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RESEARCH ARTICLE

Wavelet-Enhanced Hybrid LSTM-XGBoost Model for Predicting Time Series Containing Unpredictable Events

ALI AJDER[1,2], (Member, IEEE), HISHAM A. A. HAMZA[3], AND RAMAZAN AYAZ[1,4], (Member, IEEE)

[1]Department of Electrical Engineering, Yildiz Technical University, 34220 İstanbul, Türkiye
[2]Department of Engineering, Durham University, DH1 3DE Durham, U.K.
[3]Graduate School of Science and Engineering, Yildiz Technical University, 34220 İstanbul, Türkiye
[4]Clean Energy Technologies Institute, Yildiz Technical University, 34220 İstanbul, Türkiye

Corresponding author: Ali Ajder (ali.ajder@durham.ac.uk)

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ABSTRACT Accurate electricity consumption forecasting is essential for effective power management, especially in the presence of unpredictable events that disrupt typical consumption patterns. Using the COVID-19 pandemic as a case study for such unpredictable events, this study proposes an improved hybrid LSTM-XGBoost model with adapted wavelets to capture complex, irregular fluctuations in energy demand. The model first applies wavelet decomposition to the original data, extracting multiple frequency components that highlight short-term variations and long-term trends. By incorporating these wavelet coefficients as features, the model is sensitized to anomalous events, resulting in more accurate forecasts over a more extended period without the need for frequent retraining. The hybrid approach takes advantage of the LSTM's ability to model temporal sequences and uses XGBoost to adjust for residual errors. Experimental results show that the model can effectively forecast energy demand with minimal error, especially on regular weekdays, and achieves robust performance in the face of unforeseen anomalies. This methodology shows a promising aspect for improving the reliability of energy forecasting models with potential applications in smart grid management and sustainable energy planning.

INDEX TERMS Discrete wavelet transform, electricity consumption, hybrid LSTM-XGBoost, time series prediction, unpredictable events, wavelet-enhanced forecasting.

I. INTRODUCTION

Electricity consumption forecasting plays a vital role in addressing both economic and operational challenges in power management. Accurate predictions enable electrical companies to make informed decisions, optimize supply strategies, and minimize the risks of operational conflicts and costs associated with industrial and commercial power supply. Forecasting is particularly critical during peak demand periods, where balancing supply and demand becomes essential to ensure system reliability [1], [2], [3], [4].

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In recent years, machine learning (ML) models have shown significant promise in enhancing forecasting accuracy [5]. By incorporating various influential factors, such as renewable energy contributions and large-scale energy storage capacities, these models allow for more precise and adaptable forecasting strategies. Techniques such as Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) networks have emerged as effective tools for electricity forecasting, especially in residential contexts where incorporating weather and spatial data enhances model performance [6]. This growing focus on machine learning reflects a trend toward data-driven approaches that leverage diverse variables to tackle the complexities of modern power grids.

Historical load data forms the foundation of these forecasting models, as it helps the models capture essential consumption patterns. During pre-processing, data quality issues like missing values and outliers are corrected to ensure reliable training data. The load data is then combined with other impactful variables, including weather and event data, to improve accuracy [7]. Once aggregated, multiple models are assessed to identify the most accurate one for implementation. However, forecasting accuracy often depends on location-specific and equipment-based factors, which must be incorporated as input variables where data availability allows. Challenges such as data gaps, anomalies, and missing values can impact precision and require tailored solutions. Improving forecasting accuracy can yield substantial financial benefits for utility companies, as even a 1% reduction in mean absolute percentage error (MAPE) can significantly lower generation costs [8], [9].

Electricity demand forecasting poses unique challenges due to the complexity of power systems and variability in consumption patterns. Seasonal and periodic fluctuations, nonlinearity, and a firm reliance on past consumption values often characterize power consumption data. To address these challenges, advanced forecasting models must capture both short-term and long-term dependencies in time-series data [10]. Integrating weather, calendar, and sector-specific data into forecasting models has been shown to improve accuracy significantly. Cluster-based methods have also been employed, allowing models to learn patterns from similar buildings or contexts, which further improves predictive performance [11], [12], [13].

Deep learning architectures, particularly LSTM networks, have shown exceptional promise in capturing the sequential dependencies essential to electricity load forecasting [14]. Designed to address the long-term dependency problem of traditional recurrent neural networks (RNNs), LSTMs are capable of retaining information over extended sequences, making them highly effective for sequence-dependent tasks like load forecasting [15], [16], [17]. LSTM networks leverage non-linear transformations and high-level abstractions to automatically learn complex temporal patterns, thanks to an internal memory structure that enables them to manage long-term dependencies efficiently [18], [19].

In addition to standalone models, hybrid approaches that combine XGBoost and LSTM models have gained attention for their ability to leverage the strengths of both methods [20]. For instance, XGBoost can capture feature-based relationships effectively, while LSTM networks handle temporal dependencies within the data. Li et al. developed a hybrid approach where multiple XGBoost models are used for initial feature-based predictions, which are then refined through an LSTM model to produce a final forecast. This hybrid method has been effective in enhancing forecast accuracy by managing non-linear patterns and time-series dependencies in electricity consumption data [21]. Similarly, Jaimes et al. proposed a unique two-dimensional framework that combines XGBoost and LSTM, extending forecast horizons and improving accuracy for electricity market prices. These hybrid models address challenges associated with power system complexity and variability in consumption patterns, demonstrating their potential for efficient energy management and planning. By incorporating the capabilities of both XGBoost and LSTM models, hybrid methods provide an adaptable and accurate solution for electricity forecasting, crucial for modern power grids [22], [23].

In this study, we contribute to the literature on electricity consumption forecasting by integrating wavelet decomposition, LSTM, and XGBoost in a hybrid model specifically designed to address unpredictable events. The wavelet transformation isolates different frequency components, allowing the model to learn from diverse time scales and effectively capture sudden, unpredictable events such as the impact of COVID-19. This approach enhances the model's sensitivity not only to seasonal and cyclical variations but also to abrupt and anomalous fluctuations that challenge traditional forecasting models. By combining LSTM and XGBoost, the hybrid model capitalizes on their complementary strengths. LSTM networks excel at capturing temporal dependencies in sequential data, while XGBoost effectively models feature-based interactions and residual patterns. The hybrid LSTM-XGBoost model bridges the limitations of traditional models like ARIMA and SARIMA by combining the temporal learning capabilities of LSTM with the feature-learning strength of XGBoost [24], [25]. The adaptation results in a flexible and highly accurate forecasting framework that addresses both temporal dependencies and external factors effectively. This constructive interaction enables the hybrid model to achieve robust forecasting accuracy, particularly in scenarios involving non-linear patterns and unpredictable shifts.

Additionally, wavelet-based features enhance the model's ability to analyze diverse time scales, further improving its adaptability for both short-term and long-term forecasting horizons. This work provides valuable insights for developing more adaptable forecasting models that respond effectively to unpredictable events, which is crucial for efficient energy management amid the increasing integration of renewable energy sources and the complexities of modern power grids.

II. METHODOLOGY

A. OVERVIEW OF THE LSTM-XGBoost HYBRID MODEL

The dataset used in the study is available on the IEEE Dataport website; it includes meteorological data, as well as unpredictable changes in the electricity consumption of an unnamed region in the COVID-19 [26]. The proposed hybrid model consists of two main components: LSTM for sequential learning and XGBoost for error correction. In this way, it is aimed to model the load consumption in the dataset that exhibits both regular patterns before COVID-19 and irregular "unpredictable events" during the pandemic.

The inclusion of the Discrete Wavelet Transform (DWT) in the training data, in addition to the meteorological data, allows for a multi-resolution analysis of the time series, capturing both high and low-frequency components that are critical to addressing unpredictable variations in the data.

B. DISCRETE WAVELET TRANSFORM FOR FEATURE EXTRACTION

Let $x(t)$ represent the original time series. The Discrete Wavelet Transform (DWT) decomposes $x(t)$ into multiple frequency bands, providing a representation in both time and frequency domains. The DWT can be expressed as [27]:

$$x(t) = \sum_{j} \sum_{k} A_{j,k} \psi_{j,k}(t) \tag{1}$$

where, $\psi_{j,k}(t)$ are the wavelet basis functions, $A_{j,k}$ are the approximation coefficients (low-frequency components), j and k represent the scale and translation parameters in (1), respectively.

For this study, the wavelet transformation is used to decompose the load data into various frequency components using the Daubechies wavelet (dbN) up to level 5, generating both approximation A_j and detail D_j coefficients. This decomposition results in an approximation component (A_5) representing the long-term trends, and five detail components ($D_1 - D_5$) that capture the short-term changes. The detail components represent progressively lower frequency variations, with D_1 capturing the highest frequency changes (e.g., noise or rapid fluctuations) and D_5 representing lower-frequency localized variations. These components are particularly valuable for forecasting because they help the model identify and learn patterns associated with sudden changes, potential anomalies like 'unpredictable events', or seasonal effects [28], [29].

The wavelet decomposition at level 5 can be summarized as in (2):

$$x(t) = A_5 + D_5 + D_4 + D_3 + D_2 + D_1 \tag{2}$$

These coefficients are then used as input features for the LSTM-XGBoost hybrid model.

C. LSTM FOR SEQUENCE PREDICTION

LSTM is a recurrent neural network (RNN) architecture that is capable of learning long-term dependencies through its cell states and gating mechanisms. The key equations governing the LSTM model are given in (3), (4), (5), (6), (7) and (8) below:

Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5}$$

Cell state update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{6}$$

Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{8}$$

where, W_f, W_i, W_o are the weight matrices for the forget, input, and output gates respectively. σ is the sigmoid activation function, and tanh is the hyperbolic tangent function, h_t is the hidden state, and C_t is the cell state at time t [14].

The LSTM model takes as input the sequences generated from the original time series and the wavelet features. Let $\mathbf{X}_{\text{LSTM}} \in \mathbb{R}^{T \times d}$ be the input sequence with T time steps and d features (including wavelet features), and let $\mathbf{y} \in \mathbb{R}^T$ be the target load values [18]. The LSTM is trained to minimize the mean squared error (MSE) defined as in (9):

$$\text{MSE}_{\text{LSTM}} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{9}$$

where, y_i are the values of actual load and $\hat{y}_i$ are the values of predicted load from the LSTM model.

D. RESIDUAL ERROR CORRECTION WITH XGBoost

Once the LSTM predictions are obtained, the residual errors $\mathbf{r}_t$ are calculated as:

$$r_t = y_t - \hat{y}_t \tag{10}$$

where, y_t is the actual load value, and $\hat{y}_t$ is the LSTM prediction at time t in (10). These residuals $\mathbf{r}_t$ represent the part of the data that LSTM is unable to capture, which often corresponds to unpredictable events and short-term fluctuations.

XGBoost is used to model and correct these residuals. XGBoost operates by sequentially adding weak learners (decision trees) that fit the residual errors [30]. The objective function of XGBoost is to minimize the residual loss in (11), expressed as:

$$L(\mathbf{r}) = \sum_{i=1}^{N} l(r_i, \hat{r}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{11}$$

where, $l(r_i, \hat{r}_i)$ is the loss function (squared error) for the residuals, $\Omega(f_k)$ is the regularization term to penalize the complexity of the model, f_k represents the k-th decision tree in the ensemble [31].

The parameters of XGBoost, such as 'max_depth', 'learning_rate', and 'n_estimators', are optimized using RandomizedSearchCV to further enhance the model performance.

E. HYBRID LSTM-XGBoost PREDICTION

The final prediction $\hat{y}_t^{\text{final}}$ from the hybrid model in (12) is obtained by combining the LSTM predictions $\hat{y}_t$ with the XGBoost corrections $\hat{r}_t$ as:

$$\hat{y}_t^{\text{final}} = \hat{y}_t + \hat{r}_t \tag{12}$$

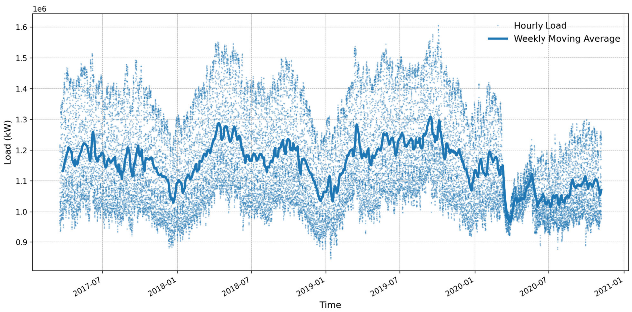

FIGURE 1. **Hourly load and weekly moving average trends over time.**

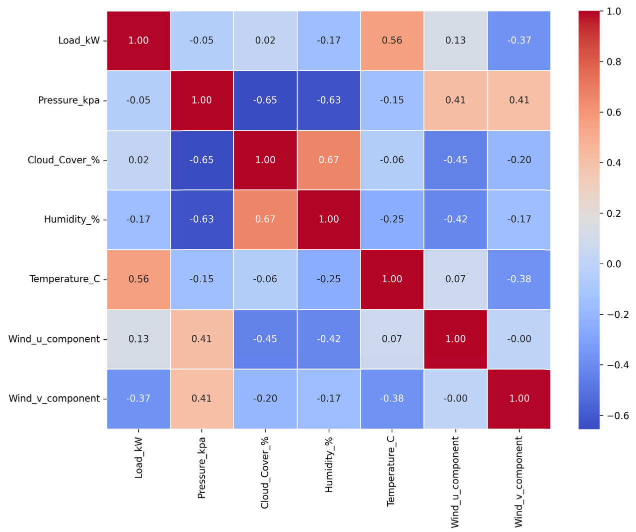

FIGURE 2. **Correlation matrix of the features used in the model.**

F. MODEL EVALUATION

The hybrid model is evaluated using the following metrics (13), (14) and (15):

Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i^{\text{final}})^2 \tag{13}$$

Root Mean Squared Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i^{\text{final}})^2} \tag{14}$$

Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i^{\text{final}}| \tag{15}$$

Willmott Index (WI):

$$\mathrm{WI} = 1 - \frac{\sum_{i=0}^{N-1}(\hat{y}_i - y_i)^2}{\sum_{i=0}^{N-1}(|\hat{y}_i - mean(y)| + |y_i - mean(y)|)^2} \tag{16}$$

where y_i represents the actual values, $\hat{y}_i^{\text{final}}$ represents the predicted values, and N is the total number of data. Lower values of *MSE*, *RMSE*, and *MAE* indicate better model performance in capturing both regular patterns and unpredictable events.

The combination of Discrete Wavelet Transform (DWT), LSTM, and XGBoost enables effective handling of datasets with unpredictable events. DWT's multi-resolution analysis, combined with LSTM's sequence-learning capability and XGBoost's residual error correction, results in a robust model capable of accurately forecasting load values in volatile time series data.

III. RESULTS

Unpredictable events, such as sudden economic shifts, natural disasters, or pandemics, pose significant challenges in time series forecasting. This study addresses these challenges by focusing on the impact of COVID-19 on energy demand as an example of an unpredictable event, employing a wavelet-enhanced hybrid LSTM-XGBoost model to improve the accuracy of predictions. Fig. 1 shows the hourly load data and the weekly moving average. Although the hourly data exhibit a wide variation, the weekly moving average makes the trend smoother and the seasonal effects more apparent. Demand variations observed throughout the year reflect the impact of cooling and heating systems on energy consumption.

The correlation between the features used in the study is shown in Fig. 2. In the figure, red colors indicate a positive correlation and blue colors indicate a negative correlation, while color intensity indicates the strength of the correlation. In particular, a significant positive correlation (+0.56) is observed between electricity consumption and temperature. This indicates that energy demand increases with temperature, which is especially significant for situations where energy demand increases, such as the use of air conditioners in hot weather. In addition, a more meaningful analysis can be made by separating the wind into horizontal (u) and vertical (v) components instead of using the wind direction and speed given in the dataset separately. Although there is no significant correlation between wind direction components and load, these components have the potential to increase the predictive power of the model.

Fig. 3 shows the model's flow diagram. The dataset is taken from IEEE Dataport [26]. The dataset covers the period from March 2017 through November 2020, capturing both pre-pandemic patterns and the initial impact phase of COVID-19, and hourly electricity consumption data shows distinct daily and weekly patterns, as expected. The training dataset contains 31912 hourly observations with corresponding meteorological variables including temperature, humidity, cloud cover, pressure, and wind components. By checking the missing values in the raw data, months, days of the week, and hours, which are highly relevant for electricity demand forecasting, are added to the data as features.

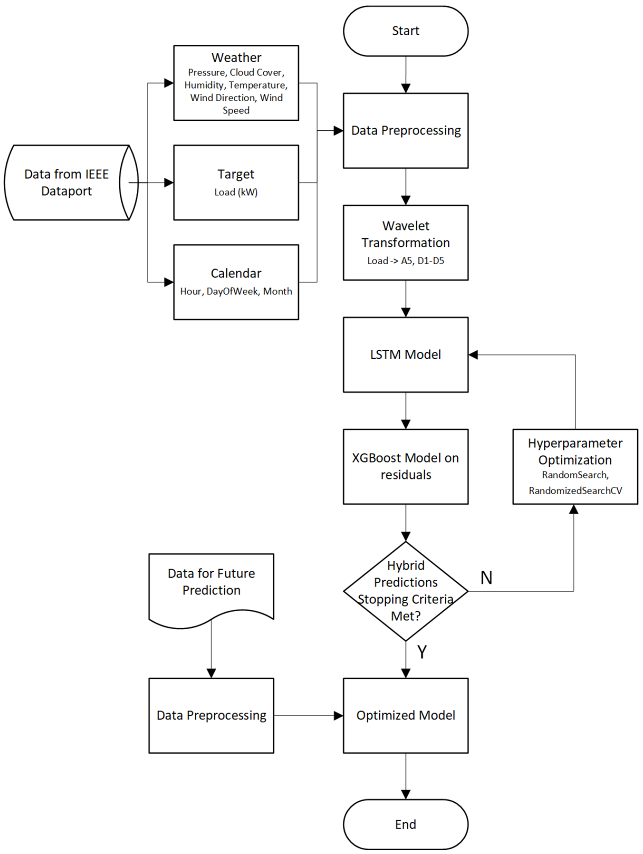

FIGURE 3. Flow chart of the wavelets enriched LSTM-XGBoost hybrid model.

To ensure data integrity, missing values are handled using statistical and machine learning-based imputation techniques. Missing meteorological variables are estimated based on correlations with historical features. After the pre-processing, the wavelet transform is applied to decompose the data into different frequency components. This decomposition separates the data into components at varying time scales, facilitating more effective learning of trends and details.

Additionally, linear interpolation is applied to align wavelet coefficients across different frequencies, ensuring consistency in the dataset. These pre-processing steps maintain robustness, particularly during irregular fluctuations such as those caused by COVID-19, allowing the model to learn temporal dependencies and feature-based relationships effectively. The wavelet coefficients are then integrated into the feature set, enhancing the model's sensitivity to sudden and unpredictable events such as COVID-19. Fig. 4 illustrates the decomposition of energy demand data into different frequency components using the wavelet transform, which is crucial for analyzing the impact of unpredictable events in the time series, the main focus of this study. The dataset is decomposed into five levels of detail and one level of approximation. The approximation component represents the long-term trends. Detail 1 and Detail 2

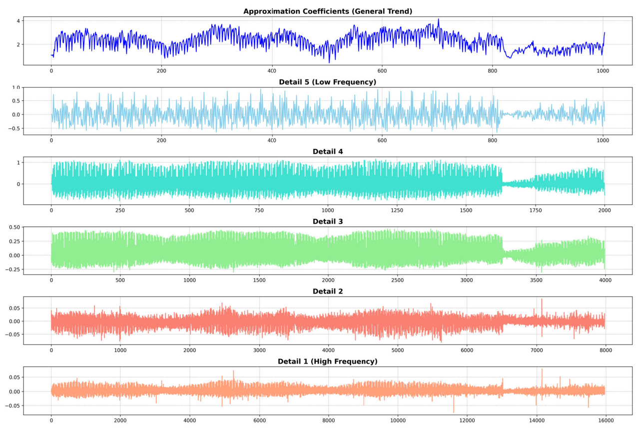

FIGURE 4. Wavelet decomposition of the load data.

correspond to the highest frequency components of the data. These components capture short-term fluctuations, including noise and rapid changes in the load data. While these high-frequency details are often less significant for overall trend forecasting, they play a crucial role in identifying anomalies or unexpected spikes in the data. For example, D_1 captures the fastest variations that may correspond to transient noise, whereas D_2 represents slightly slower, high-frequency changes. Detail 3, Detail 4 and Detail 5 represent the lower frequency components that correspond to medium- and long-term variations, respectively, capturing significant fluctuations in the data. It is evident from Fig. 4 that the frequency components have different lengths. To ensure uniformity in the feature set, interpolation is applied to make all wavelet components the same length before integrating them into the model.

Then, the LSTM model is used to train the model for forecasting time series data. The LSTM model is expected to be particularly effective on wavelet transform enriched data due to its ability to learn long-term dependencies. In this step, the hyperparameters (e.g., number of layers, learning rate) of the model in Table 1 are selected and adjusted by optimization processes.

TABLE 1. LSTM model parameters.

Parameter	Value
LSTM Layers	1 or 2 (depending on tuning result)
Units per LSTM Layer	50-200 (based on hyperparameter tuning)
Dropout Rate	0.2-0.5 (adjusted for each LSTM layer)
Learning Rate	0.01, 0.001, or 0.0001 (tuned value)
Regularization (L2)	0.01-0.05 (for each LSTM layer)
Maximum Epochs	50
Early Stopping Criteria	Patience of 5 epochs
Batch Size	32, 64, or 128 (depending on tuning)
Optimization Algorithm	Adam
Learning Rate Scheduler	Exponential decay after 10 epochs

Prediction errors (residuals) are calculated over the predictions obtained from the LSTM model. These errors are corrected by processing with the XGBoost model,

TABLE 2. XGBoost model parameters.

Parameter	Value
Max Depth	3, 4, 5, or 6 (based on hyperparameter tuning)
Learning Rate	0.001, 0.01, 0.1, or 0.2 (tuned value)
Number of Estimators	50, 100, or 200 (chosen during tuning)
Minimum Child Weight	1, 5, or 10 (selected by tuning)
Subsample Ratio	0.8 or 1.0
Column Subsample Ratio	0.8 or 1.0 (colsample_bytree)
Cross-Validation Folds	3
Number of Random Search Iterations	20
Scoring Metric	Negative Mean Squared Error (MSE)

which is optimized with different parameter values given in Table 2. XGBoost aims to make more accurate forecasts at these points by learning the points where LSTM makes errors. Thus, a more powerful hybrid prediction model is obtained by combining the two models.

A validation process evaluates the model's performance. Here, a stopping criterion is determined by analyzing the prediction errors on the validation set. These criteria are optimized so that the validation loss is reduced to a certain level and a certain number of iterations are reached. If the stopping criteria are not met, different values for the model's hyperparameters are tried.

Hyperparameter tuning plays a crucial role in optimizing the predictive performance of models. The optimal parameters are determined as 100 units, an L2 regularizer of 0.07, a dropout rate of 0.3, and a learning rate of 0.0001 for the LSTM model. Similarly, for the XGBoost model, the best-performing configuration, identified using RandomizedSearchCV, includes a max depth of 6, a min child weight of 1, a learning rate of 0.1, and 200 estimators.

To ensure systematic optimization, we employ RandomSearch within the Keras Tuner library for LSTM, minimizing validation loss across five trials with three executions per trial for reliable results. We utilize RandomizedSearchCV from Scikit-Learn, which efficiently explores the hyperparameter space with 20 iterations and 3-fold cross-validation, optimizing for the negative mean squared error (MSE) metric for XGBoost.

These optimizations significantly contributed to the improved accuracy of the hybrid LSTM-XGBoost model, ensuring a balance between generalization and computational efficiency. Finally, once the optimization process is complete, the model is ready to be used for future data predictions. This version of the model is trained on wavelet transform-enriched dataset and optimized to correct the prediction errors. In this process, it is observed that the wavelet transform provides better capture of unpredictable events by separating the data into different frequency components, and the hybrid LSTM-XGBoost approach improves the overall prediction performance of the model.

The dataset is published in IEEE Dataport as part of a forecasting competition in which daily forecasts were made using the entire dataset. At the end of each day, the actual values were disclosed, allowing the model to be retrained for the next day's predictions. In this study, we aim to train the model for a full one-month forecasting period covered by the competition. To evaluate the performance of the proposed hybrid LSTM-XGBoost model, a comparative study is conducted with a standalone LSTM model and a standalone LSTM model without wavelet components. Table 3 presents comparative results, showing that the hybrid model consistently outperformed the standalone methods in terms of MAE, RMSE, MAPE and WI.

TABLE 3. Error metrics for different models.

Model	MAE	RMSE	MAPE	WI
LSTM-XGBoost Hybrid	19875.15	26595.62	1.78	0.98
A Standalone LSTM	43284.72	57403.58	3.86	0.94
LSTM without Wavelets	52681.58	67329.62	4.64	0.92

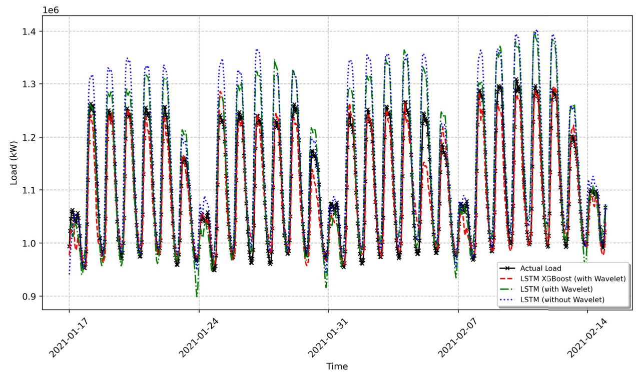

FIGURE 5. Comparison of actual and predicted load (kW) using different models.

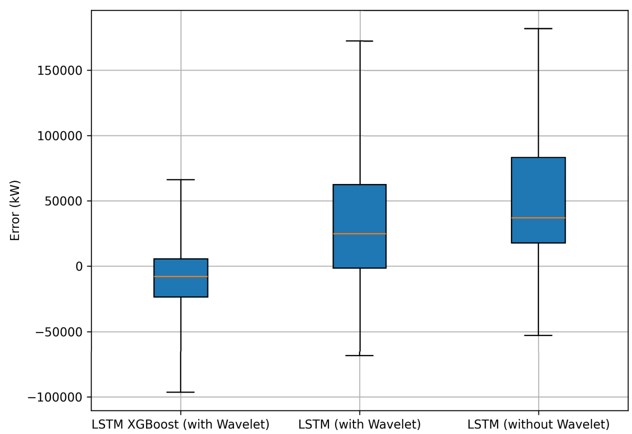

FIGURE 6. Error distribution of hybrid model and the state-of-art models.

These findings highlight the complementary strengths of the hybrid approach, where LSTM effectively captures temporal dependencies and XGBoost enhances feature-based learning. Furthermore, the hybrid model demonstrated better adaptability in capturing abrupt changes in load data,

TABLE 4. Time of day analysis for load forecasting metrics.

Time of Day	MAE	RMSE	MAPE	WI
Morning	13744.74	18588.75	1.39	0.79
Afternoon	14975.59	20090.96	1.34	0.99
Evening	25554.87	32395.96	2.13	0.95
Night	25225.38	32103.31	2.28	0.90

underscoring its suitability for real-world forecasting applications. The one-month forecast results of the comparative study are presented in the Fig. 5.

Fig. 6 highlights the hybrid LSTM-XGBoost model's superior adaptability, particularly in handling the structural shift in electricity consumption caused by COVID-19. Since pre-COVID data is abundant, models relying solely on historical patterns, such as LSTM with wavelet features and LSTM without wavelets, exhibit a positive bias in post-COVID predictions, overestimating demand due to the sharp consumption decline. However, the hybrid approach mitigates this problem by using wavelets and XGBoost to model non-linear relationships. The LSTM-XGBoost model provides a balanced error distribution, proving its robustness to unpredictable changes in energy demand and strengthening its suitability for real-world applications.

The performance of the hybrid model is then analyzed in different periods of the day (Morning, Afternoon, Evening, and Night), as shown in Table 4. These results highlight how the accuracy of the model varies depending on the time of day and reflects the different consumption patterns and operational challenges. In addition, the hourly analysis provides insight into the temporal aspects of electricity consumption forecasting and the ability of the model to adapt to these changes. Despite the hybrid model's overall good performance during morning hours, as indicated by traditional error metrics, the lower Willmott's Index suggests that the model is less successful at fully capturing consumption dynamics in this period compared to other times of day. Moreover, for the morning, a Standalone LSTM and LSTM without Wavelets models have WI values of 0.62 and 0.73, respectively, indicating they perform significantly worse than the hybrid model in capturing the underlying patterns during this period. Besides, the increased error rates during the evening and nighttime hours suggest that incorporating additional features or training-specific models for these periods can improve accuracy. This temporal analysis not only highlights the strengths and weaknesses of the model but also provides essential insights for improving forecasting accuracy in energy management systems. Aligning forecasting models with daily consumption patterns can lead to more reliable and responsive energy management strategies.

Despite the encouraging results of the proposed hybrid LSTM-XGBoost model, some limitations should be taken into account. Since consumption patterns on public holidays are not included in the dataset, the accuracy of the model may be affected when forecasts coincide with holidays. Supply-side disruptions such as grid failures and power outages are not directly accounted for in the model may influence forecasting accuracy. Likewise, uncommon events such as policy-driven energy transitions or large-scale industrial changes are not extensively represented in the training data, potentially affecting performance. Additionally, long-term shifts, such as economic downturns or regulatory modifications, may necessitate periodic retraining to ensure sustained accuracy. Future studies could enhance the model's robustness by integrating external contextual data, real-time supply-side information, and adaptive retraining strategies.

IV. CONCLUSION

In this study, a wavelet-enhanced hybrid LSTM-XGBoost model is developed to forecast electricity consumption in the presence of unpredictable events, specifically demonstrated through the impact of COVID-19 on energy demand. The dataset utilized is designed for daily forecasting in the IEEE Dataport competition, where models were retrained regularly with daily updates. However, our approach diverges by aiming to predict an entire month's energy consumption without continuous retraining, which presents a challenging scenario for time series models. By decomposing the original data into multiple frequency components through wavelet transformation, we extract approximation and detail coefficients, capturing both short-term fluctuations and long-term trends. This decomposition enables the hybrid model to gain sensitivity to sudden, irregular events, which are typically difficult for traditional time series models to handle.

The hybrid approach leverages LSTM's ability to learn sequential dependencies, while the XGBoost model is used to correct residual errors, enhancing overall prediction accuracy. The model has achieved promising results, especially for intraday morning and afternoon forecasts, but it has been observed that it does not work well on some particular days. These differences highlight the potential for further improvements, such as the inclusion of day-specific patterns or additional context-sensitive features. For example, the hybrid model can be adapted for global-scale disruptions by integrating economic indicators (e.g., GDP, unemployment rates) for economic crises and incorporating real-time meteorological data for significant weather events. Enhancements like transfer learning, scenario-specific training, and real-time data inputs strengthen the model's ability to handle dynamic changes in electricity consumption.

In conclusion, the integration of wavelet transformation with a hybrid LSTM-XGBoost model offers a robust framework for energy forecasting under conditions of high volatility and uncertainty. This methodology not only enhances the model's adaptability but also improves its predictive accuracy by dynamically responding to complex temporal patterns. Future research may extend this work by exploring additional real-world datasets, optimizing model parameters for specific seasonal or calendar effects, and incorporating adaptive learning mechanisms to handle day-to-day fluctuations more effectively. This approach contributes a robust forecasting framework for energy systems, which is essential for grid stability, economic planning, and effective energy management amid evolving challenges.

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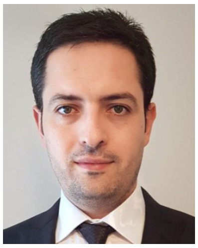

ALI AJDER (Member, IEEE) received the B.Sc. degree in electrical engineering and the Double Major degree in business administration from Yildiz Technical University (YTU), İstanbul, Türkiye, in 2008 and 2009, respectively, and the M.Sc. and Ph.D. degrees in power systems from the YTU Institute of Natural and Applied Sciences, in 2011 and 2017, respectively. He continued his studies with Technische Universität Kaiserslautern, Germany, from 2006 to 2007. He is currently a Postdoctoral Researcher with the Department of Engineering, Durham University, U.K. He is also an Associate Professor with the Department of Electrical Engineering, YTU. His research interests include energy economics, renewable energy, and power systems.

HISHAM A. A. HAMZA received the bachelor's degree from Omdurman Islamic University (OIU), Omdurman, Sudan, in 2020. He is currently pursuing the master's degree in electrical engineering with Yildiz Technical University (YTU), İstanbul, Türkiye. He was an Assistant Teacher with the Department of Electrical and Electronics Engineering.

RAMAZAN AYAZ (Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees from the Department of Electrical Engineering, Yildiz Technical University (YTU), in 2010, 2012, and 2018, respectively. He was a Researcher with Aalto University, Finland, with the Scientific and Technological Research Council of Türkiye (TÜBİTAK) Doctoral Research Fellowship, from 2015 to 2016. He is currently an Assistant Professor with the Department of Electrical Engineering, YTU, Türkiye. He is currently a Certificated Energy Manager and a Certificated Energy Auditor. He has published several peer-reviewed articles in esteemed scientific journals. He also has a patent titled a Warning Sphere with Light. His research interests include energy efficiency, photovoltaic systems, advanced lighting technologies, and road lighting. He has also participated in many international conferences in his field.