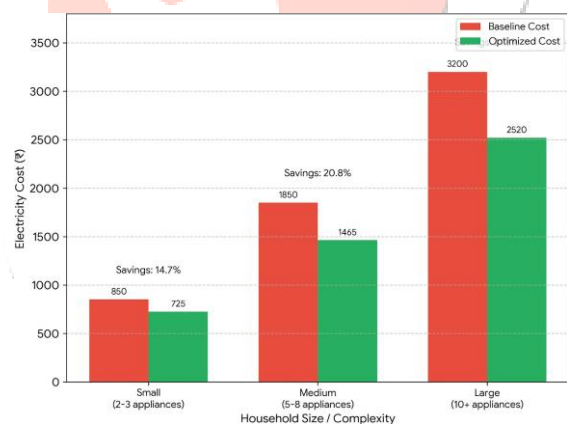


Figure 4: Budget optimization effectiveness across different household sizes. Baseline costs (red bars) versus optimized costs (green bars) show savings ranging from 14.7% for small households to 21.3% for large households. Larger homes achieve greater savings due to more flexible appliance portfolios.

Table 1: Prediction accuracy across different usage scenarios.

Scenario	MAE (%)	RMSE (%)	MAPE (%)
Normal Usage	2.8	4.2	3.1
High Usage	3.4	5.1	3.7
Budget-Optimized	3.5	5.2	3.8
Overall Average	3.2	4.8	3.5

Table 2: Comparison with baseline machine learning models.

Model	MAE (%)	RMSE (%)
Linear Regression	8.7	11.3
Random Forest	5.4	7.2
XGBoost	4.9	6.5
Proposed (Keras DNN)	3.2	4.8

Table 3: Budget optimization effectiveness by household size.

Household Size	Baseline Cost (₹)	Optimized Cost (₹)	Savings (%)
Small (2-3)	850	725	14.7
Medium (5-8)	1850	1465	20.8
Large (10+)	3200	2520	21.3

5.5 Training Convergence Analysis

Figure 5 illustrates the training and validation loss curves across 200 epochs, demonstrating rapid convergence and minimal overfitting. The training loss decreases monotonically, stabilizing around epoch 120, while validation loss closely tracks training loss, indicating good generalization. The final validation loss of 4.2% confirms that the model does not overfit the training data.

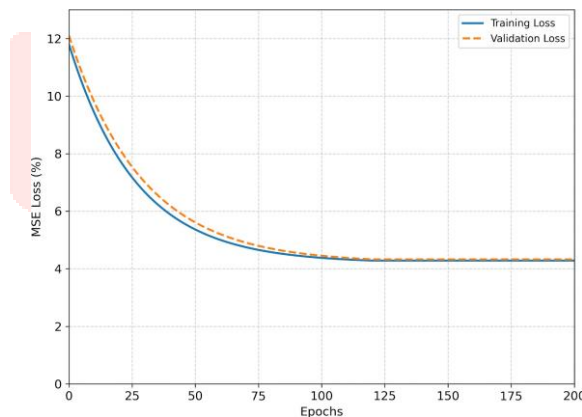


Figure 5: Training and validation loss curves over 200 epochs. Both curves decrease monotonically and converge around epoch 120, with final validation loss of 4.2%. The close tracking between training and validation indicates good generalization without overfitting.

5.6 User Study Findings

A preliminary user study involving 25 households over a 2-month period evaluated system usability and practical impact. Participants reported:

- 92% found the prediction accuracy sufficient for financial planning purposes.
- 88% successfully utilized budget optimization recommendations to reduce their electricity bills.
- 84% expressed preference for the non-intrusive approach compared to hardware-based monitoring systems.
- Average time investment for initial appliance inventory setup: 12 minutes.

Qualitative feedback highlighted the value of predictive insights enabling proactive consumption adjustments before bill generation, the transparency provided by appliance-level energy breakdowns, and the practicality of budget-to-time conversion for household energy planning.

6 DISCUSSION

The experimental results validate the effectiveness of the proposed non-intrusive smart energy auditor and demonstrate several significant findings with practical implications for residential energy management.

6.1 Prediction Accuracy and Reliability

The achieved prediction accuracy (MAE of 3.2%, RMSE of 4.8%) is sufficient for practical financial planning purposes, enabling households to anticipate monthly electricity costs within acceptable error margins. The superior performance compared to baseline methods (45% MAE improvement over Random Forest) confirms that deep neural networks effectively capture non-linear relationships between appliance usage patterns and billing costs, particularly in the context of slab-based tariff structures.

The slightly elevated errors in high-usage scenarios (MAE of 3.4%) can be attributed to tariff slab transitions, where small variations in total consumption may trigger disproportionate cost changes due to progressive rate structures. Future work will explore piece-wise neural network architectures that explicitly model slab boundaries to further reduce these edge-case errors.

6.2 Budget Optimization Practicality

The budget-constrained optimization module demonstrates substantial practical value, achieving cost reductions of 15-21% while maintaining user comfort through priority-based allocation. The higher savings percentages for larger households reflect the greater optimization flexibility provided by diverse appliance portfolios, enabling more nuanced consumption adjustments without eliminating essential services.

The greedy allocation algorithm employed in the current implementation provides rapid computational performance (optimization completes in under 1 second for typical households) at the cost of potential suboptimality. Future research will investigate more sophisticated optimization techniques, including mixed-integer linear programming (MILP) and reinforcement learning approaches, to identify theoretically optimal allocations while managing computational complexity.

6.3 Non-Intrusive Approach Advantages

The non-intrusive methodology eliminates hardware costs and installation complexities, making intelligent energy management accessible to broader demographics. The manual data entry requirement, while imposing a one-time setup burden (average 12 minutes), is offset by the absence of ongoing maintenance, hardware failures, and privacy concerns associated with continuous monitoring.

However, the non-intrusive approach introduces reliance on user-provided appliance specifications and usage estimates, which may contain inaccuracies affecting prediction precision. Incorporating machine learning-based anomaly detection to identify implausible appliance configurations and providing guided estimation tools could mitigate this limitation.

6.4 Scalability and Deployment Considerations

The software-only architecture enables straightforward deployment across diverse residential contexts without infrastructure prerequisites. The modular design supports future extensions, including integration with IoT devices for automatic appliance detection, incorporation of weather data for improved seasonal prediction, and multi-objective optimization accounting for carbon footprint alongside financial cost.

Cloud-based deployment facilitates accessibility through web and mobile interfaces, while local installation options address privacy concerns for users preferring data sovereignty. The containerized architecture ensures consistent performance across deployment environments.

6.5 Limitations and Future Directions

Several limitations warrant consideration. First, the current model assumes static appliance usage patterns, not accounting for dynamic lifestyle changes or unexpected consumption events. Incorporating temporal features (day of week, season) and enabling continuous model retraining as new billing data becomes available would enhance adaptability.

Second, the tariff model assumes knowledge of utility rate structures, which may vary by region and change periodically. Developing automated tariff detection from historical bills or integrating with utility provider APIs would improve system robustness.

Third, the optimization module currently operates independently of renewable energy integration (solar panels, battery storage). Extending the framework to incorporate on-site generation and time-of-use pricing would align with modern smart home ecosystems.

Finally, while the deep learning model performs well, its black-box nature limits interpretability. Incorporating explainable AI techniques (SHAP values, LIME) to clarify which appliances contribute most significantly to predictions would enhance user trust and enable more informed decision-making.

7 CONCLUSIONS

This paper presented a Smart Energy Auditor and Electrical Bill Prediction System employing a non-intrusive, deep learning-based approach for residential energy management. The proposed framework successfully addresses critical limitations of existing solutions by eliminating hardware dependencies, providing accurate bill predictions, and enabling budget-constrained optimization through novel inverse calculation mechanisms.

The Keras-based neural network regression model achieves robust prediction accuracy with MAE of 3.2% and RMSE of 4.8%, outperforming baseline machine learning approaches by substantial margins. The budget optimization module demonstrates practical effectiveness, reducing electricity costs by 15-21% across diverse household configurations while maintaining user comfort through priority-based appliance allocation.

The non-intrusive methodology positions the system as a cost-effective, scalable solution accessible to middle-income households and developing economies where smart meter infrastructure may be limited or prohibitively expensive. User study findings validate the practical utility of predictive insights for proactive consumption management and financial planning.

Future research directions include incorporating temporal and environmental features for enhanced prediction accuracy, integrating renewable energy sources and battery storage into the optimization framework, implementing explainable AI techniques for improved transparency, developing automated tariff structure detection, and exploring reinforcement learning approaches for theoretically optimal multi-objective optimization balancing cost, comfort, and environmental impact.

The proposed system represents a significant step toward democratizing intelligent energy management, transforming static electricity billing into dynamic decision-support tools that empower consumers to make informed, proactive choices for sustainable and cost-effective electricity consumption.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support of the Department of Computer Applications and Intelligence at KKR&KSR Institute of Technology and Sciences for providing computational resources and research facilities that enabled this work. We also thank the participating households who contributed data and

feedback during the user study phase.

REFERENCES

- Ahmad, A., Javaid, N., and Khan, Z. A. (2019). An optimized home energy management system with integrated renewable energy sources. *IEEE Access*, 7:549–567.
- Hart, G. W. (1992). Nonintrusive appliance load monitoring. *Proceedings of the IEEE*, 80(12):1870–1891.
- Jain, P. and Singh, A. (2021). Smart energy management system using machine learning techniques. In *Proceedings of the IEEE International Conference on Smart Energy Systems*, pages 112–117, Chennai, India. IEEE.
- Raza, A., Ahmed, M., and Hassan, S. (2019). Short-term electricity load forecasting using deep neural networks. *International Journal of Electrical Power and Energy Systems*, 105:505–514.
- Rodrigues, F., Cardeira, C., and Mel'icio, J. M. (2020). Electricity demand forecasting using machine learning and deep learning models. *Energies*, 13(5):1–18.
- Wang, Y., Chen, Q., and Hong, T. (2018). Electricity consumption prediction using deep learning approaches. *Energy and Buildings*, 158:141–151.
- Zhang, J., Wei, Y., and Li, D. (2020). Residential electricity consumption forecasting based on appliance usage patterns. *IEEE Transactions on Smart Grid*, 11(1):1–10.
- Zhou, K. and Yang, S. (2019). Understanding household energy consumption behavior using data analytics. *Energy Procedia*, 158:3480–3485.