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Seasonal Pattern Recognition-based Advanced Hybrid Machine Learning Methods for Residential Energy Consumption Forecasting in Smart Grid Networks

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Abstract

This research explores machine learning (ML) techniques, with an emphasis on neural networks (NNs), to predict household energy consumption in the context of smart grids. The study evaluates algorithms such as CNN, LSTM, RF, AdaBoost, and CatBoost with a primary focus on hybrid models to enhance forecast precision. The research adopts a comprehensive data collection strategy while dividing the time series data into training (80%) and testing (20%) segments for rigorous model evaluation. Hybrid approaches that combine several algorithms significantly outperform single models, and LSTM-CatBoost is at the forefront by exhibiting lower error rates and higher R^2 values. To avoid overfitting, the research employs cross-validation in conjunction with early stopping, thus, producing robust and trustworthy models. The paper provides a wealth of information on energy forecasting that paves the way for the energy efficiency and sustainability of smart grids, which are essentially energy management systems based on the latest technology and consumer feedback mechanisms.

Keywords

energy forecasting, hybrid schemes, seasonality, cyclic patterns, energy consumption forecasting

1 Introduction

The smart grid advancement signifies a fundamental transformation in power generation, distribution, and consumption. It is an essential transformation for optimized energy management in a more intelligent, affordable, and reliable way. The smart grid is composed of many modern technologies, including automation devices, protective equipment, and complex communication protocols. The active involvement of consumers in changing their consumption behavior in nearly real time is a crucial problem in energy utilization and system management using more efficient communication and feedback mechanisms [1]. These technological and architectural advancements will ensure that grids are reliable and their reconciliation with demand, a challenge in the energy supply and demand nature of power systems worldwide [2]. Moreover, smart networks are more environmentally friendly in energy generation and transmission, producing less harmful impact on nature as Energy is generated and sent to users. But the potential of smart grids in creating the residential energy management industry is enormous if they disregard the most important problems. Therefore, the global power consumption is intensified by residential properties, which are responsible for an estimated 30–40% of the total electricity used in various regions of the world [3]. This trend is likely to accelerate regarding the growth of urbanization and population in many parts of the world, increasing the number of residential units around the world. This has made home power use harder to predict and regulate as electric appliances for domestic use, and equipment that uses considerable energy, are mushrooming. Energy demand forecasting is accurate, which is important for power networks' operation in a correct way and in households for the correct energy management. To plan and make decisions on power system planning, forecasting consumer electricity demand is essential as it directly dictates effective use of energy and continuous flow of electricity supply to consumers [4]. Particularly, this scenario will feature finding a balance between energy production and consumption to provide system stability in a large power system as well as within smaller, local micro-grids [5]. Electricity is

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an essential component of contemporary power systems, characterized by its fundamental necessity and elastic demand that varies by time and location. The persistent population growth, urban development, and rising electrification rates have resulted in heightened power consumption. Optimal generation and consumption techniques are required to optimally utilize energy resources, ensuring that the power supply is both technically possible and economically sustainable. Accurate forecasting of electricity demand is essential for energy utilities, system operators, policy-makers, regulatory organizations, and power-producing resources. Prompt and precise demand forecasting will prevent shortages, mitigate load swings, and guarantee optimal utilization of generating capacity. Demand forecasting enables power managers to predict changes in electricity use patterns, which enables them to develop better energy conservation programs for the ongoing greenhouse gas reduction during the transition to sustainable energy systems [6]. The analysis of consumer behaviors enables demand response prediction, together with the usage patterns of domestic electrical appliances, which leads to understanding power consumption patterns. Analyzing such behavior for efficiency improvement solutions is beneficial for home level sustainable energy utilization, utility and policy formulation. It is at this point that the actual role of smart meters becomes very evident [7]. A smart meter is a piece of electrical equipment that is aimed at measuring and recording electrical energy consumption very accurately at certain time intervals, and it may also send this information for monitoring and billing purposes. In contrast to conventional meters that merely track electrical power consumption over a long period, smart meters log energy consumption at much shorter intervals – seconds or minutes [8]. This allows the smart meter to define usage patterns. The availability of detailed data has opened up a whole new set of possibilities for energy analysts and data scientists to study consumption patterns and discover significant trends in energy usage. By continuously monitoring power usage at very detailed levels, peak demand hours can be very explicitly predicted, especially for times when power is used during the day. A precise forecasting of the peak demand is necessary because power managers and system operators need to distribute resources appropriately in the grid load management so that no overloading and blackout occurs. Along with these, anticipation of peak demand is an indicator to the suppliers of energy of the kind of customers that are eligible for demand response programs. Demand response programs are a system of remuneration to users for reducing their power consumption during peak times, such as an economic incentive or rate reduction [9]. Peak demand is marked by a high degree of fluctuation in any number of periods, including daily changes, seasonal fluctuations, and annual cycles. Smart metering system facilitates the reduction of total power consumption due to higher customer awareness toward their energy consumption patterns and adoption of more energy-saving behavior [10]. With such a resource of information, a consumer would be in a better position to inform him/herself about when and how to use power, subsequently achieving a great total reduction in consumption. This helps customers lower prices and helps in creating an improved, balanced, and sustainable energy system [11]. The implementation of smart meters on a large scale is a major step forward for energy management systems, which also include smart grid technology. The innovations offer more detailed power consumption data, which is beneficial for both energy efficiency and energy supply security, and at the same time, it leads to the development of a sustainable energy system. The next change of power grids to smart networks relies on the interaction possibilities between consumers and utilities, which will make smart grids and smart metering systems capable of being efficient, agile, and responsive electricity grids. These systems have to fulfill the increasing demands of future energy consumption [12–14]. Along with machine learning (ML) methods, smart grids enhance their load forecasting capabilities through ANNs that are used for household appliance control. To forecast the future consumption patterns and peak demand, generic methods dealing with voluminous datasets of real smart meter readings are required. Artificial Neural Networks (ANN) employ Long Short-Term Memory (LSTM) for both time series data analysis and variance detection, while energy efficiency is also optimized. ML models for smart homes work as fully automatic systems that can control appliances in such a way that the power consumption of high-usage equipment during a peak period is decreased while the level of residential comfort is still maintained. ML and ANNs can foresee how customers will behave in case of a change in prices, which in turn is a strong point of demand response strategies. The system thus achieves the optimum of energy management simultaneously, as it is causing less harm to the environment, and microgrid load forecasting is also enhanced, as well as the integration of renewable energy. The research carried out leads the way to the conclusion that ML and ANN techniques offer novel ways for power consumption management of home appliances due to their higher precision and faster reactions, as well as their contributions to the environment [15, 16].

ML algorithms show a wide range of potential for residential energy demand management as they improve energy use patterns and the efficiency of appliances during the period of peak load. ML-based Demand Response (DR) mechanisms have been confirmed in scientific research as effective in forecasting user price responses, which results in grid stability being improved in conjunction with energy efficiency [17]. Yet the present models have difficulty dealing with seasonal changes and temporal generalization despite several advancements having been made. The studies performed recently have brought to light the hybrid systems that combine DL with boosting methods for achieving better accuracy and robustness in residential energy demand forecasting. For example, Khan et al. [18] developed a deep NN (DNN)-based smart home load forecasting system whose short-term load prediction accuracy was greatly improved. Bani Ahmad et al. [19] came up with a hybrid DL solution that facilitated short-term energy prediction and was less flexible for user behavior changes. Wang et al. [20] introduced Convolutional Neural Network (CNN)–LSTM, capturing both spatial and temporal dependencies in household energy data. Chen and Ren [21] used boosting-based NNs to address noise and fluctuation problems typical of residential load profiles and at the same time, achieve stable generalization over different time windows. These results point to the importance of investigating hybrid ensemble architectures in the case of smart grid environments, where energy demand is very dynamic and nonlinear and in other scenarios. Although the arguments put forth by these papers that ML and hybrid methods have the potential for residential energy forecasting are quite convincing, these approaches are still insufficient when it comes to dealing with intricate seasonal patterns, being able to adjust to dynamic user behavior, and balancing robustness with interpretability. The current models frequently give less than satisfactory results when they have to deal with highly non-linear and variable energy demand in smart grid environments. To improve their forecasting accuracy, reliability, and generalizability, there is a need for sophisticated hybrid architectures that can meld the advantages of different ML techniques and address the current shortcomings.

1.1 Main contribution

This research employs sophisticated ML techniques to predict the energy consumption of various household appliances. The work uses innovative ML methods, including CNN combined with LSTM, RF, AdaBoost, and CatBoost, to examine the aspects that influence consumption patterns. The extensive comparative studies were the main focus of different models, including ANNs, implemented within hybrid frameworks. The central point was to figure out how different methods could be used to increase the reliability of home appliance consumption predictions. The current research is important because it helps clarify the predictive power of ML and NN in this area. Energy consumption predictions are made more efficient when the use of hybrid modeling is less of an enigma. This paper is structured as follows: Section 2 provides a detailed description of the forecasting models, the proposed models, and the optimization procedures used. Section 3 is about the results, Section 3 presents the outputs precisely to ensure detailed assessment. Lastly, Section 4 summarizes the key findings and considers the broader implications of the study.

2 Methodology

This study explored advanced ML techniques, especially neural networks, to predict household appliances' energy consumption. The paper highlights the use of algorithms such as CNN, LSTM, RF, AdaBoost, and CatBoost within a hybrid modeling framework to enhance prediction accuracy. Their combined operation leverages their unique abilities to manage time-series data and complex energy usage patterns. While CNNs excel at capturing local time-based patterns, long short-term memory networks are better suited for analyzing longer-term relationships. Ensemble methods like RF, AdaBoost, and CatBoost provide strong protection against overfitting, ensuring stable predictions. Evaluating individual algorithms before combining them allows us to maximize their respective strengths for improved forecasting accuracy and dependability. Statistical analysis, along with systematic train-test data partitioning, validates the findings and assesses their broader applicability. An extensive comparison uses rigorous statistical techniques to identify the most reliable methods. The research involves large-scale data collection, detailed analysis, and strict validation procedures. To ensure accuracy and robustness, the time series data is split into 80% training and 20% testing sets for model performance evaluation. The modeling process occurs in two phases: first, the predictive capabilities of CNN, LSTM, RF, AdaBoost, and CatBoost are assessed individually. Then, hybrid models combining these frameworks are developed to leverage their complementary strengths for better overall predictions. Fig. 1 illustrates the structures and procedures used in this research.

2.1 Data

The study utilized a dataset of hourly energy consumption data for many systems within the building, including heating, ventilation, and air conditioning (HVAC), lighting, and electrical devices [22]. A comprehensive statistical analysis of the principal variables, as shown in Table 1, provides a robust empirical foundation for further study and analysis.

The dataset was split into 80% for training and 20% for testing. The training dataset was split into 80% and 20% for the *k*-fold cross-validation process. Additionally, 5-fold cross-validation was applied to the training set to ensure robust model evaluation and reduce overfitting. From the entire dataset, 20% was reserved as the test set, which was not used during training or validation. This subset was used solely for final model evaluation. The test data maintains the same statistical distribution as the training and validation sets to ensure consistency and fairness in model comparison.

The test dataset preserves the same statistical distribution as the training and validation sets, ensuring consistency and fairness in model evaluation. The input parameters and their corresponding descriptive statistics are summarized in Table 1. This dataset provides comprehensive coverage of temporal patterns, seasonal variations, and typical usage behaviors, enabling robust evaluation of hybrid ML models for residential energy consumption forecasting.

2.2 Machine learning methods

The chosen schemes (CNN, LSTM, RF, AdaBoost, CatBoost) were adopted for their demonstrated capabilities

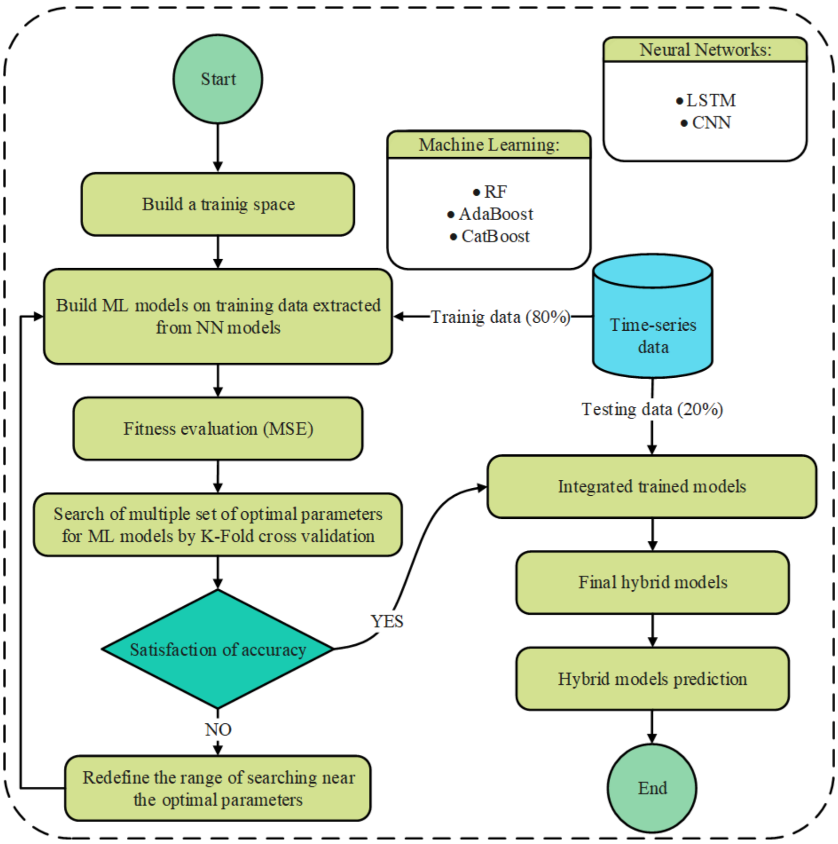


Fig. 1 The flowchart of this exploration

Table 1 The input parameters and their corresponding statistical particulars

Variables	Mean	STD	Min	25%	50%	75%	Max
Month	6.53	3.45	1.00	4.00	7.00	10.00	12.00
Hour	12.50	6.92	1.00	6.75	12.50	18.25	24.00
Day type	4.13	2.08	1.00	2.00	4.00	6.00	8.00
Electric appliances consumption (kWh)	24.83	17.09	7.44	12.09	15.88	42.62	70.91

in processing non-linear and both temporal and categorical patterns within time series data. Each model possesses distinct advantages because LSTM focuses on sequential relationships, while CNN detects local patterns, and ensemble methods ensure generalization robustness.

Section 2.2 depicts a thorough analysis of the prediction methods that forecast the energy consumption of residential appliances. The study makes use of high-level predictive mechanisms such as CNN, LSTM, RF, AdaBoost, and CatBoost to achieve maximum prediction accuracy. The process of choosing the model was strict as it intended to enhance not only the accuracy but also the robustness of the models. More detailed information about this essential methodological point will be disclosed in Sections 2.2.1 to 2.2.6. Schemes are complex and deliberate optimization has been applied to boost model performance, so the reliability and overall efficacy of the energy consumption forecast are improved.

2.2.1 LSTM

A specific kind of recurrent NN (RNN) is the LSTM NN, which differs from conventional low-cell neurons by replacing them with more intricate internal structures [23]. LSTM still shares the basic characteristic of RNNs, which treat the input data as a time-sensitive sequence. Second, its internal structure is as sophisticated as it is to tackle the exploding and vanishing gradients challenges [24]. The four key parts of the LSTM model are cell state, input gate, forget gate, and the output gate. These gates are vital to the management of information update, maintenance, and removal in the cell state. Thus, the forward computation process is represented as the following (Eqs. (1) and (6)):

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right), \tag{1}$$

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right), \tag{2}$$

$$\tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right), \tag{3}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t, \tag{4}$$

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right), \tag{5}$$

$$h_t = \tanh\left(C_t\right). \tag{6}$$

The variables C_t, C_{t-1}, and correspond to the current cell state value, the previous time step's cell state value, and the updated cell state value, respectively. f_t, i_t, and o_t denote the forget, input, and output gates, respectively. Given appropriate parameter settings, the output value ht is computed using both and C_{t-1}, as defined by Eqs. (4) and (6). Additionally, all weight matrices, including W_f, W_i, W_C, and W_o, are adjusted through the back-propagation through time (BPTT) algorithm [25], drawing on the error between the predicted output and the actual value.

2.2.2 CNN

CNNs are a type of DL technology that effectively processes image, text, and signal inputs. Each CNN varies in architecture based on the number of layers in the network, which entails convolutional layers followed by pooling layers, culminating in fully connected layers, as inferred from the arrangement of the visual cortex's simple and complex cells [26]. The process starts with the input layer, where raw data is introduced for preliminary processing and feature modification. The features are then extracted in the convolutional and pooling layers. The completely linked layers then integrate the information derived from these layers. The output layer generates and disseminates the final product. The convolutional layer is crucial in CNN design for feature extraction and information acquisition from input data, utilizing convolutional kernels. Typically, the dimensions of the input matrix exceed those of the convolutional kernels employed. A convolution process is employed by the convolutional layer for feature mapping, rather than a generic matrix mapping operation. The value of each element in the resultant feature map is determined Eq. (7):

$$S_{i,j}^{out} = f_{con}\left(\sum_{x=0}^{p}\sum_{y=0}^{p}\omega_{x,y}\boldsymbol{s}_{\boldsymbol{i+y,j+y}}^{\boldsymbol{in}} + b\right). \tag{7}$$

Herein, $S_{i,j}^{out}$ is the output value of the feature map, and $\boldsymbol{s}_{\boldsymbol{i+y,j+y}}^{\boldsymbol{in}}$ is the input matrix. Consequently, f_{con} is an appropriate activation function that will be introduced to boost the productivity of the scheme. The notations $\omega_{x,y}$ and b are used for weights and bias of convolution kernel. Down-sampling resources, were used in a pooling layer to decrease the dimensions of the previous feature map. Finally, the fully-connected layer serves to flatten the features obtained from the convolution and pooling layers for their integration to form the output.

2.2.3 Random forest (RF)

The RF classifier represents an ensemble methodology composed of many tree-structured classifiers and represents an improvement of the Bagging technique [27], increasing its randomness. While in standard methods at each node, the best split is determined considering all possible variables, RF selects the best split among a randomly chosen subset of predictors at each node. The RF algorithm obtains a new training dataset by bootstrapping with replacement from the original dataset and constructs trees by feature random selection without pruning [28]. This approach likely improves the accuracy of the scheme, which may avoid overfitting and allow the generation of many trees easily. Two parameters, to be indeed, will initialize the RF algorithm: N corresponding to the count of trees to be grown and m, representing the count of variables used for node splitting. First, N bootstrap samples are drawn from two thirds of the training dataset. The one-third remaining will be called Out-Of-Bag (OOB) data; it will be used later to get an unbiased estimation of the prediction error. Each bootstrap sample is used to grow an unpruned tree, with m predictors randomly selected at each internal node for consideration as the best split [29, 30]. The count of variables chosen should be such that they are minimally correlated yet informatively predictive. Usually, $m = \sqrt{M}$ is recommended for optimal performance of the method. RF constructs trees using the Classification and Regression Tree-P CART-algorithm. Most importantly, RF splitting of nodes is data-driven and depends on several factors, including GINI index, which makes a measurement of class homogeneity.

$$\sum\sum j \neq i\left(\frac{f\left(C_i,T\right)}{|T|}\right)\left(\frac{f\left(C_i,T\right)}{|T|}\right) \tag{8}$$

2.2.4 Adaptive Boosting (AdaBoost)

Boosting has long been considered one of the effective techniques to boost the productivity of any learning algorithm in ML. The very first concept of boosting has been given by Schapire [31], and Freund and Schapire [32]. Drawing inspiration from the pioneering work done by Schapire [31], and Freund and Schapire [32], they then came up with the following generation of boosting algorithms and named it Adaptive Boosting-AdaBoost- [33, 34]. They claimed that AdaBoost enjoys many evident advantages over previously described boosting algorithms in terms of practicality and ease to be implemented. Based on the original AdaBoost framework proposed by Schapire [31], and Freund and Schapire [32], further development led to the Version AdaBoost.M1 and AdaBoost.M2. While the two versions are equivalent in binary classification problems, the difference exists in their strategy when dealing with multi-class problems. AdaBoost.M1 invokes a learning algorithm repeatedly on distributions over the training set: AdaBoost.M1 distribution is defined by:

$$D_{t+1(i)} = \frac{D_t\left(i\right)}{Z_t} \times \begin{cases} \beta_t \text{ if } h_t\left(x_i\right) = y_i \\ 1 \text{ otherwise} \end{cases}. \tag{9}$$

In Eq. (9), Z_t serves as a normalization factor, ensuring that D_{t+1} represents a valid probability distribution. The WeakLearn algorithm generates a hypothesis or classifier aimed at accurately classifying all instances in the test dataset. As previously mentioned, instances that are misclassified are assigned higher weights in subsequent iterations. Finally, the boosting algorithm combines all individual hypotheses to create a single, final hypothesis.

$$h_{fin}\left(x\right) = \arg\max_{y \in Y} \sum_{t:h_t(x)=y} \log\frac{1}{\beta_t} \tag{10}$$

2.2.5 CatBoost

CatBoost presents a new gradient boosting algorithm given by Prokhorenkova et al. [35] and Dorogush et al. [36], with state of the art compared to the problem of Fernandes et al. regarding handling categorical features with less information loss. Targeting target leakage through ordered boosting, it differs from other algorithms and is very efficient on small datasets. On the pre-processing step, CatBoost treats the categorical features, converting them into numerical values. Its versatility has been demonstrated in diversified data types, especially in finance and time series applications. CatBoost also avoids overfitting by its random permutations while selecting the tree structure, using binary decision trees as base predictors [36].

$$Z = H\left(x_i\right) = \sum_{j=1}^{j} cj1\left\{x \in R_j\right\} \tag{11}$$

In this context, let $H(x_i)$ be a DT function applied to the explanatory variables x_i. Let R_j denote the distinct region associated with the corresponding leaf nodes of the tree.

2.2.6 Partial/Autocorrelation Function (PACF) (ACF)

To forecast time series, we have to analyze the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the given model to select an appropriate time series forecasting scheme [37]. Using these statistical tools is an essential key to understanding the relationship between an individual data point in a time series to its historic or forecasted value. For this reason, time series analysis depends on ACF and PACF. In particular, ACF and PACF are important for deciding ARMA model order when developing and forecasting schemes [38]. Additionally, the ACF and PACF can be utilized for evaluation regarding stationarity of a time series – a critical step in recognizing trends and seasonal patterns [39]. For this analysis, the use of a widely used method of investigating the correlation is to develop correlograms, which present ACF and PACF plots, and used to find any patterns and detect stationarity. The ACF equation, akin to the correlation coefficient (R^2), measures the correlation between variables in the same time series (X_t and X_t-k). Thus, the ACF equation (R_k) is expressed as [40]:

$$R_k = \frac{\frac{1}{N-k}\sum_{i=1}^{N-k}\left(X_i-\bar{X}\right)\left(X_{i-k}-\bar{X}\right)}{\frac{1}{N-k}\sum_{i=1}^{N}\left(X_i-\bar{X}\right)^2}. \tag{12}$$

The Moving Average (MA) process has an order specified by the coefficients of the ACF. Whereas PACF is the correlation between current and lag k past observations when controlling for intermediate observations. To construct a system of correlation equations for each lag, we formulate the PACF by applying linear regression to express $X\{t-k\}$ and get the system of equations of $X\{t-k\}$ = linear regression. Cramer's rule can be applied to these equations in matrix form. The PACF coefficients are described in simplified equations (referred to in McCleary et al. [41]), which relate them to the ACF. Let's give as an example, for example, the PACF equations (Eqs. (13) to (15)) for the first three lags provided in McCleary et al. [41] as follows:

$$\mathrm{PACF}(1) = \mathrm{ACF}(1), \tag{13}$$

$$\mathrm{PACF}(2) = \frac{\mathrm{ACF}(2)-\left(\mathrm{ACF}(1)\right)^2}{1-\left(\mathrm{ACF}(1)\right)^2}, \tag{14}$$

$$\mathrm{PACF}(3) = \frac{-2\mathrm{ACF}(1)\mathrm{ACF}(2)-\left(\mathrm{ACF}(1)\right)^2\mathrm{ACF}(3)}{1+2\left(\mathrm{ACF}(1)\right)^2\mathrm{ACF}(2)-\left(\mathrm{ACF}(2)\right)^2-\left(\mathrm{ACF}(1)\right)^2}. \tag{15}$$

The autocorrelation function (ACF) coefficients corresponding to lag times 1, 2, and 3 are denoted as ACF (1), ACF (2), and ACF (3), respectively. Depending upon the coefficients of PACF, the order of the autoregressive (AR) is identified.

2.3 Model verification and evaluation

To evaluate the recommended schemes, several performance metrics and analytical techniques have to be used to rigorously determine their accuracy. They are created to find the difference between the observed and predicted data by looking at residual errors. In Rastgoo and Khajavi [42], these are the performance metrics used in this research, namely: MAE, MSE, RMSE, R2, PCD, and A10. Formulations for these statistical measures are given in Table 2.

Table 2 Statistical evaluation indexes

Statistics	Criteria	Equation
MAE	Mean Absolute Error	$\frac{\sum_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert}{n}$
MSE	Mean Squared Error	$\frac{\sum_{i=0}^{N-1}\left(y_i-\hat{y}_i\right)^2}{N}$
A10	A10 index	$\frac{1}{n}\sum_{i=1}^{n}\begin{cases}1, \text{if } \frac{\lvert\hat{y}_i-y_i\rvert}{y_i}\le 0.1\\ 0, \quad \text{otherwise}\end{cases}$
RMSE	Root Mean Square Error	$\sqrt{\frac{\sum_{i=0}^{N-1}\left(y_i-\hat{y}_i\right)^2}{N}}$
R^2	Coefficient of Determination	$1-\frac{\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2}$
PCD	Prediction of Change in Direction	$\frac{1}{n-1}\sum_{i=2}^{n}\left(\left(f_i-f_{i-1}\right)\left(y_i-y_{i-1}\right)\right)>0$

2.4 Methodology/model selection and justification

The study employs a set of advanced ML algorithms – CNN, LSTM, RF, AdaBoost, and CatBoost – chosen for their complementary strengths in modeling residential energy consumption patterns:

1. CNN: it is a powerful tool for extracting spatial features and local correlations from energy consumption data, which is structured. CNN effectively captures the recurring patterns both in the households and the time intervals.
2. LSTM: it is a model that is used to represent temporal dependencies as well as long-term patterns in time-series data. This is especially relevant when it is necessary to identify seasonal and cyclic changes in residential energy demand.
3. RF: a strong and diverse-unit approach that can manage noisy and high-dimensional data, thus being able to provide stable predictions for irregular energy consumption profiles.
4. AdaBoost and CatBoost: these are two gradient boosting algorithms that improve the prediction accuracy by one combining multiple weak learners into a single more powerful model. CatBoost is very effective in dealing with categorical features, such as appliances or user profiles that are the most common in residential datasets.

2.4.1 Rationale for hybrid approach

Single models frequently have difficulty in capturing both spatial and temporal dependencies at the same time, handling noise, and generalizing for different seasons. A combination of LSTM and a boosting algorithm like CatBoost can help in temporal feature extraction along with noise/error correction, thus leading to predictions that are more accurate and stable. In the same way, the combination of a CNN with LSTM makes it possible to model not only the local patterns but also the long-term dependencies.

These hybrid architectures help overcome the three major challenges in residential energy forecasting:

- Seasonality and temporal variability: captured by LSTM and CNN–LSTM.
- Noise and fluctuations in consumption data: handled by RF and boosting methods.
- Model robustness and generalization: achieved via ensemble and hybrid mechanisms.

Different methods, including training/testing splits, cross-validation, and early stopping, have been employed for model evaluation to ward off overfitting and thus performance be stable in a variety of residential energy scenarios.

2.4.2 Necessity and sufficiency of the employed method set

The chosen ensemble of machine learning methods:

- convolutional neural network,
- long short-term memory,
- random forest,
- AdaBoost,
- CatBoost.

These methods are minimal yet complete sets that can achieve high accuracy in forecasting residential energy consumption.

The residential energy consumption data are characterized by complex features, such as temporal dependencies, seasonal and cyclic patterns, noise, and nonlinearity. Single models fail to capture these aspects thoroughly:

- To capture local spatial correlations in appliance usage at different time intervals, a CNN is a must.
- For the purpose of modeling long-term temporal dependencies and getting seasonal variations, LSTM is indispensable.
- The use of RF is necessary for the handling of noise, high-dimensional features, and irregular consumption patterns.
- The use of these two methods (AdaBoost and CatBoost) is very important to improve the prediction accuracy and to eliminate the residual errors, especially in non-linear and noisy data sets.

By combining these techniques in hybrid architectures, one can achieve a practically complete coverage of the main challenges of residential energy forecasting:

- CNN-LSTM captures both spatial and temporal correlations.
- LSTM-CatBoost fuses temporal feature extraction with strong boosting for error correction.
- RF and ensemble methods provide consistency and generalization over different seasons and user behaviors.

Together, these methods are enough to produce dependable and precise predictions in various situations, thus they can handle noise, variability, and nonlinearity without the need for further algorithms.

3 Results and discussion

Section 3 of the research report is primarily concerned with the related findings of household energy consumption forecasts by local integrated modeling methodologies. It covers various schemes, including CNN, LSTM, RF, AdaBoost, and CatBoost, in detail. The outcomes of these experiments are displayed in systematic manners through visuals along with Table 3 and other display formats. Apart from this, the report also provides a complete as well as a critical evaluation of the study findings by closely scrutinizing the presented data.

The ACF and PACF plots in Fig. 2 represent an exhaustive examination of time series data. The ACF plot shows prominent peaks at regular intervals, thus identifying strongly defined seasonal patterns or changes in home energy use cycles. To be specific, positive spikes of quite large magnitudes are observed at the lags of 20, 40, 60, 80, and 100, thus it is obvious that there is a clear relationship between using energy now and that from the successive intervals up to 100 as well. On the other hand, throughout these intervals, negative fluctuations signify inverse correlations, i.e., energy consumption will decrease owing to the cyclic nature of the patterns. The PACF plot pinpoints a very substantial threshold at lag 25, beyond which the partial autocorrelations drop to the level of random noise. In other words, this is the maximum point where significant autocorrelation is present, and at values that go beyond this threshold, one can hardly expect to get useful predictions. The peak at lag 97 indicates a long-term periodic pattern, presumably reflecting the impact of severe events on home energy usage, as evidenced by the data.

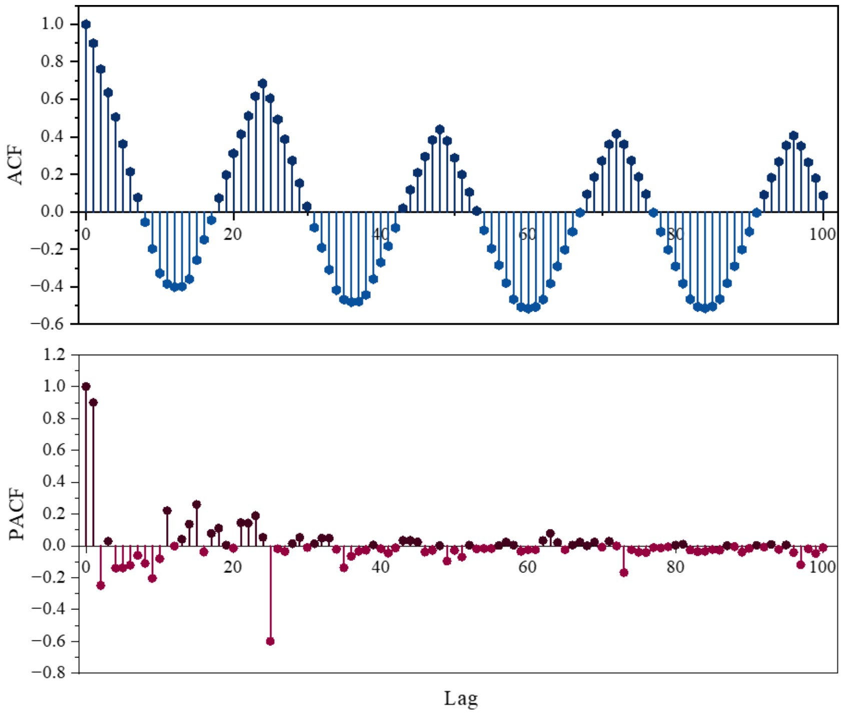


Fig. 2 ACF and PACF plots of the residential energy consumption dataset, illustrating the temporal dependencies and lagged correlations that inform the selection of appropriate time-series forecasting models

Fig. 3 depicts the cross-validation methodology utilized to mitigate the problem of overfitting. To ensure model robustness, the time series data was split into three distinct sets: 80% for training, 20% of the training dataset for validation, and 20% for testing. A stratified 5-fold cross-validation strategy was applied to the training set to tune hyperparameters and reduce overfitting.

The time series data are presented in Fig. 4, which includes both the training datasets and the testing datasets for a variety of schemes, including CNN, LSTM, RF, AdaBoost, and CatBoost configurations. According to the findings of the investigation, the hybrid LSTM–CatBoost schemes exhibit higher performance in comparison to the other schemes, as evidenced by the much-reduced error rates that were determined to be present in the testing dataset. Fig. 4 The hybrid LSTM–CatBoost model showed visibly reduced error margins across time compared to CNN and RF-based schemes, suggesting its superiority in capturing temporal dependencies. Conversely, RF and AdaBoost exhibited lag in sudden consumption shifts, reflecting lower responsiveness to non-linear dynamics.

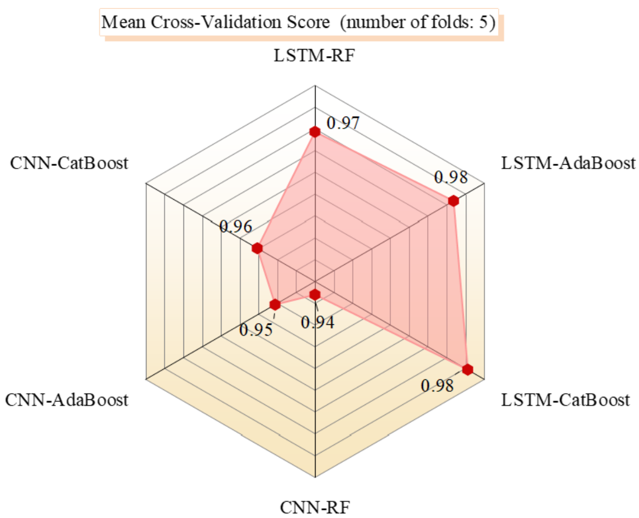


Fig. 3 Result of the used 5-fold cross-validation based on R^2

Fig. 5 shows the scatter plots that visually demonstrate the comparative assessment of the hybrid schemes' performance along with the statistical R^2 index. An exhaustive examination of these plots reveals that the test data of the hybrid LSTM–CatBoost model have less spread and are more concentrated around the line of unity ($x = y$). The high R^2 of 0.9802 for the scheme confirms the finding of its outstanding prediction accuracy.

The scatter diagram in Fig. 5 illustrates a robust linear correlation between actual and forecasted energy figures for the LSTM-CatBoost hybrid scheme. The dots are very close to the diagonal ($x = y$) line, indicating high prediction accuracy. The R^2 of 0.9802 obtained from the data is strong evidence of the scheme's effectiveness in capturing consumption patterns. In contrast to baseline schemes, this hybrid strategy has substantially lowered

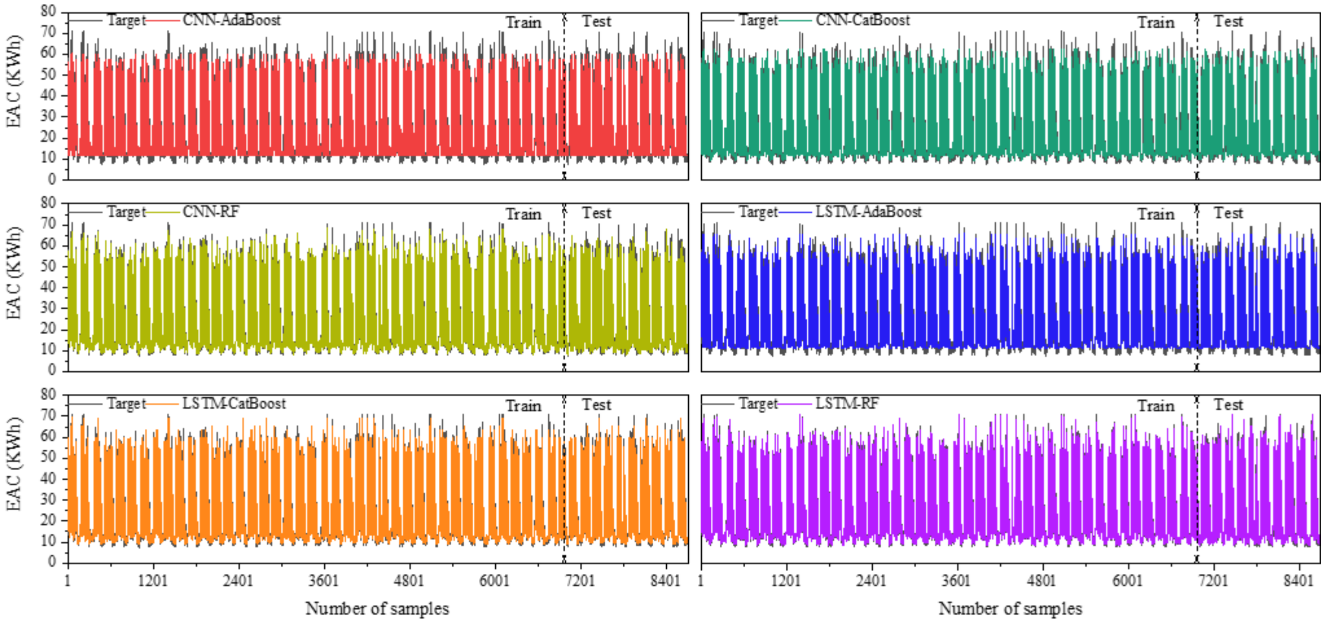


Fig. 4 Hybrid schemes with CNN, LSTM, RF, AdaBoost, and CatBoost algorithms-generated temporal sequences depicting the actual versus predicted residential energy consumption

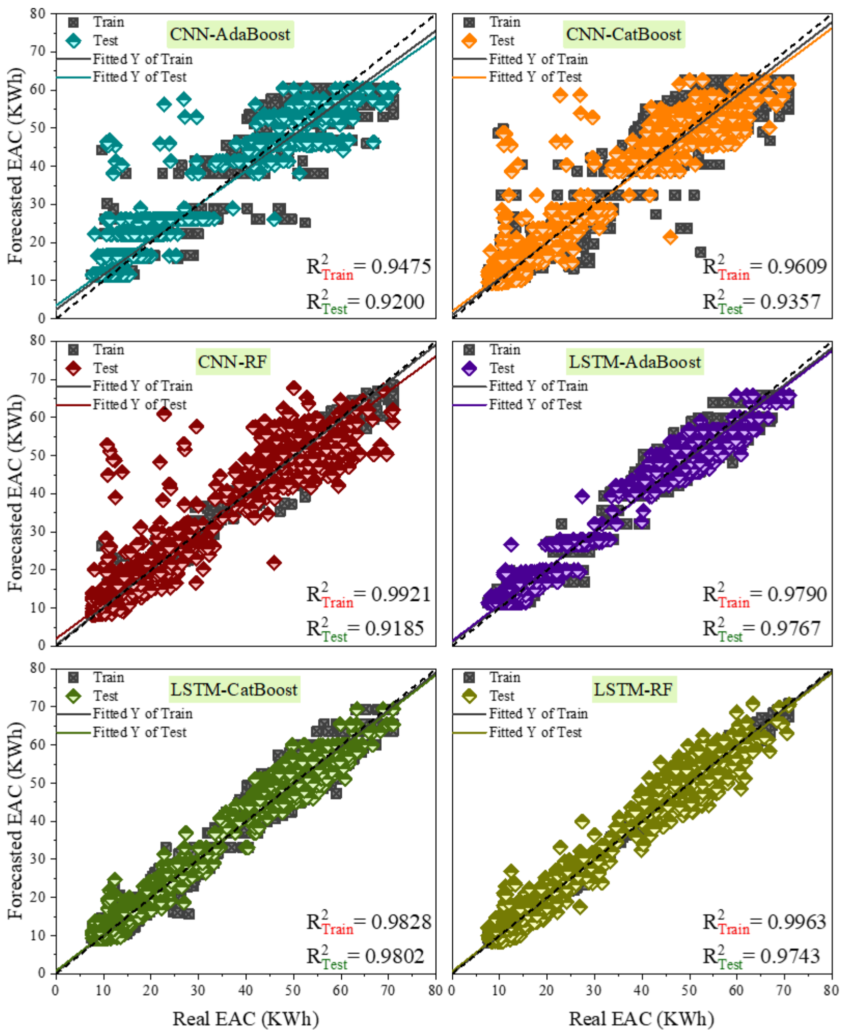


Fig. 5 Scatter plot for the relationship between observed and predicted energy consumption across all hybrid schemes

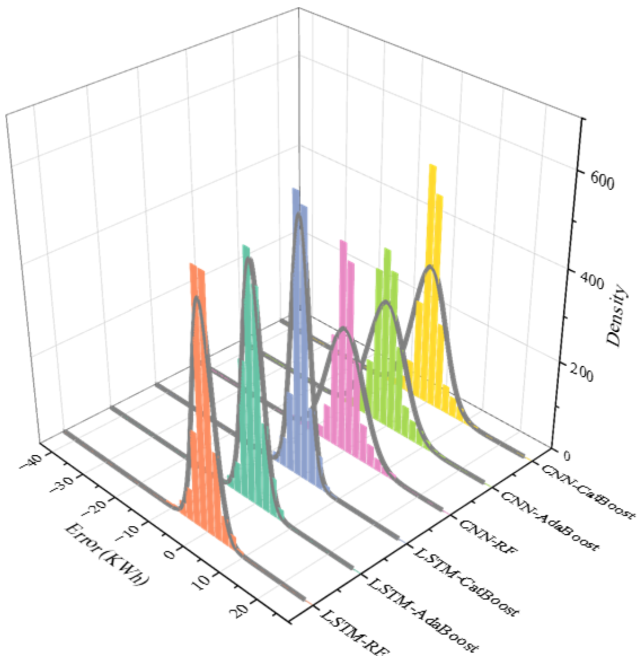
the prediction error and enhanced the generalization capability. These findings point to the advantages of integrating sequential learning LSTM with gradient boosting (CatBoost) for energy forecasting tasks.

Table 3 presents a detailed description of the evaluation metric indices for the hybrid schemes. An analysis of the RMSE and MAE values indicates that the schemes often demonstrate robust predictive efficacy. The hybrid CNN-RF model attains the greatest RMSE, indicating superior accuracy, whereas the hybrid LSTM-CatBoost model registers the lowest RMSE. This tendency is seen in other statistical metrics as well, underscoring the higher efficacy of the CNN-based model relative to its counterparts. For broader context, the performance of a standalone XGBoost model was also evaluated. It demonstrated a Test RMSE of 3.36 and R^2 of 0.9141 on the same dataset, which confirms that the LSTM-CatBoost hybrid consistently outperformed it.

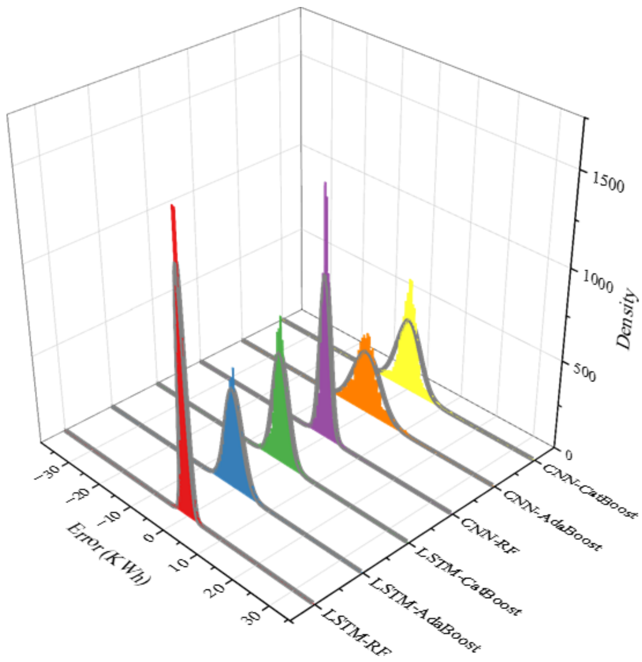
Fig. 6 displays the effects of implementing various schemes, such as CNN, LSTM, RF, AdaBoost, and CatBoost, on both training and testing datasets. The hybrid LSTM-RF model has less fluctuation and a smaller error range among other schemes during training, with its

Table 3 Performance indicators derived from the application of CNN, LSTM, RF, AdaBoost, and CatBoost hybrid schemes

Metric	LSTM–RF	LSTM–AdaBoost	LSTM–CatBoost	CNN–RF	CNN–AdaBoost	CNN–CatBoost
Train						
MAE	0.7586	1.9152	1.6441	1.0134	2.8663	2.2744
MSE	1.0764	6.111	4.988	2.3051	15.2486	11.3619
RMSE	1.0375	2.472	2.2334	1.5183	3.9049	3.3707
R^2	0.9963	0.979	0.9828	0.9921	0.9475	0.9609
PCD	0.8239	0.4914	0.6364	0.8349	0.4126	0.6586
A10	0.9652	0.6382	0.7412	0.9213	0.4628	0.5901
Test						
MAE	1.9863	2.038	1.7673	3.0294	3.278	2.6483
MSE	7.73	6.9944	5.9595	24.5159	24.0645	19.3456
RMSE	2.7803	2.6447	2.4412	4.9514	4.9056	4.3984
R^2	0.9743	0.9767	0.9802	0.9185	0.92	0.9357
PCD	0.6179	0.4704	0.619	0.6336	0.3955	0.6382
A10	0.6454	0.5995	0.7011	0.4945	0.4283	0.5485



(a)



(b)

Fig. 6 Histogram and normal distribution plots of error measurements for CNN, LSTM, RF, AdaBoost, and CatBoost hybrid schemes during the testing and training phases: (a) title of part (a); (b) title of part (b) median line being close to zero. This means that LSTM–RF is the best one among the training datasets. However, a drop in performance is observed in the testing phase, which shows that the LSTM–RF model's effectiveness is reduced. Conversely, the LSTM–CatBoost hybrid models show good performance in the testing phase, having a smaller error margin, which means a higher prediction accuracy. Fig. 6 presents boxplots of prediction errors as a means of model performance. LSTM–RF had the narrowest error range during training. However, its performance dropped significantly in the test phase, likely due to overfitting. Conversely, LSTM–CatBoost maintained a compact error distribution in both phases, confirming its generalization capability. The standalone XGBoost, included as a baseline, showed higher error variance with a Test RMSE of 3.36 and R^2 of 0.9141, reaffirming the hybrid scheme's superior performance.

Fig. 7 displays a runtime performance assessment of the hybrid schemes under evaluation. The findings reveal that LSTM-RF demonstrates the longest execution duration, finishing its operation in 288.88 s. In contrast, the CNN-AdaBoost model has the briefest duration, concluding in 34.38 s. Several variables contribute to these variances in runtime, including the employed search algorithms and the schemes' convergence characteristics, both of which greatly affect the entire execution time.

Fig. 8 depicts the convergence characteristics of many hybrid schemes – namely CNN, LSTM, RF, AdaBoost,

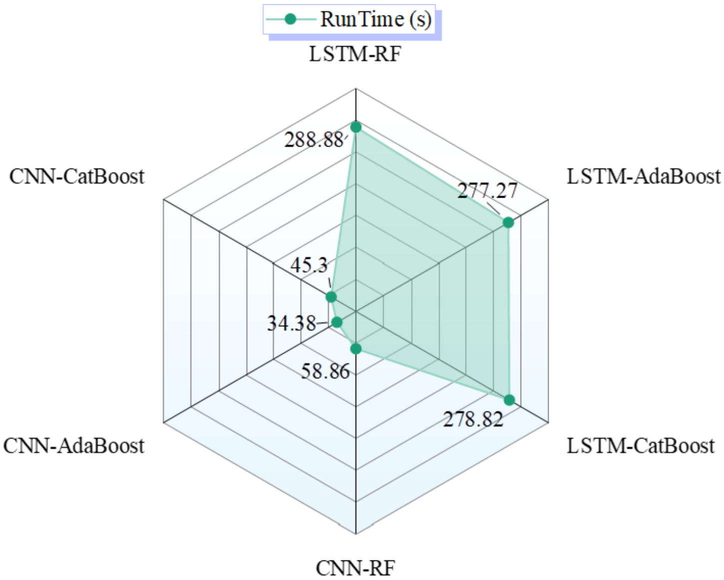


Fig. 7 Comparison of computational runtime for the different hybrid machine learning schemes

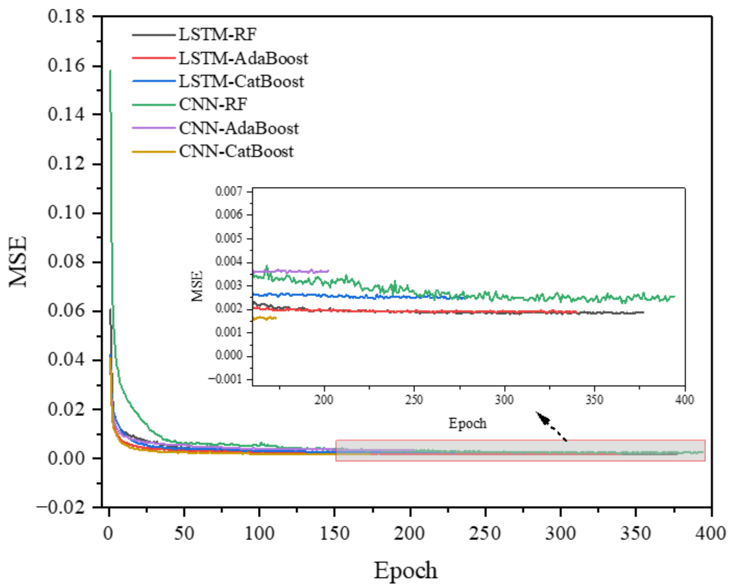


Fig. 8 Convergence plots for CNN, LSTM, RF, AdaBoost, and CatBoost-based hybrid schemes, showing the progression of training and validation loss over epochs

and CatBoost – evaluated by the MSE metric. The CNN-CatBoost and LSTM-AdaBoost schemes have the quickest convergence, as indicated by their much reduced MSE values. This underscores their enhanced efficiency in achieving convergence relative to the other schemes. The graphic illustrates the implementation of early stopping, utilized to prevent overfitting after the schemes attain stability after a certain number of iterations.

4 Conclusion

This research, by integrating schemes such as CNN, LSTM, RF, AdaBoost, and CatBoost, explores the method of forecasting household energy consumption. The data reveal the main factors and changes in the data, among which is the seasonality shown in the ACF and PACF representations. According to R^2 values and error metrics, the LSTM-CatBoost model is the one that most closely approximates the actual outcome. The performance of hybrid models, especially those of LSTM-CatBoost and CNN-based models, is higher. In this respect, LSTM-CatBoost models are exceptionally potent. A runtime study reveals significant differences in the performance of the schemes, with CNN-AdaBoost being the most efficient and LSTM-RF being the least efficient. Cross-validation methods are a way of successfully preventing overfitting, and the convergence analysis is a way of showing the point of early stopping as a way of leading to better model stability. The findings of the study, taken as a whole, demonstrate the efficacy of hybrid schemes in obtaining accurate energy consumption projections while simultaneously minimizing error, hence offering useful insights for the development of future schemes.

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