

AI-Based Energy Consumption Prediction and Scheduling for Smart Homes

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Abstract- The consumption of electricity in households shows growing levels of unpredictability and peaks in demand, which negatively affect the stability of power grids and decreases the efficiency of energy consumption. Many research works have been dedicated to short-term load forecasting and demand-side management; however, only a small number of studies pay attention to the combination of artificial intelligence algorithms that would allow for the integration of accurate load forecasting and optimal scheduling of the appliance in the household. The present work aims to provide a framework for AI-based residential energy management, which integrates hybrid SWT-LSTM load forecasting with Genetic Algorithm for optimal appliance scheduling. First, the forecasting model was developed and tested on the UK Domestic Appliance-Level Electricity (UK-DALE) data set, in which high levels of the model's forecasting accuracy were reached with Mean Absolute Error of 20.46 W, Root Mean Square Error of 44.25 W and R² coefficient of 0.9868. Then, the forecasted load profile was used in the Genetic Algorithm to determine the schedule for the washing machine, dishwasher, water pump, and iron in order to reach the reduction of the average peak demand level on 25.73%, PAR reduction on 25.73%, increase in the Load Factor on 38.62% and reduction of Peak Energy on 10.32%. For evaluating the robustness and the ability to be generalized to other types of operating conditions, the developed load forecasting model was validated on the solar powered energy consumption data set provided by the Centre for Embedded AI and Smart Energy Systems, and resulted in Mean Absolute Error of 83.09 W, Root Mean Square Error of 195.32 W and achieved the coefficient of determination R² of 0.9823.

Index Terms- Artificial Intelligence; Stationary Wavelet Transform; Long Short-Term Memory; Genetic Algorithm; Residential Energy Management; Load Forecasting; Demand Side Management; Smart Grid.

I. INTRODUCTION

Smart homes have become an essential part of the contemporary power supply system because of the growing use of IoT, smart meters, and intelligent household devices. The ability to monitor, automate,

and control consumption of electricity by users is the key feature of the intelligent home that brings numerous advantages [1]. Nonetheless, rising residential power needs have also been linked to peak load problems, higher operational costs, and inefficient utilization of energy resources [2], [3]. Given that residential consumption of electricity is going to rise in the next few years, HEMS are becoming ever more relevant in terms of energy efficiency and demand management [4].

Short term load forecasting is essential for HEMS since it supplies the necessary data for energy management and load management [5]. Traditionally employed models like ARIMA, SARIMA, and ANN have been proven to be effective in electricity forecasting; however, their effectiveness can be hindered by the nonlinear nature of electricity consumption, which is time-varying and non-stationary in nature [5]–[9]. Deep learning methods, especially LSTM networks, have received a great deal of attention due to their capacity to recognize temporal dependencies in the electricity load profile [10]–[14]. Recent research has also been conducted on hybrid architectures such as CNN-LSTM, federated LSTM, Transformer architecture and SWT assisted LSTM for enhanced feature extraction and forecasting performance [12], [18]–[23]. Among all the developed techniques, SWT-LSTM is a hybrid algorithm that utilizes the advantages of SWT and LSTM by incorporating signal decomposition using SWT and temporal learning using LSTM for forecasting load signals [10], [12].

Although forecasting must be accurate, for efficient HEMS, intelligent demand side management (DSM) needs to play an important role in deciding on which

time the flexible loads will operate. Load shifting, peak shaving, and demand response are examples of the DSM strategy used to change the pattern of electricity usage depending on the demand and price of electricity [24], [25]. Genetic Algorithms (GA) have been extensively used in the context of scheduling of residential appliances owing to the inherent capability of solving nonlinear optimization problems [26], [27]. There are other methods like Binary Orientation Search Algorithm (BOSA), Binary Sparrow Search Algorithm (BSSA), and hybrid meta-heuristic methods that have proven successful in minimizing electricity cost, peak demand, and PAR. [28]–[30].

However, even with these advancements, research in forecasting and appliance scheduling has been commonly done separately. In most of the scheduling models, the assumption of availability of future load information has been considered, while the forecast models have been developed with the primary aim of predicting load only [28], [29], [31]. In addition, several studies rely on single, simulated, or limited datasets, restricting assessment of model robustness and generalization under different operating conditions. Consequently, there is a need for an integrated framework that combines accurate load forecasting with forecast-driven appliance scheduling and evaluates its performance across independent datasets.

To address this gap, this study developed an Artificial Intelligence (AI)-driven residential energy management framework integrating SWT-LSTM for short-term electricity load forecasting with a GA-based DSM strategy for flexible appliance scheduling under Time-of-Use (ToU) conditions. The framework was developed and evaluated using the UK Domestic Appliance-Level Electricity (UK-DALE) dataset and further validated using an independent electricity consumption dataset collected from the Centre for Embedded Artificial Intelligence and Smart Energy Systems (CESAI), Abubakar Tafawa Balewa University, Bauchi. The study therefore aims to develop an accurate SWT-LSTM forecasting model, design a GA-based appliance scheduling strategy for reducing peak demand and improving load distribution, and evaluate the robustness of the

integrated framework using the two independent datasets.

II. METHODOLOGY

This study developed an integrated Artificial Intelligence (AI)-driven residential energy management framework that combines accurate short-term load forecasting with intelligent appliance scheduling to improve household energy efficiency and support grid stability. The developed framework integrates a hybrid Stationary Wavelet Transform–Long Short-Term Memory (SWT-LSTM) model for residential load forecasting with a Genetic Algorithm (GA)-based demand-side management strategy under Time-of-Use (ToU). The methodology follows a systematic workflow comprising data acquisition, preprocessing, load forecasting, appliance scheduling, and performance evaluation, thereby providing a unified framework for predictive and optimized residential energy management.

The framework was designed to address the three objectives of this study through four interconnected stages. First, historical household electricity consumption data are acquired and preprocessed to generate high-quality time-series inputs for model development. Second, the preprocessed load signal is decomposed using the Stationary Wavelet Transform and processed by a Long Short-Term Memory network to generate accurate short-term electricity demand forecasts. Third, the forecasted load profile is supplied to a Genetic Algorithm that determines optimal operating schedules for flexible household appliances while satisfying operational constraints and minimizing electricity cost and peak demand. Finally, the forecasting and scheduling performances are quantitatively evaluated using appropriate prediction and demand-side management metrics. Figure 1 illustrates the overall workflow of the developed intelligent residential energy management framework.

The developed Artificial Intelligence (AI)-driven residential energy management framework was designed to integrate accurate short-term load forecasting with intelligent demand-side management within a unified system. The framework consists of four interconnected stages: (i) data

acquisition and preprocessing, (ii) SWT-LSTM-based load forecasting, (iii) Genetic Algorithm (GA)-based appliance scheduling, and (iv) performance evaluation and model validation. These stages operate sequentially to transform raw electricity consumption data into optimized appliance schedules that improve household energy efficiency while supporting grid stability. Figure 1 presents the overall workflow of the developed framework.

The methodology begins with the acquisition of historical electricity consumption data from the UK Domestic Appliance-Level Electricity (UK-DALE) dataset, which serves as the primary benchmark for model development. To evaluate the adaptability and generalization capability of the developed forecasting model, operational energy consumption data obtained from the Centre for Embedded AI and Smart Energy Systems, Abubakar Tafawa Balewa University, Bauchi, are also incorporated during the validation stage. Both datasets undergo preprocessing, including data cleaning, timestamp standardization, resampling into uniform 10-minute intervals, normalization using Min-Max scaling, and transformation into supervised learning sequences through a sliding-window approach.

Following preprocessing, the normalized load signal is decomposed using the Stationary Wavelet Transform (SWT) to separate long-term consumption trends from high-frequency fluctuations while preserving the temporal characteristics of the data. The decomposed signals are subsequently used to train a Long Short-Term Memory (LSTM) network for short-term residential load forecasting. The forecasted load profile is then analyzed to identify potential peak-demand periods, after which a Genetic Algorithm optimizes the operating schedules of flexible household appliances under Time-of-Use (ToU) satisfying appliance operational constraints. Finally, the developed framework is evaluated using forecasting metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), together with demand-side management metrics such as Peak Demand Reduction, Peak-to-Average Ratio (PAR) Reduction, Load Factor Improvement, and Peak Energy Reduction. The forecasting model is further validated using the independent institutional dataset

to assess its robustness and applicability under a different energy consumption environment. Figure 1 presents the overall workflow of the developed framework.

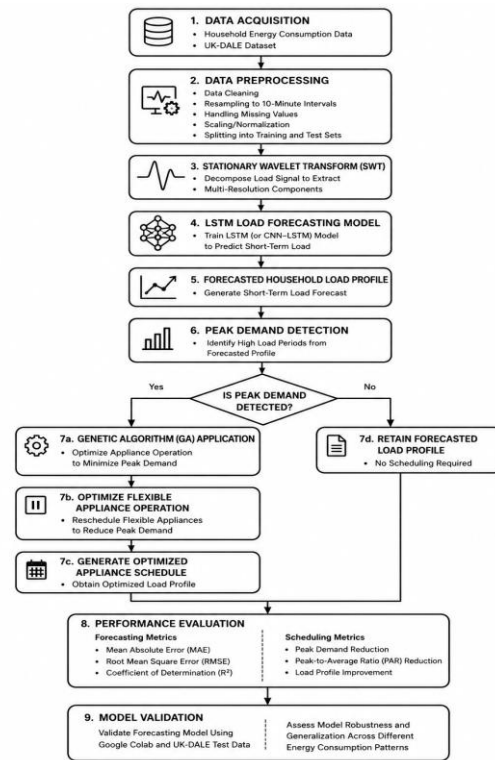


Figure 1. Overall workflow

2.1 Datasets

2.1.1 UK-DALE Dataset

The UK Domestic Appliance-Level Electricity (UK-DALE) dataset was used to achieve the first and second goals of this study. The dataset was created by researchers at Imperial College London for use in studies related to residential energy monitoring, load forecasting, energy disaggregation, and demand-side management. This dataset includes high-resolution recordings of household electricity consumption and the power consumed by each household appliance from multiple occupied households within the United Kingdom.

One of the main benefits of the UK-DALE dataset is that it provides measurements of the consumption of each household appliance in addition to measurements of aggregate electricity consumption. Thus, it is appropriate to use this dataset to create intelligent load forecasting algorithms and evaluate scheduling techniques. The ability to measure the

consumption of individual appliances allows for re-scheduling flexible household loads while adhering to appliance operating constraints.

In this study, the data on aggregate electricity consumption of households were taken from the UK-DALE dataset and used to create the SWT-LSTM load forecasting algorithm. Additionally, four controllable household appliances were selected for demand-side management using the Genetic Algorithm. These four appliances have flexible operating periods that can be changed without having a considerable impact on user comfort. The selected appliances are Washing Machine, Dishwasher, Water Pump and Electric Iron.

First, the electricity consumption records were resampled into regular time intervals of 10 minutes to ensure consistency throughout the forecasting procedure. After data preprocessing, the records were then split into train and test sets in an 80:20 split ratio. Historical data for 48-time steps lookback window was used to forecast the future electricity demand.

The SWT-LSTM based electricity consumption forecasting method utilized Daubechies-4 (db4) wavelet with decomposition level equal to two. In the developed forecasting network, two stacked Long Short-Term Memory layers with 256 and 128 neurons in each one were used respectively. Dropout layers with a probability of 0.2 were added after each LSTM layer to avoid overfitting during training procedure. For the training of the network, a batch size of 32 was used for a maximum number of 120 epochs.

Finally, the resulting predicted load profile was passed to the Genetic Algorithm-based Optimization algorithm when the predicted electricity consumption exceeded the defined peak demand threshold, which corresponds to 80th percentile of daily load profile. Parameters that were used for algorithm implementation were as follows: population size was equal to 80 chromosomes, the number of generations was 100, elite preservation size was 10 and mutation probability was set to 0.20. These parameters allow the algorithm to find optimal appliance schedules, which can reduce the peak load demand.

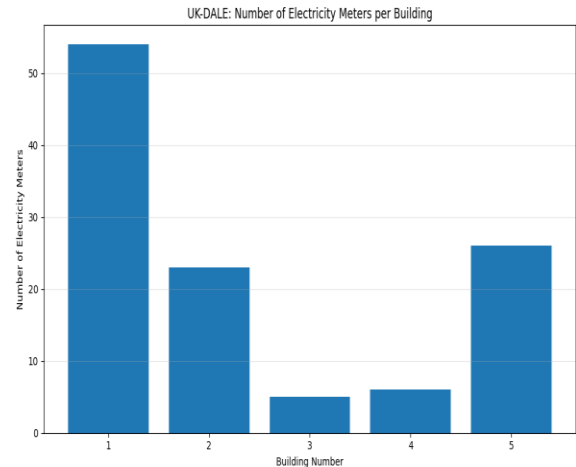


Figure 7: Electricity consumption time series for Building 1, Meter 1.

Figure 7 illustrates the distribution of electricity meters across the five buildings contained in the UK-DALE dataset. The figure shows that Building 1 has the highest number of electricity meters, with approximately 54 meters, followed by Building 5 with 26 meters and Building 2 with 23 meters. Buildings 3 and 4 have considerably fewer meters, with approximately 5 and 6 meters, respectively. This variation indicates that the level of electrical monitoring differs among the buildings and that Building 1 provides a comparatively rich source of electricity measurements. For this study, building 1 was selected as the primary building for the forecasting analysis, with the /building1/elec/meter1 measurement used to obtain the electricity load signal. The relatively large number of meters available in Building 1 provides a broader monitoring environment and supports the selection of a representative household electricity signal for the subsequent forecasting analysis. The selected meter provides the load measurements that were subsequently processed and transformed before being supplied to the forecasting framework.

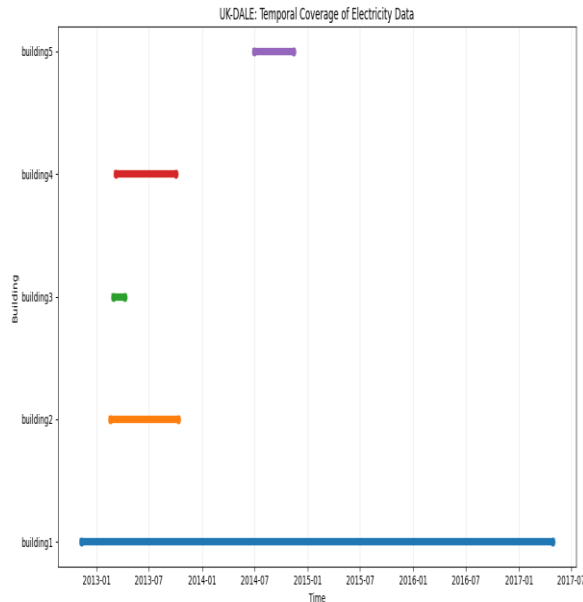


Figure 8: Temporal coverage of UK-DALE electricity data

Figure 3.2 presents the temporal coverage of electricity consumption measurements for the five buildings in the UK-DALE dataset. The figure demonstrates that the duration of data collection varies substantially between buildings. Building 1 has the longest period of recorded measurements, extending from approximately 2012 to 2017, whereas the other buildings have shorter observation periods. This difference in temporal coverage is important for a time-series forecasting study because the quantity and continuity of historical observations influence the amount of information available for identifying consumption patterns. The extensive temporal coverage of Building 1 provides a substantial historical record from which electricity consumption behaviour can be investigated. Consequently, building 1 was selected for the present study. The longer observation period allows the forecasting framework to be developed using a relatively large number of historical observations while also providing sufficient data for separating the observations into training and testing periods. This supports the subsequent application of the Stationary Wavelet Transform (SWT) and Long Short-Term Memory (LSTM) model for short-term residential electricity load forecasting.

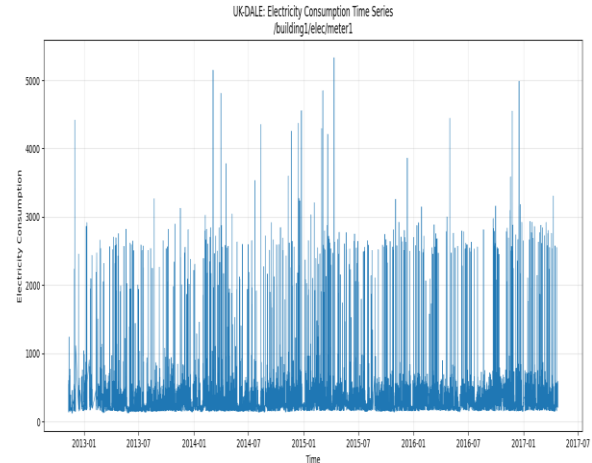


Figure 9: Electricity consumption time series for Building 1, Meter 1

Figure 9 presents the electricity consumption time series obtained from /building1/elec/meter1. The figure shows considerable variation in electricity consumption throughout the observation period. Although the signal generally maintains a lower consumption range for substantial portions of the period, numerous short-duration increases and high-amplitude peaks can also be observed. Some of these peaks exceed approximately 5,000 on the plotted consumption scale. The presence of these fluctuations demonstrates the dynamic nature of residential electricity demand.

The observed variability is particularly relevant to the forecasting problem addressed in this study. Residential electricity consumption is influenced by the operation of household appliances and changes in household activities, resulting in both relatively smooth changes and sudden load variations. Therefore, the load signal contains different characteristics that must be captured adequately by the forecasting model. The complexity and variability observed in Figure 3.3 provide the motivation for applying signal decomposition before the LSTM forecasting stage. In this study, the Stationary Wavelet Transform is employed to separate the load signal into approximation and detail components, allowing different characteristics of the electricity consumption signal to be represented before forecasting.

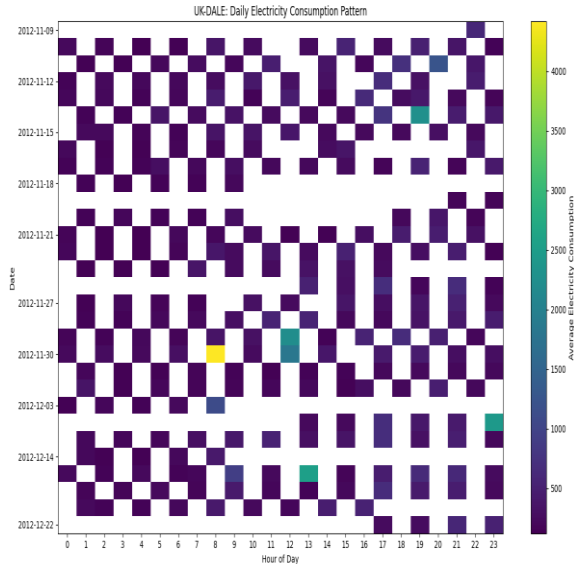


Figure 10: Daily electricity consumption pattern for Building 1, Meter 1

Figure 3.4 presents a heatmap of the daily electricity consumption pattern for the selected electricity meter. The horizontal axis represents the 24 hours of the day, while the vertical axis represents the observation dates. The colour intensity represents the magnitude of average electricity consumption for a particular hour and date. The figures show that electricity consumption is not uniform throughout the day. Instead, periods of relatively low consumption occur alongside periods of substantially higher consumption.

The occurrence of higher-intensity regions at particular hours indicates that residential electricity demand varies according to the time of day. The heatmap also demonstrates that the magnitude of consumption differs from one date to another, indicating temporal variability in household electricity usage. For example, some observations show considerably higher consumption values than the surrounding periods. These variations provide evidence of temporal patterns within the electricity load and further support the treatment of the dataset as a time-series forecasting problem.

The observed hourly and daily variations are important to the developed forecasting framework because the model must learn both the underlying consumption behavior and short-term changes in

demand. The presence of these temporal characteristics supports the use of LSTM, which is designed to learn dependencies within sequential data. Furthermore, the rapid changes and fluctuations observed in the load signal justify the use of SWT as a preprocessing and decomposition technique before the LSTM forecasting stage.

2.1.2 Centre for Embedded Artificial Intelligence and Smart Energy Systems Dataset

An independent dataset on electricity usage was created using the electric load data from the Centre for Embedded Artificial Intelligence and Smart Energy Systems (CESAI), Abubakar Tafawa Balewa University, Bauchi, to evaluate the robustness and generalization capability of the developed framework. Unlike the residential UK-DALE dataset, the CESAI data set contains electricity consumption behavior of a solar-powered institutional setting. This dataset was obtained from the data collected based on rated power, time of operation, location, and operating schedule of the electrical loads per day within various rooms in the offices, laboratories, lecture rooms, conference rooms, and other academic departments. The loads were summed up to create the building load profile. Analysis of the framework based on these two data sets reveals its effectiveness in different operating conditions.

2.1.3 Data Preprocessing

Before building the models, UK-DALE and CESAI datasets went through the same preprocessing process to ensure the quality and synchronization of the data. The steps involved in the preprocessing process included data cleaning, synchronization of timestamps, resampling, normalization, creation of supervised sequences, and splitting of the datasets. The invalid and missing entries were filtered out before sorting the time-series data into chronological order and resampling it in 10-minute intervals. After that, the data were normalized between 0 and 1 by Min-Max scaling to increase the numerical stability of the model training process. The final step was transforming the normalized time series data into supervised sequences using a window size of 48 and an 80:20 split between training and test sets. This preprocessing procedure ensured consistent data preparation for forecasting, optimization, and cross-dataset validation.

2.2 SWT-LSTM Forecasting Procedure

The normalized load signal was decomposed using SWT, and the resulting components were converted into supervised sequences using a 48-time-step lookback window for LSTM training. The predicted components were reconstructed using the Inverse SWT to get the final short-term load forecast, which was assessed using MAE, RMSE, and R^2 . The forecast was subsequently supplied to the GA scheduling module when predicted demand exceeded the defined peak threshold.

2.3 GA-Based Appliance Scheduling

The forecasted load was used as input to a Genetic Algorithm (GA) for proactive scheduling of four flexible appliances: washing machine, dishwasher, water pump, and electric iron, while the refrigerator was retained as a non-shiftable base load. Peak-demand periods were identified using the 80th percentile of the daily forecasted load as a dynamic threshold; when this threshold was exceeded, the forecast was passed to the GA for optimization.

Each chromosome represented a complete daily appliance schedule, with genes corresponding to appliance start times. Scheduling was performed at 10-minute intervals over a 24-hour horizon, subject to appliance operating constraints. GA iteratively refined candidate schedules through selection, crossover, mutation, and elitism. The fitness can be stated as:

$$F = w_1 P_{\text{peak}} + w_2 E_{\text{peak}} + w_3 PAR + w_4 \sigma \quad (1)$$

where P_{peak} denotes the maximum predicted household load, E_{peak} represents the total energy consumed during predicted peak-demand periods, PAR is the Peak-to-Average Ratio of the load profile, and σ is the standard deviation of the scheduled load profile, which measures load variability. The weighting coefficients w_1 , w_2 , w_3 , and w_4 were assigned values of 1.0, 1.0, 0.5, and 0.3, respectively, to prioritize peak demand reduction while simultaneously encouraging balanced energy consumption and smooth load distribution.

2.4 GA-Based Appliance Scheduling

Load forecast was optimized by Genetic Algorithm (GA) by scheduling four shiftable loads: washing machine, dishwasher, water pump, and electric iron, with the refrigerator being the non-shiftable base load. The chromosome encoding comprised the start times of appliances and was limited within the feasible daily scheduling period for each candidate solution. Initially, 80 chromosomes were evaluated based on the defined multi-objective fitness function. The following parameters were used in the process: tournament selection with tournament size = 5, single point crossover, mutation rate of 0.20, and elitism of 10 chromosomes over 100 generations. The chromosome with the least fitness value was selected as the optimal schedule. The optimal appliance schedules were then used together with the load forecast to construct the final daily load curve.

2.5 Performance Evaluation

Performance of the developed framework was analyzed through forecasting performance and demand side management performance indicators. The forecasting performance analysis was achieved using of MAE, RMSE, and R^2 coefficient while genetic algorithm scheduling strategy performance was evaluated based on peak reduction, PAR reduction, load factor improvement, and peak energy reduction.

2.5.1 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) measures the average absolute difference between the predicted and actual load values. Lower MAE values indicate better forecast performance.

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

where y_i represents the actual load value, $\hat{y}_i$ denotes the predicted load value, and n is the total number of observations used during model evaluation.

2.5.2 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) evaluates the standard deviation of the prediction errors by assigning greater weight to larger forecasting errors. Consequently, RMSE is particularly useful for

assessing the overall prediction performance of the forecasting model.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

Where y_i is the actual load value, $\hat{y}_i$ is, the predicted load value, and n denotes the total number of observations.

2.5.3 Coefficient of Determination (R^2)

The Coefficient of Determination (R^2) measures how well the forecasting model explains the variability in the observed electricity consumption data. Values closer to one indicate better agreement between the predicted and actual load values.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

Where y_i denotes the actual load value, $\hat{y}_i$ represents the predicted load value, $\bar{y}$ is the mean of the actual load values, and n is the total number of observations.

2.5.4 Peak Reduction

Peak Reduction measures the percentage decrease in the maximum electricity demand after the application of the scheduling algorithm. It indicates the effectiveness of the developed demand-side management strategy in reducing peak demand.

$$Peak\ Reduction\ (\%) = \frac{Peak_{Before} - Peak_{After}}{Peak_{Before}} \times 100 \quad (5)$$

where $Peak_{Before}$ is the maximum load before scheduling, while $Peak_{After}$ is the maximum load after scheduling.

2.5.5 Peak-to-Average Ratio (PAR) Reduction

The Peak-to-Average Ratio (PAR) is a commonly used indicator for evaluating the smoothness of an electricity load profile. It is computed as the ratio of the peak load to the average load. Lower PAR values indicate a more balanced load distribution.

$$PAR = \frac{P_{peak}}{P_{average}} \quad (6)$$

where P_{peak} is the maximum load and $P_{average}$ represents the average load over the scheduling period.

The percentage reduction in PAR after scheduling is calculated as:

$$PAR\ Reduction\ (\%) = \frac{PAR_{Before} - PAR_{After}}{PAR_{Before}} \times 100 \quad (7)$$

where PAR_{Before} and PAR_{After} represent the Peak-to-Average Ratio before and after optimization, respectively.

2.5.6 Peak Energy Reduction

Peak Energy Reduction measures the percentage decrease in the total energy consumed during identified peak-demand periods after optimization. This metric evaluates the effectiveness of the scheduling algorithm in shifting electricity consumption away from peak periods.

$$Peak\ Energy\ Reduction\ (\%) = \frac{PE_{Before} - PE_{After}}{PE_{Before}} \times 100 \quad (8)$$

where PE_{Before} represents the total energy consumed during peak-demand periods before scheduling, while PE_{After} denotes the corresponding energy consumption after optimization.

III. RESULTS AND DISCUSSION

This section includes information about the hardware and software used, sources of the dataset, preliminary data analysis, results, and results analysis. Visual representation of results using figures, graphs, and tables would be a great idea for this part. Formulas or methods of evaluation are to be presented as well. There should be discussion/analysis, and you can't simply rewrite your results in sentence form; instead, you have to interpret the link between the results and your initial hypothesis.

3.1 SWT-LSTM Forecasting Performance

To evaluate the forecasting capability of the developed SWT-LSTM model, experiments were conducted using the UK-DALE dataset. The forecasting performance was assessed using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2).

Fig. 2 compares the actual versus predicted household electricity load, while Table 1 summarizes the quantitative performance metrics.

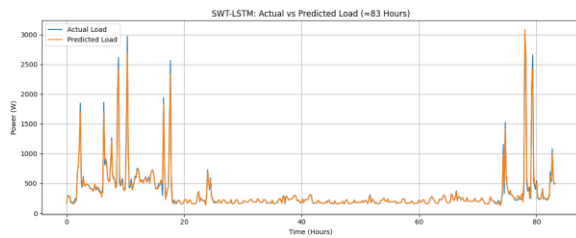


Figure 2. Actual versus predicted household load of the developed SWT-LSTM model.

As illustrated in Fig. 2, the estimated load curve is like real household power consumption for the entire period of testing. Thus, the model not only considers the usual pattern of consumption but also predicts the peaks of high-power consumption, which demonstrates that the nonlinear temporal properties of residential electricity consumption have been learned by the model. Although discrepancies occur in case of sudden load variations, the estimated load curve remains highly correlated with the actual load. Figure 3. Residual errors of the developed SWT-LSTM model.

Figure 3 shows the correlation between the residual and the load observed. The residuals tend to center around zero in case of low and mid-level loads, which show that the model predicts well. However, in case of high load values, the residuals vary more due to the difficulty in predicting sudden peaks in demand. Nevertheless, the residuals remain relatively small compared with the overall load magnitude, confirming the robustness of the developed forecasting model.

Table 1. Forecasting results of SWT-LSTM model
The above results from the quantification also support the efficacy of the forecasting model. In this case, the MAE and RMSE of 20.4571 W and 44.2508 W, respectively, show small prediction errors. On the other hand, the coefficient of determination (R^2) is 0.9868, which means that about 98.68 percent of the variation in the actual load is explained by the model. The results show that the integration of Stationary Wavelet Transform with the LSTM gives effective short-term residential load forecasting.

3.2 Genetic Algorithm Scheduling Performance

The performance of the demand-side management approach developed by the Genetic Algorithm (GA) was assessed based on the load forecasts obtained from the SWT-LSTM model for households. This optimization technique changed the working schedule of four shiftable household devices such that the peak demand is reduced, the improved load curve is achieved, and the energy consumption during high-demand times is reduced. The performance of the developed scheduling technique was measured based on Peak Reduction, PAR Reduction, Load Factor Improvement, and Peak Energy Reduction.

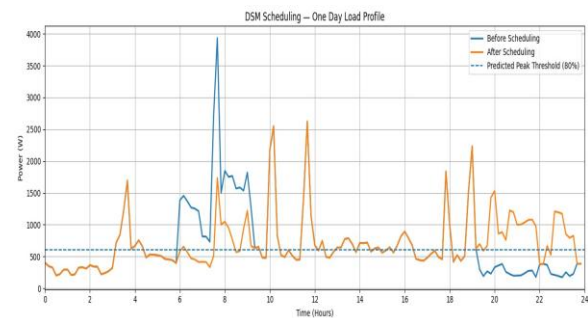


Figure 4. Household load profile before and after Genetic Algorithm-based appliance scheduling.

As shown in Figure 4, the adopted scheduling system has been able to transfer the appliance loading pattern to lower demand times thus leading to smoothening of the entire load profile. While the initial load curve shows a peak value of about 3.93 kW, the load after scheduling is lowered to a peak value of about 2.62 kW, thus showing about a 33.31% peak lowering for that particular day. While some appliances have been rescheduled to operate at later times, there is no new peak generated due to the scheduling. This shows that the load scheduling algorithm has succeeded in smoothening the daily load profile.

Table 2. Overall scheduling performance of the developed Genetic Algorithm over ten evaluation days.

Metric	Value
MAE (W)	20.4571
RMSE (W)	44.2508
R^2	0.9868

Results in Table 2 are the averages for the 10-day evaluation period. It was observed that the genetic algorithm generated on average 25.73% saving in peak demand as well as 25.73% in the Peak to Average Ratio (PAR) values, which is an indication of better balancing of household electricity demand in a day. In addition to that, the average load factor is increased by 38.62%. The developed optimization algorithm was able to save energy consumption during the predicted peak-demand time by 10.32%. Regarding the robustness of the algorithm, the positive reduction in peak demand and PAR was observed on all 10 days, whereas positive reduction in energy consumption during the peak period was obtained on 9 out of 10 days.

3.3 Cross-Dataset Validation Using the CESAI Dataset

To analyze the generalizability of the developed forecasting framework, the SWT-LSTM method was validated with CESAI data set that is different from the UK-DALE data set, which had been utilized for evaluating the method at first. This was done to examine whether the developed approach can perform reliably when applied to a different consumption profile.

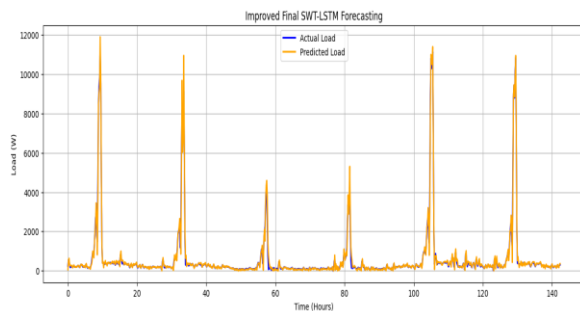


Figure 5. Performance of the developed SWT-LSTM model on the CESAI dataset.

As illustrated in Figure 5, the predicted load tracks the actual electricity load of the households almost consistently over the entire period of analysis, regardless of the normal operation period or high-demand periods. Despite a small margin of deviation seen during some spikes in the peak load, the SWT-LSTM model proves itself capable of capturing the general characteristics of the load time series as well as major demand changes seen in the CESAI dataset.

Table 3. Performance of the developed SWT-LSTM model on the CESAI dataset.

Metric	Value
MAE (W)	84.40
RMSE (W)	202.23
R ²	0.9823

Quantitative findings also show the strength of the developed predictive model. The SWT-LSTM algorithm produced an MAE of 84.40 W, RMSE of 202.23 W, and the R² value of 0.9823, meaning there was good correlation between predicted and measured values of electricity load. A very high R² value means that the model accounts for more than 98% of the variance of the observed household electricity consumption, while the relatively low MAE and RMSE mean that prediction errors were small.

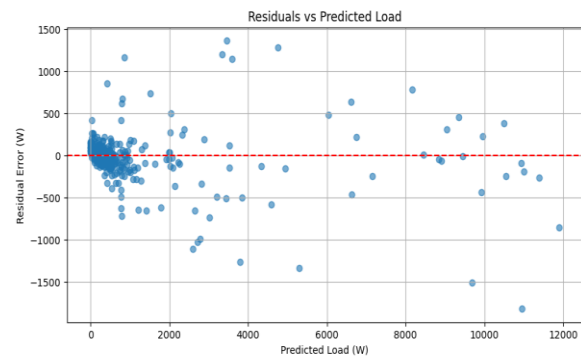


Figure 6. Residuals versus predicted load for the developed SWT-LSTM forecasting model on the CESAI dataset.

Residuals of the constructed SWT-LSTM model for the CESAI data are depicted in Figure 6. The residuals appear to be randomly scattered across the zero-error line, which indicates that the predictions generated by the model are unbiased. Though there are some larger errors while modeling high-load conditions, most of the residuals still lie around the zero-error level, proving the robustness and accuracy of the predictions made by the developed model.

3.4 Comparison with Existing Studies

Comparison between the developed framework and other related literature on residential load forecasting and demand side management is provided in Table 4.

Earlier research mainly concentrated on developing efficient forecasting methods [12],[30].

IV. CONCLUSION

This study developed an intelligent residential energy management framework that integrates Stationary Wavelet Transform–Long Short-Term Memory (SWT-LSTM) for short-term electricity load forecasting with a Genetic Algorithm (GA) for appliance scheduling. The developed framework was evaluated using the UK-DALE dataset and further validated on the CESAI dataset to assess its forecasting accuracy and generalization capability. The results demonstrated that the SWT-LSTM model achieved high forecasting accuracy, while the GA-based scheduling strategy effectively reduced peak demand and Peak-to-Average Ratio (PAR) and improved the load factor. These results clearly show that the developed framework was successful in accomplishing the objectives of the research as it was able to use accurate load forecasting along with intelligent appliance scheduling in a combined way through an energy management system in the residential domain. Different from many existing approaches where only forecasting or optimization is considered, the developed framework considers both and is able to validate the framework using two different residential datasets. Despite obtaining positive results from the developed framework, this framework was only validated through simulation in this study using publicly available datasets without considering the actual implementation of the framework with distributed energy resources and electric vehicles. Therefore, the future research work should be based on the actual implementation of the framework with the consideration of these resources.

REFERENCES

- [1] N. Raj, A. Sinha, S. Bharddwaj, and A. L. Yadav, "AI-Powered Energy Consumption Optimization for Smart Homes Using IoT," in *Proceedings - 2024 International Conference on Computational Intelligence and Computing Applications, ICCICA 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 231–236. [IEEE](#)
- [2] O. Reddy Polu, "AI - Based Smart Energy Consumption Prediction for IoT - Connected Homes," *Int. J. Sci. Res.*, vol. 13, no. 12, pp. 1836–1841, Dec. 2024. [International Journal of Science and Research](#)
- [3] M. A. Fotouhi Ghazvini, K. Antoniadou-Plytaria, D. Steen, and L. A. Tuan, "Two-stage demand-side management in energy flexible residential buildings," *J. Eng.*, vol. 2024, no. 4, pp. 1–14, 2024. [Wiley](#)
- [4] A. Raza, L. Jingzhao, Y. Ghadi, M. Adnan, and M. Ali, "Smart home energy management systems: Research challenges and survey," *Alexandria Eng. J.*, vol. 92, no. July 2023, pp. 117–170, 2024. [ScienceDirect](#)
- [5] S. Akhtar *et al.*, "Progress , and the Road Ahead," 2023.
- [6] S. Muzaffar and A. Afshari, "Short-term load forecasts using LSTM networks," in *Energy Procedia*, Elsevier Ltd., 2019, pp. 2922–2927. [ScienceDirect](#)
- [7] Q. Ma, "Comparison_of_ARIMA_ANN_and_LSTM_f or_Stock_Price_P.pdf," vol. 01026, pp. 1–5, 2020.
- [8] G. Mao *et al.*, "Comprehensive comparison of artificial neural networks and long short-term memory networks for rainfall-runoff simulation," *Phys. Chem. Earth*, vol. 123, Art. no. 103026, 2021. [ScienceDirect](#)
- [9] H. Wentz, J. N. Maciel, J. J. G. Ledesma, and O. H. A. Junior, "Solar Irradiance Forecasting to Short-Term PV Power: Accuracy Comparison of ANN and LSTM Models," *Energies*, vol. 15, no. 7, pp. 1–23, 2022. [MDPI](#)
- [10] A. Guenoukpati, A. P. Agbessi, A. A. Salami, and Y. A. Bakpo, "Hybrid Long Short-Term Memory Wavelet Transform Models for Short-Term Electricity Load Forecasting," *Energies*, vol. 17, no. 19, pp. 1–21, 2024. [MDPI](#)
- [11] B. Biswal, S. Deb, S. Datta, T. Selim, and U. Cali, "Review on smart grid load forecasting for smart energy management using machine learning and deep learning techniques," *Energy Reports*, vol. 12, no. September, pp. 3654–3670, 2024. [ScienceDirect](#)

- [12] K. Yan, W. Li, Z. Ji, M. Qi, and Y. Du, "A Hybrid LSTM Neural Network for Energy Consumption Forecasting of Individual Households," *IEEE Access*, vol. 7, pp. 157633–157642, 2019. [IEEE](#)
- [13] S. H. Rafi, N. Al-Masood, S. R. Deeba, and E. Hossain, "A short-term load forecasting method using integrated CNN and LSTM network," *IEEE Access*, vol. 9, pp. 32436–32448, 2021. [IEEE](#)
- [14] M. Razghandi, "Load Forecasting and Synthetic Data Generation for Smart Home Energy Management System," 2022. [University of Central Florida](#)
- [15] C. Bharathi and D. Rekha, "Load Forecasting for Demand Side Management in Smart Grid using Non-Linear Machine Learning Technique," vol. 1, pp. 200–214, 2023. [JOWUA](#)
- [16] M. M. Iqbal *et al.*, "Optimal scheduling of residential home appliances by considering energy storage and stochastically modelled photovoltaics in a grid exchange environment using hybrid grey wolf genetic algorithm optimizer," *Appl. Sci.*, vol. 9, no. 23, Dec. 2019. [MDPI](#)
- [17] D. Latoń, J. Grela, and A. Ożadowicz, "Applications of Deep Reinforcement Learning for Home Energy Management Systems: A Review," Dec. 01, 2024, Multidisciplinary Digital Publishing Institute (MDPI). [MDPI](#)
- [18] P. Zhao *et al.*, "Enhancing multivariate, multi-step residential load forecasting with spatiotemporal graph attention-enabled transformer," *Int. J. Electr. Power Energy Syst.*, vol. 160, no. January, Art. no. 110074, 2024. [ScienceDirect](#)
- [19] A. Bekkar, B. Hssina, S. Douzi, and K. Douzi, "Air - pollution prediction in smart city , deep learning approach," *J. Big Data*, pp. 1–22, 2021. [Springer](#)
- [20] S. F. Stefenon and K. C. Yow, "Adaptive filter-driven optimized attention-based CNN-LSTM for load forecasting in microgrids," *Results Eng.*, vol. 28, no. October, 2025. [ScienceDirect](#)
- [21] A. Rizwan *et al.*, "Enhancing energy consumption prediction in smart homes: a convergence-aware federated transfer learning approach," *Sci. Technol. Energy Transit.*, vol. 79, 2024. [Science and Technology for Energy Transition](#)
- [22] A. Gangwar, S. Singh, R. Mishra, and S. Prakash, "The State-of-the-Art in Air Pollution Monitoring and Forecasting Systems Using IoT, Big Data, and Machine Learning," *Wirel. Pers. Commun.*, vol. 130, no. 3, pp. 1699–1729, 2023. [Springer](#)
- [23] S. Gao *et al.*, "Short-term residential load forecasting via transfer learning and multi-attention fusion for EVs' coordinated charging," *Int. J. Electr. Power Energy Syst.*, vol. 164, no. November 2024, Art. no. 110349, 2025. [ScienceDirect](#)
- [24] A. Shewale, A. Mokhade, N. Funde, and N. D. Bokde, "A Survey of Efficient Demand-Side Management Techniques for the Residential Appliance Scheduling Problem in Smart Homes," pp. 1–34, 2022.
- [25] E. Sarker *et al.*, "Progress on the demand side management in smart grid and optimization approaches," *Int. J. Energy Res.*, vol. 45, no. 1, pp. 36–64, 2021. [Wiley](#)
- [26] X. Wang, H. Wang, B. Bhandari, and L. Cheng, "AI-Empowered Methods for Smart Energy Consumption: A Review of Load Forecasting, Anomaly Detection and Demand Response," May 01, 2024, Korean Society for Precision Engineering. [Springer](#)
- [27] M. Sakib, T. S. Id, S. Mustajab, R. Muneer, and A. Id, "An ensemble deep learning framework for energy demand forecasting using genetic algorithm-based feature selection," pp. 1–28, 2025.
- [28] M. S. Bakare, A. Abdulkarim, M. Zeeshan, and A. N. Shuaibu, "A comprehensive overview on demand side energy management towards smart grids : challenges , solutions , and future direction," 2023. [Springer](#)
- [29] A. M. Jasim, B. H. Jasim, and B. Neagu, "Management Program for Smart Grid Residential Load," 2023.
- [30] T. Singh, A. Solanki, S. K. Sharma, N. Z. Jhanjhi, and R. M. Ghoniem, "Grey Wolf Optimization-Based CNN-LSTM Network for the Prediction of Energy Consumption in Smart

Home Environment,” *IEEE Access*, vol. 11, pp. 114917–114935, 2023. [IEEE](#)

- [31] N. Mounir, S. El Bakali, S. Gheouany, N. Mounir, and S. El, “ScienceDirect,” 2024.
- [32] A. Mehmood, K. T. Lee, and D. H. Kim, “Energy Prediction and Optimization for Smart Homes with Weather Metric-Weight Coefficients,” *Sensors*, vol. 23, no. 7, Apr. 2023. [MDPI](#)