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Enhancing Short-Term Electrical Load Forecasting Using SARIMA, XGBoost, LSTM, and VMD-Based Signal Decomposition

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Abstract: Short-term electric load forecasting is essential for stable power system management, yet remains inherently uncertain due to volatile demand patterns, weather variability, and irregular consumption behaviour. The proliferation of smart metering infrastructure has made high-resolution consumption data widely available, enabling machine learning and deep learning methods to model complex non-linear temporal patterns that conventional statistical approaches cannot capture. In this context this work proposes a framework for a comparative evaluation of four representative forecasting methods: the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, Extreme Gradient Boosting (XGBoost), the Long Short-Term Memory (LSTM) neural network, and a hybrid Variational Mode Decomposition–LSTM (VMD-LSTM) model. In the hybrid approach, VMD is first adopted to decompose the load time series into several intrinsic mode functions, which are then modelled individually with LSTM to improve forecasting accuracy. RMSE, MAE, R^2, and MAPE are used to evaluate the effect of model selection on forecasting uncertainty. The results indicate that the VMD-LSTM model exhibits the most favourable performance for the considered dataset (RMSE: 2731.95, MAE: 2190.34, R^2: 0.9641, MAPE: 5.15%). However, forecasting performance may vary depending on data characteristics and modelling conditions; therefore, SARIMA and XGBoost can also provide effective results in different scenarios of short-term electricity load forecasting.
***Index Terms:** Electricity Load Forecasting, SARIMA, XGBoost, LSTM, Time Series, Deep Learning, Smart Grid, Energy Management.*

I. INTRODUCTION

It has been observed that reliable electric load forecasting is of prime importance for efficient power system operation, such as generation scheduling and reserve requirement planning. Research has shown that the selection of an efficient forecasting method can significantly influence the reliability and economic performance of energy systems [1]. Also, with the integration of distributed generation, electric vehicles, and smart metering, the complexity of power systems is increasing and accurate short-term load forecasting has become very important in electric power system [2].

Short-term load forecasting is the prediction of the load, in a time frame of minutes to a few days. It is affected by many factors such as weather conditions, time of the day, weekdays, weekends and other calendar effects. These factors make the electric load demand pattern very complex and difficult to be predicted by a single method [3].

The SARIMA model has been traditionally applied extensively as a statistical model due to its mathematical simplicity [4]. However, the SARIMA model faces difficulties in handling non-linear patterns in electrical demand. Research shows that SARIMA model is not working well for highly complex time-series data [5].

The use of machine learning methods such as XGBoost can be useful in dealing with the complicated relationships between variables and can deal efficiently with non-linear patterns [6]. In contrast, deep learning techniques such as the LSTM model, introduced by Hochreiter and Schmidhuber , can efficiently learn long-term dependencies in time-series data. Research indicates that the LSTM model can efficiently perform in the context of electric load forecasting tasks [8].

Although numerous research works have been conducted on the application of these models individually, comparative analysis of these models based on a single dataset and evaluation framework is lacking. In this context, the current research aims to perform comparative analysis of the SARIMA, XGBoost, and LSTM models in the context of short-term electric load forecasting based on a single dataset and evaluation framework [9].

II. RELATED WORK

Electricity load forecasting is a extensively studied area of research, covering classical statistical models, machine learning techniques and deep learning architectures. Statistical models such as SARIMA provided early baselines for periodic and seasonal demand series, while gradient-boosted techniques such as XGBoost showed competitive accuracy on structured tabular data at a much lower computational overhead . The advent of deep learning, especially Long Short-Term Memory (LSTM) networks, enhanced the predictive power by modeling intricate temporal relationships in time-series load data. Despite progress within each of the three paradigms, comparative evaluations under the same experimental conditions are still scarce. This is the motivation for the present

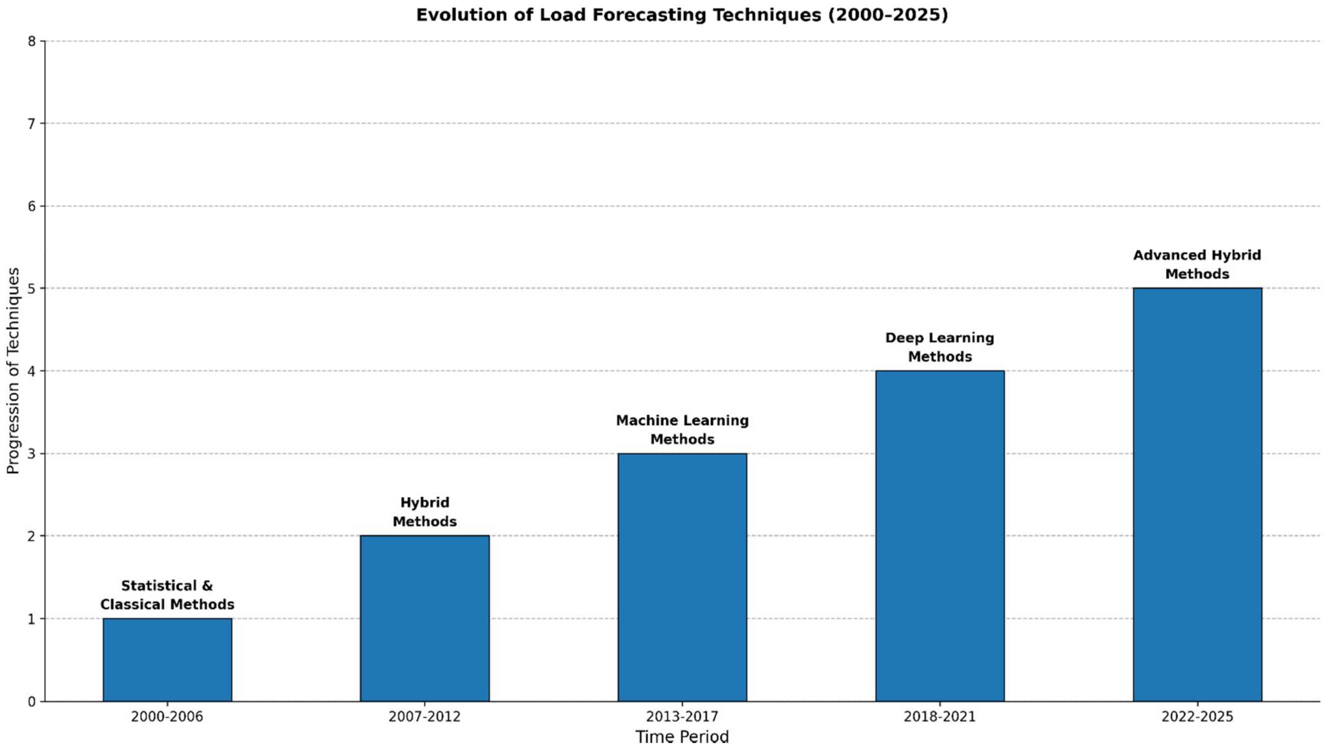

Fig. 1. Chronological evolution of Short-Term Load Forecasting methods (2000–2025).

A. SARIMA

The SARIMA model is still under active research for its practical application in electricity load forecasting. [10] proposed an online adaptive version of the SARIMA model, which is an improvement over the traditional batch-fitting methods, recalibrating its parameters in real-time using new smart meter data. The authors' method was effective to forecast the hourly electricity consumption data from northern Vietnam, with a MAPE of 4.57%, a strong result for a periodic and stable data series. For city-scale networks, [22] demonstrated the utility of the SARIMA model for near-stationary demand series by using systematic methods to determine the order of the SARIMA model for the Hanoi distribution network and obtaining reliable 24-hour-ahead load forecasts. An important cross-method perspective was provided by [12] who conducted a benchmarking study for ARMA, SARIMA, ARMAX and LSTM models over a range of four forecast horizons from 24 hours to 30 days. Their results indicated that although the SARIMA model showed a competitive MAPE of 6.53% for the shortest horizon, it was consistently outperformed by LSTM as the forecast horizon increased.

B. XGBoost

Gradient-boosted tree ensembles have shown to be strong performers against both traditional statistics and deep learning for structured electricity consumption data. [13] developed a forecasting pipeline where the historical series is first encoded into lag features, rolling window statistics and calendar features and then passed through an XGBoost regressor.The paper presented in this section was accepted at the 2023 IEEE Conference on Energy Technologies for Future Grids.

It showed that well-designed tabular features can recover most of the predictive signal in a given dataset without resorting to deep learning. In a more recent paper, [14] extended the comparison in to a large set of machine learning and deep learning algorithms on a real-world electricity consumption dataset. Again, gradient-boosted trees were found to be among the top-performing algorithms, but training times were significantly shorter than those of recurrent neural networks. [15] have recently taken the ensemble approach to a new level by introducing a multi-lag feature approach along with a stacked Prophet-XGBoost-CatBoost architecture. They achieved state-of-the-art accuracy on very short-term industrial prediction tasks but at a significant increase in implementation complexity.

C. LSTM

Deep recurrent architectures, and specifically LSTM networks, have become the most popular choice for electricity forecasting modeling. [16] studied LSTM robustness under noisy measurement conditions, concluding that the network is able to sustain a MAPE of 1.5% and an RMSE of 26.5 units even under significant sensor-level noise included within the training set, a significant result from a practical perspective due to the naturally imperfect quality of smart meter readings. [17] took LSTM accuracy one step further by adding a pre-processing Discrete Wavelet Transform decomposition stage, where the load is split into separate frequency bands, each being processed by a separate LSTM branch, resulting in a DWT-LSTM hybrid network that achieved reductions in several error metrics compared to a standard LSTM network, albeit at the cost of added pipeline complexity. The multi-step prediction problem was tackled by [18] by incorporating a self-attention module into the structure of an LSTM network and testing the new structure on the electrical consumption of the agricultural sector, yielding better look-ahead prediction, although the results were not necessarily generalizable across all load profiles with different seasonal characteristics. [19] tackled the issue of the small temporal receptive field of regular stacked LSTMs by incorporating dilated connections in the recurrent layers along with an attention layer, yielding better modeling of long-range dependencies without increasing the depth of the network.

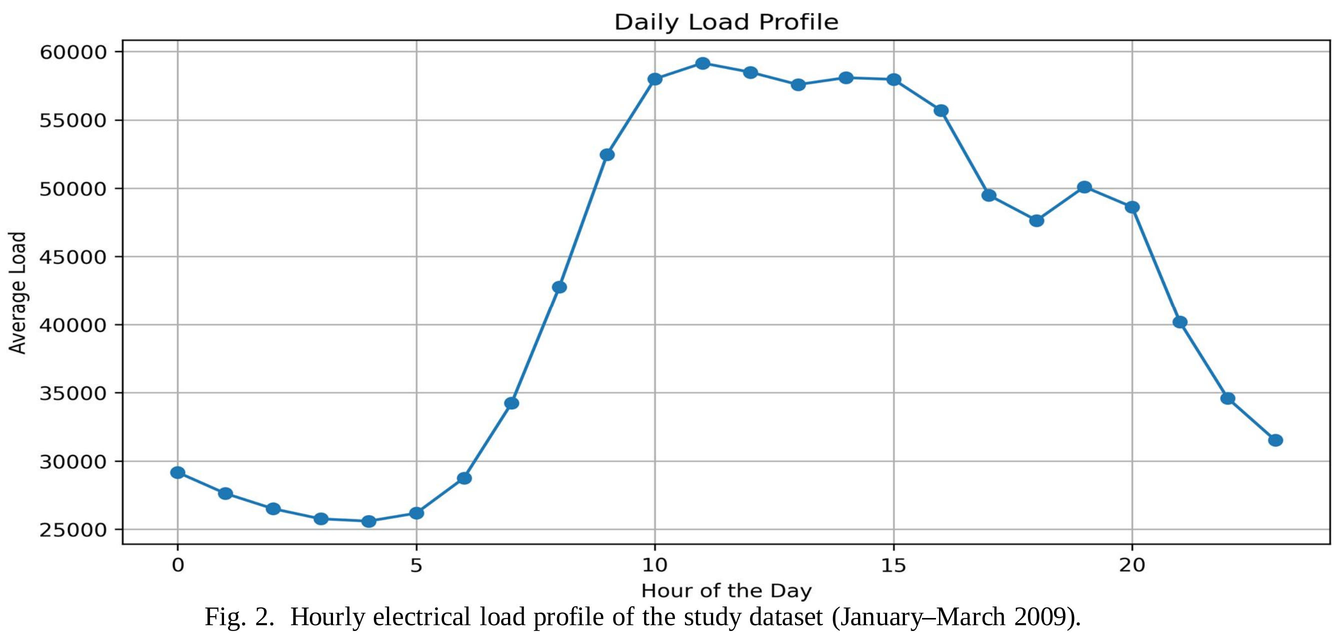

Fig. 2. Hourly electrical load profile of the study dataset (January–March 2009).

D. Comparative Studies

Multi-model comparative research is increasingly playing a significant role in reinforcing empirical knowledge in the field of forecasting. [20] compared single-layer and hybrid LSTM-CNN models on a variety of power system datasets and demonstrated that hybrid models outperform their individual constituents, although at the cost of higher sensitivity to hyperparameters. [21] provided a comprehensive survey of various machine learning and deep learning models for managing smart grid electrical load and concluded that none of these models is superior across all dataset sizes, forecasting horizons, and hardware constraints and that the best model should be chosen on a case-by-case basis depending on the constraints of the application. This research contributes to this growing body of work by testing all three models under exactly the same conditions.

TABLE I
SUMMARY OF REPRESENTATIVE PRIOR STUDIES ON SARIMA, XGBOOST, AND LSTM FOR SHORT-TERM ELECTRICITY LOAD FORECASTING

Method	Reference	Key Contribution	Key Finding / Limitation
SARIMA			
SARIMA	Kien, Huong and Minh (2023) [22]	ACF/PACF order selection for city-scale 24-hour load forecasting applied to Hanoi network.	Reliable for near-stationary periodic series; linear form restricts performance on ir-regular profiles.
SARIMA	Bozkurt, Biricik and Tays¸i (2017) [23]	Compared SARIMA with ANN in a real electricity market setting.	Useful for short-term fore-casting, but less flexible than nonlinear models in dynamic load conditions.
SARIMA	Andoh, Sekyere, Mensah and Dzebre (2021) [24]	Applied SARIMA model to forecast electricity de-mand in Ghana.	Effective in capturing sea-sonal load patterns, but limited with irregular de-mand changes.
XGBoost			
XGBoost	Abbasi, Javaid, Ghuman, Khan, Ur Rehman and Amanullah (2019) [25]	Used lagged load, rolling-window averages, weather, workday, and holiday fea-tures.	Strong speed and accu-racy versus random forest, Bayesian, and KNN meth-ods, but depends heavily on manual feature engi-neering.
XGBoost	Yao, Fu and Zong (2022) [26]	Combined feature selection with LightGBM/XGBoost for load prediction.	Improved forecasting accuracy and robustness, but pipeline still relies on feature-selection design.
XGBoost	Zhao, Zhao and Guo (2022) [27]	Window-based XGBoost with real-time electricity price.	Fewer errors than deep learning baselines, but model performance depends on carefully designed windows.
LSTM			
LSTM	Nespoli, Ogliari, Pretto, Gavazzeni, Vigani and Paccanelli (2021) [28]	Studied how data quality affects LSTM load fore-casting.	Data preprocessing is cru-cial; highlights robustness issues tied to outliers and noisy input data.
LSTM	Semmelmann, Henni and Weinhardt (2022) [29]	Hybrid bi-directional LSTM-XGBoost model for smart-meter-based forecasting.	Outperformed standard profiles and LSTM baselines, but is a hybrid pipeline.
LSTM	Wang, Jiang, Wang, Song, Zhang, Dong and Li (2023) [30]	Multilayer dilated LSTM with attention for long load sequences.	More accurate and stable than comparison methods, but more complex than standard LSTM.

III. METHODOLOGY

The proposed methodology for Short-Term Load Forecasting (STLF) is shown in Fig. 3. Raw power load data including historical consumption, temperature, humidity and calendar variables are collected and preprocessed by handling missing values, removing outliers and min-max normalization. Then three forecasting models-LSTM, SARIMA and XGBoost-are implemented on the preprocessed data. LSTM captures temporal dependencies, SARIMA handles seasonality and XGBoost models non-linear relationships. All the three models are evaluated by RMSE, MAE, MAPE and R2 score and the model with minimum error is selected as optimal. Experimental results indicate that the LSTM is the best forecasting model because it performs better in learning sequential load patterns.

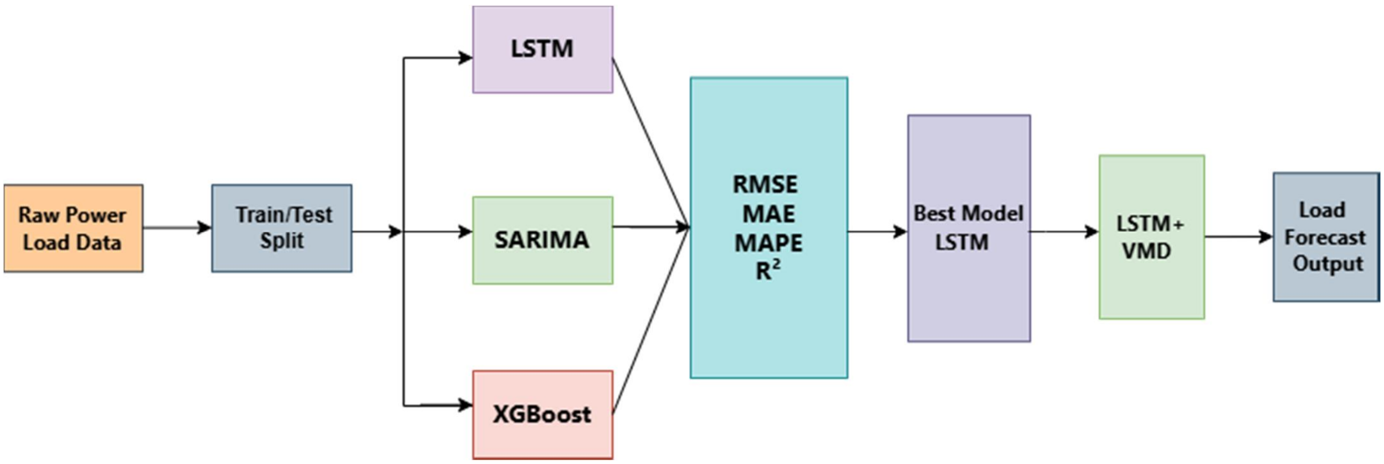

Fig. 3. Block diagram of the proposed STLF methodology.

A. SARIMA Model

The seasonal auto-regressive integrated moving average (SARIMA) model is represented by $(p, d, q)(P, D, Q)_m$, where p, d and q represent the non-seasonal auto-regressive order, the differencing degree and the moving-average order, respectively, and P, D, Q and m are the seasonal parameters [31]. The model models the load as a linear combination of lagged observations and lagged residuals. The model is most appropriate for series with a regular, stable seasonal cycle in electricity demand forecasting [32]. Seasonal and ordinary differencing were used to make the series stationary and the other orders were chosen through ACF and PACF tests. The final models were chosen by minimising the Akaike Information Criterion (AIC) on a grid search . The generated models offered one-step ahead recursive predictions over the test window, which is a common choice in short-term load forecasting research works.

$$\Phi_P(B^s)\,\phi_p(B)\,(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\,\theta_q(B)\,\varepsilon_t \qquad (1)$$

B. XGBoost Model

XGBoost uses an iterative approach to build an ensemble of decision trees where each decision tree is trained to predict the negative gradient of the loss function of the residuals of the previous ensemble, while an additive regularization term is included to limit the complexity of the decision trees [33]. The time series problem is transformed into a supervised tabular regression problem by creating the one-step autoregressive lag feature x_t = load(t−1), removing rows with missing values due to the lag shift. An XGBRegressor object is created with a squared error objective (reg:squarederror) and 50 estimators.

The training is done on 80% of the feature matrix, while the rest 20% is reserved for the validation set. This is a common setting for the training-validation split in the recent literature on load forecasting [34].

$$L(\phi) = \sum_{i=1}^{n} l\,(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\,(f_k) \qquad (2)$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2 \qquad (3)$$

C. LSTM Model

The Long Short-Term Memory network was proposed to solve the vanishing gradient problem of standard RNNs by introducing a memory cell that is modulated by three multiplicative gates (forget gate, input gate and output gate) [35]. The proposed model in the paper is a network structure of a single layer of LSTM network with 10 hidden units and ReLU activation, and a fully connected neuron in the output layer. In addition, the Adam optimizer was used with the mean squared error as the cost function for 20 epochs of training, which is common in load forecasting models based on the LSTM network in recent studies [36]. The input-output pairs are generated by a single step look-back window from the normalized input at time t to the target at time t+1 . The inverse transformation of the Min-MaxScaler was computed after prediction in order to calculate the metrics.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (4)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (6)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (7)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (8)$$

$$h_t = o_t \odot \tanh(C_t) \quad (9)$$

D. Variational Mode Decomposition (VMD)

In the proposed work, VMD is used as a pre-processing method for the hourly electrical load dataset prior to LSTM training. The load dataset consists of 2,134 observations for one hour between January 1, 2009, to March 30, 2009, having a load ranging between 21,919 MW to 75,447 MW and a mean load of 42,770 MW. As the raw load time series comprises both low-frequency and high-frequency patterns such as long-term trend patterns, weekly periodical patterns, daily consumption patterns, and noise, it will result in poor forecasting accuracy in case an LSTM network is directly trained on it [37]. In VMD, the original load time series is split into K distinct frequency components termed as IMFs [38].

1) *Mathematical Formulation:* VMD decomposes the input load series f (t) into K band-limited IMFs by solving the following constrained variational problem [39]:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad (10)$$

Subject to: $\sum_{k=1}^{K} u_k(t) = f(t)$ (11)

where u_k is the k-th decomposed mode and ω_k is its center frequency. To solve this, a quadratic penalty term α and Lagrange multiplier $\lambda(t)$ are introduced:

$$L(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \quad (12)$$

The optimal solution is obtained iteratively via the Alternating Direction Method of Multipliers (ADMM) until the following convergence criterion is satisfied:

$$\frac{\sum_k \|u_k^{n+1} - u_k^n\|_2^2}{\|u_k^n\|_2^2} < \tau \quad (13)$$

2) *Parameter Configuration:* All VMD parameters used in this study are listed in Table II.

The number of modes $K = 5$ is determined by testing candidate values $K \in [3, 8]$ and the one with the smallest reconstruction error [40].

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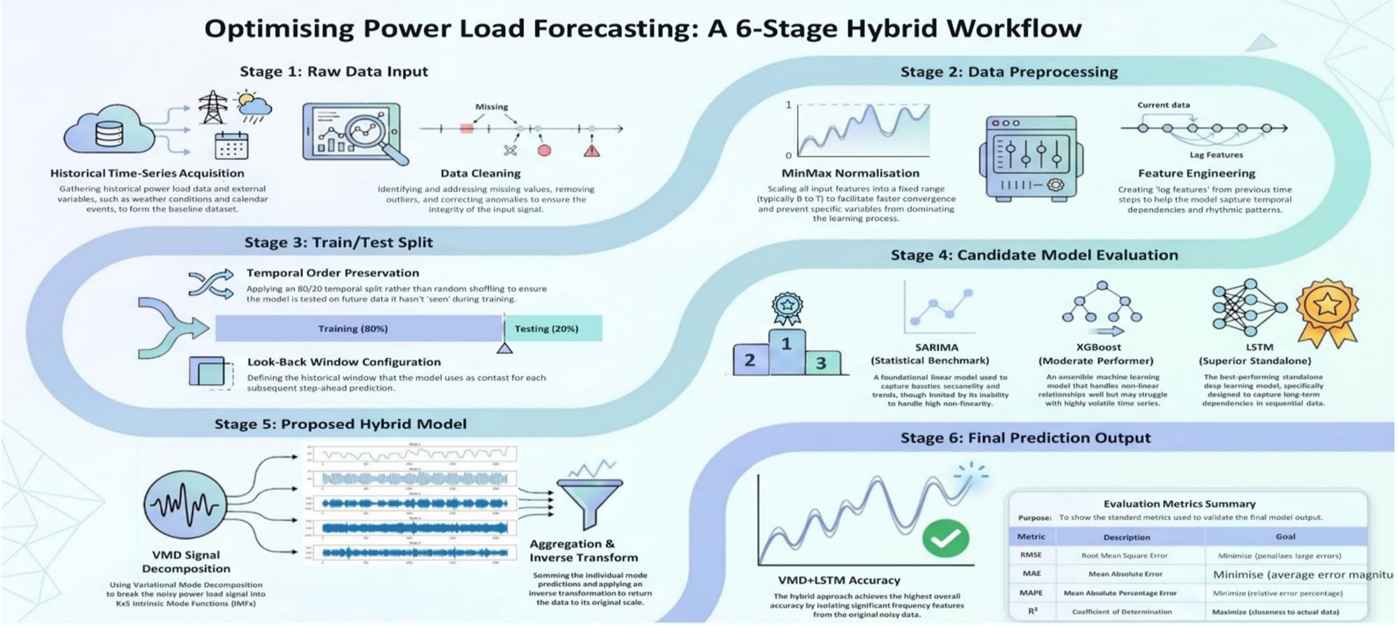

Fig. 4. The VMD-LSTM HYbrid Workflow

TABLE II
VMD PARAMETER SETTINGS

Parameter	Symbol	Value	Role
Number of modes	K	5	Controls number of IMFs extracted
Penalty factor	α	2000	Controls bandwidth of each mode
Noise tolerance	τ	10^{-7}	Convergence stopping criterion
DC component	DC	0	DC part not separated
Initialization	init	1	Mode centers initialized uniformly
Dual ascent step	τ	0	No dual ascent assumed

3) *Extracted IMF Components:* Applying VMD with $K = 5$ and $\alpha = 2000$ to the load dataset produces five IMFs whose characteristics are presented in Table III.

IMF_1 captures the long-term load trend with center frequency $\omega_1 = 0.000106$, contributing 10.15% of total signal variance. IMF_2 is the dominant mode with $\omega_2 = 0.041632$, accounting for 88.15% of signal variance and representing the primary weekly and seasonal load periodicity. IMF_3 and IMF_4, with center frequencies $\omega_3 = 0.158643$ and $\omega_4 = 0.207791$, represent medium-frequency intra-day consumption patterns. IMF_5 with $\omega_5 = 0.286701$ captures high-frequency residual noise, contributing only 0.12% of total variance [42].

TABLE III
CHARACTERISTICS OF EXTRACTED IMF COMPONENTS

Mode	Center Freq. (ω)	Std Dev (MW)	Variance	Nature
IMF_1	0.000106	4,297.0	10.15%	Long-term trend
IMF_2	0.041632	12,662.3	88.15%	Dominant seasonal cycle
IMF_3	0.158643	1,281.9	0.90%	Daily consumption pattern
IMF_4	0.207791	1,112.4	0.68%	Sub-daily variation
IMF_5	0.286701	463.2	0.12%	High-frequency noise

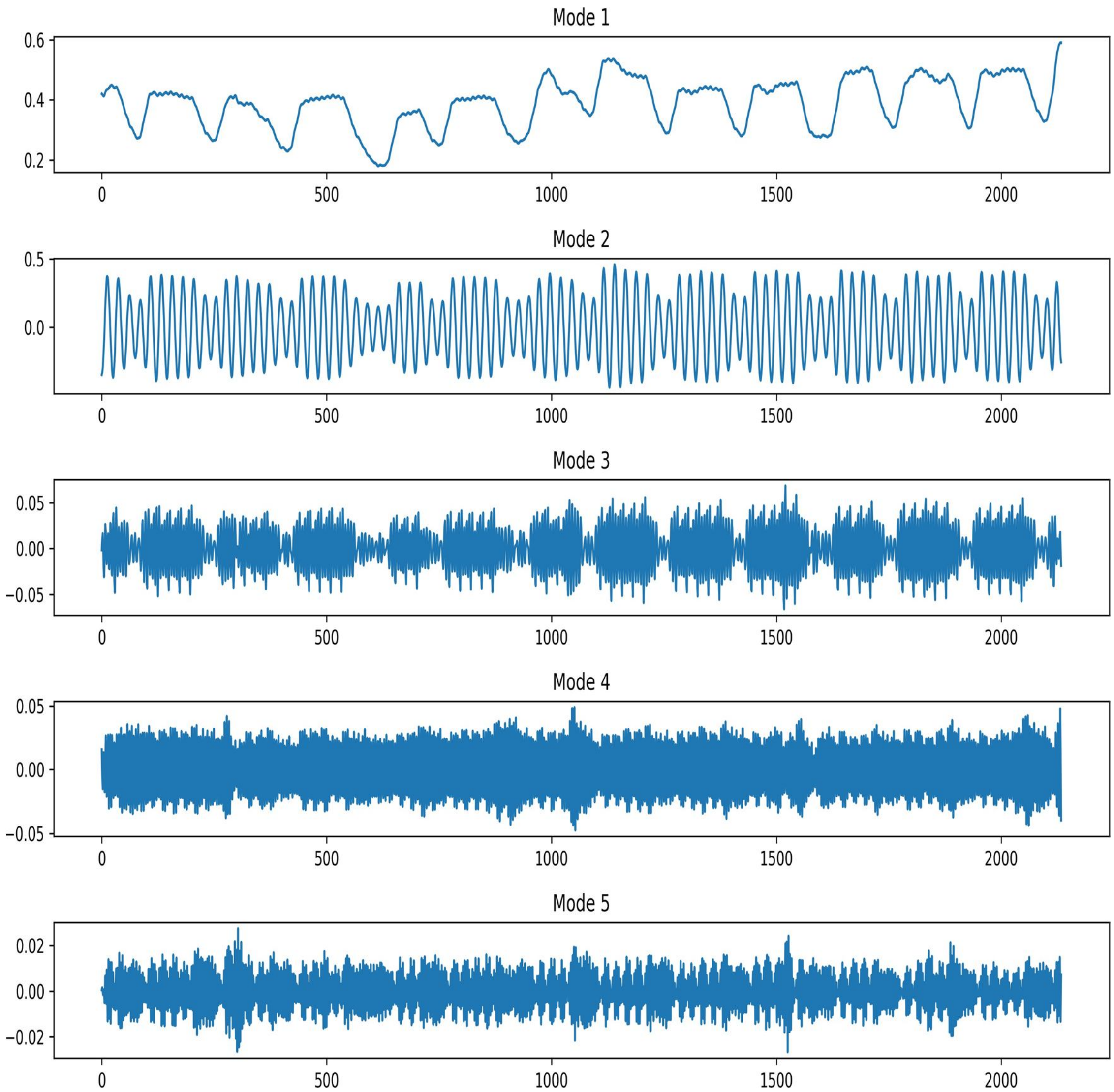

Fig. 5. Intrinsic Mode Functions (IMFs) Obtained by Variational Mode Decomposition (VMD) of the Electrical Load Time Series (Mode 1 to Mode 5)

4) *VMD-LSTM Integration:* For each of the five IMFs, a dedicated LSTM sub-model with 10 layers is used. Training separate LSTM networks for each IMF allows each model to be specialized on the temporal dynamics of a single frequency band [43]. All sub-models are optimized by Adam optimizer, with the mean squared error (MSE) as the loss function. The final load forecast is reconstructed as [44]:

$$\hat{f}(t) = \hat{u}_1(t) + \hat{u}_2(t) + \hat{u}_3(t) + \hat{u}_4(t) + \hat{u}_5(t) \quad (14)$$

The complete forecasting procedure is as follows:

- Min-max normalize the raw load series to [0, 1] by the following
- Decompose the signal into five IMFs using VMD with K = 5, and α = 2000.
- Generate separate input feature matrix for each IMF.
- Train a specific 10-layer LSTM sub-model for each IMF.
- Obtain individual IMF forecasts uˆk(t) from each sub-model.
- Reconstruct the final forecast from equation (5).
- Inverse min-max normalization to recover predictions in MW scale.

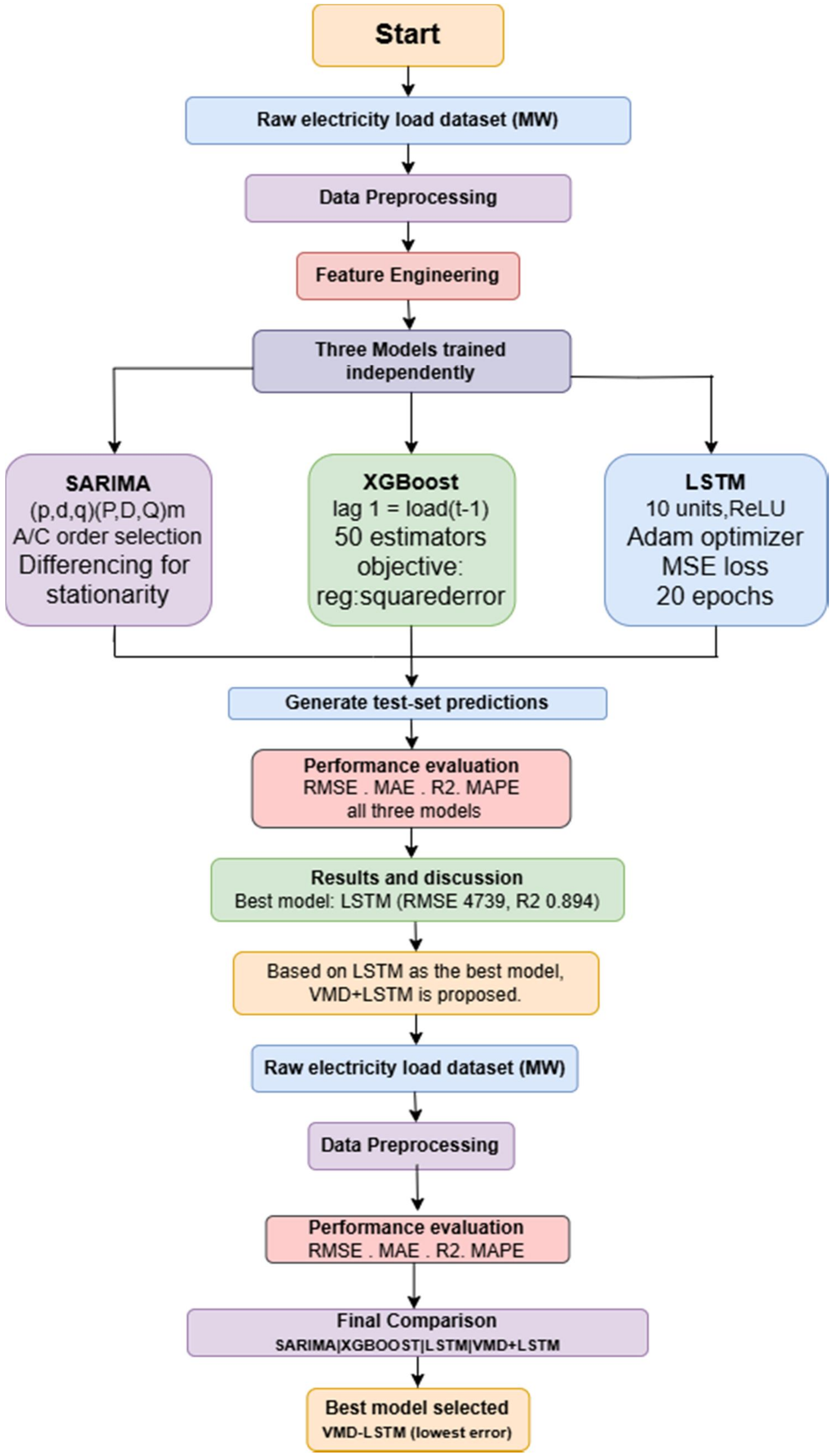

Fig. 6. Methodology flowchart for short-term electricity load forecasting using SARIMA, XGBoost ,LSTM and VMD+LSTM

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Evaluation Metrics

Four complementary metrics were used to quantify forecasting performance.

- RMSE (Root Mean Square Error): gives higher weight to larger errors because residuals are squared before averaging [46]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad ()17$$

- MAE (Mean Absolute Error): measures the average absolute deviation and is less sensitive to outlier errors than RMSE:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (16)$$

R^2 (Coefficient of Determination): quantifies the fraction of variance in the actual series accounted for by the model forecast, with 1.0 representing a perfect fit:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (17)$$

- MAPE (Mean Absolute Percentage Error): expresses the average error as a proportion of the actual value, providing a scale-independent measure suited to cross-dataset comparison [47]:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \quad (18)$$

B. Performance Comparison

Table IV reports all four metrics and the overall performance rank for each model on the held-out test set.Bold entries mark the best result in each column.

TABLE IV

COMPARATIVE PERFORMANCE ON THE TEST SET: RMSE, MAE, R^2 AND MAPE (%)

Model	RMSE	MAE	R^2	MAPE (%)
SARIMA	7494.41	6133.30	0.7353	12.78%
XGBoost	4942.08	3673.38	0.8849	8.31%
LSTM	4739.25	3623.47	0.8942	8.46%
VMD-LSTM (Proposed)	2731.95	2190.34	0.9641	5.15%

1) *Fig.7-Number of modes K=5:* compares the actual electrical load and the forecasting performance of the SARIMA, XGBoost, LSTM and VMD-LSTM models. The VMD-LSTM model was implemented with K = 5 VMD modes. The model captured the overall load pattern, but predictions were not close to the actual load especially in peak demand periods. Hence, a higher number of VMD modes (K=8) was explored to improve the accuracy of prediction.

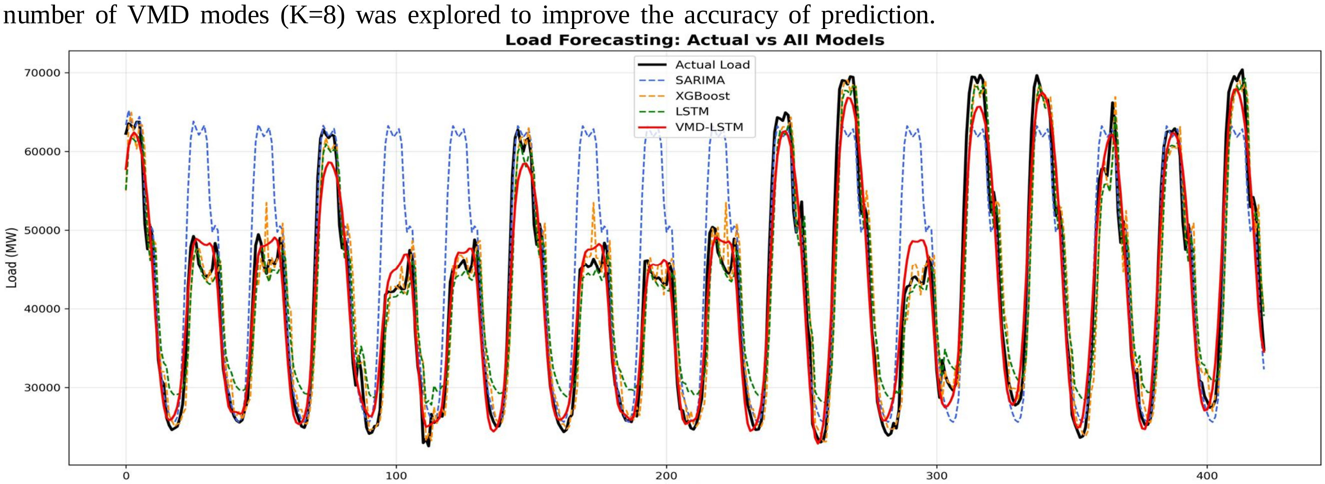

Fig. 7. Comparative Analysis of Actual Load vs. Predicted Load by SARIMA, XGBoost, LSTM, and VMD-LSTM Models over the Test Period.

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2) *Fig.8-Number of modes K=8:* The forecasting performance of the four models, SARIMA, XGBoost, LSTM and the proposed VMD-LSTM, against the actual load for around 400 test time steps. The VMD-LSTM model was set to $K = 8$ VMD modes and a look-back window of 24 time steps, which means the model was able to capture one full diurnal cycle of the historical load data before each prediction. The decomposition into eight intrinsic mode functions (IMFs) allows the model to learn the low-frequency trend components and high-frequency fluctuation components separately, which improves the reconstruction fidelity in the regions of both the peak and the trough. In the figure, we can see that the SARIMA model (blue dotted line) has a systematic positive bias, significantly overestimating the load for the whole test horizon, as it is bound by which is due to its limited ability to model the non-linear and non-stationary dynamics inherent in electrical load signals. The XGBoost model (orange dashed line) captures the general shape of the load curve, but there are significant amplitude errors at the peak points of the load, especially after time step 200. The baseline LSTM model (green dashed line) follows the load profile with moderate accuracy, but underestimates trough values and exhibits phase misalignment at several peak transitions. However, the proposed VMD-LSTM model (red solid line) can well track the actual load trajectory in most of the test period, which indicates its better peak tracking ability and lower amplitude error. The better accuracy of VMD-LSTM model is thanks to the cooperative combination of VMD-based signal decomposition which reduces noise and isolates the main oscillatory components and the LSTM network's ability to learn temporal dependencies within each decomposed mode. The results confirm that the proposed VMD-LSTM framework achieves the best overall performance in forecasting compared to all the models examined.

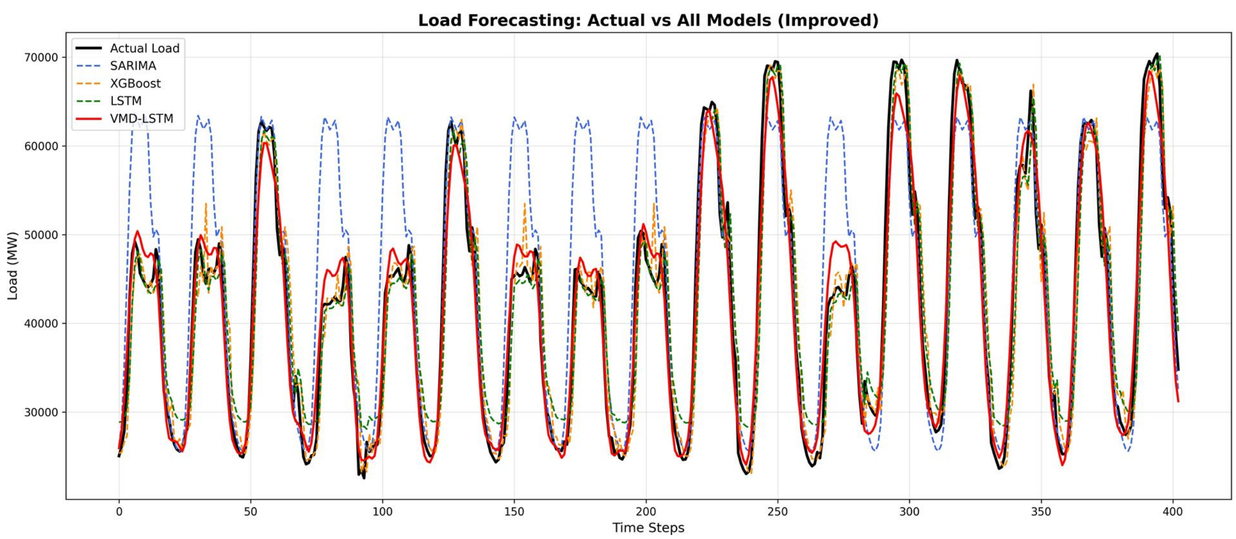

Fig. 8. Comparison of load forecasting models: Actual load versus SARIMA, XGBoost, LSTM, and the proposed VMD-LSTM model over the test period.

C. Discussion

In this section, the comparison of the three models considered in this study, namely, SARIMA, XGBoost and LSTM is discussed. In order to compare the performance of the models in an unbiased and fair way, all models were trained and tested under the same experimental conditions. The results are presented in terms of four error measures which are RMSE, MAE, R2 and MAPE.

1) *SARIMA:* had the highest error values for all four criteria: RMSE - 7494.41, MAE - 6133.30, R^2 - 0.7353, MAPE - 12.78%. The value of R^2 is 0.7353, which means that the model could only explain 73.5% of the data in the test set. This is consistent with the observations in [48] where it was shown that linear ensemble based time series models cannot effectively model the non-linear variations in the demand profile observed in modern distribution networks. In a more general review [49] concluded that SARIMA-type methods should only be considered for near-stationary or weakly non-linear load series.
2) *XGBoost:* achieved a considerable improvement over SARIMA, reducing the error (measured by RMSE) by 34% (4942.08) and increasing the value of R^2 to 0.8849. The minimum feature is a single-lag feature, which gave the ensemble enough temporal context to identify and track the main autocorrelation in the electricity load series. No overfitting occurred thanks to XGBoost's regularisation properties. The gradient-boosted tree ensemble is demonstrated to have a very competitive accuracy-to-cost ratio for electricity forecasting.

3) *LSTM:* had the least error in RMSE (4739.25), MAE (3623.47) and R^2 (0.8942). Its MAPE of 8.46% is however just 0.15% larger than that of XGBoost at 8.31%. The difference is operationally insignificant [50]. The clear advantage of **LSTM** in terms of RMSE and R^2 is attributed to its ability to automatically abstract temporal dependencies directly from the normalised sequence of loads. This is particularly effective in reducing large peak-error events that can significantly increase the value of the RMSE and reduce R^2.

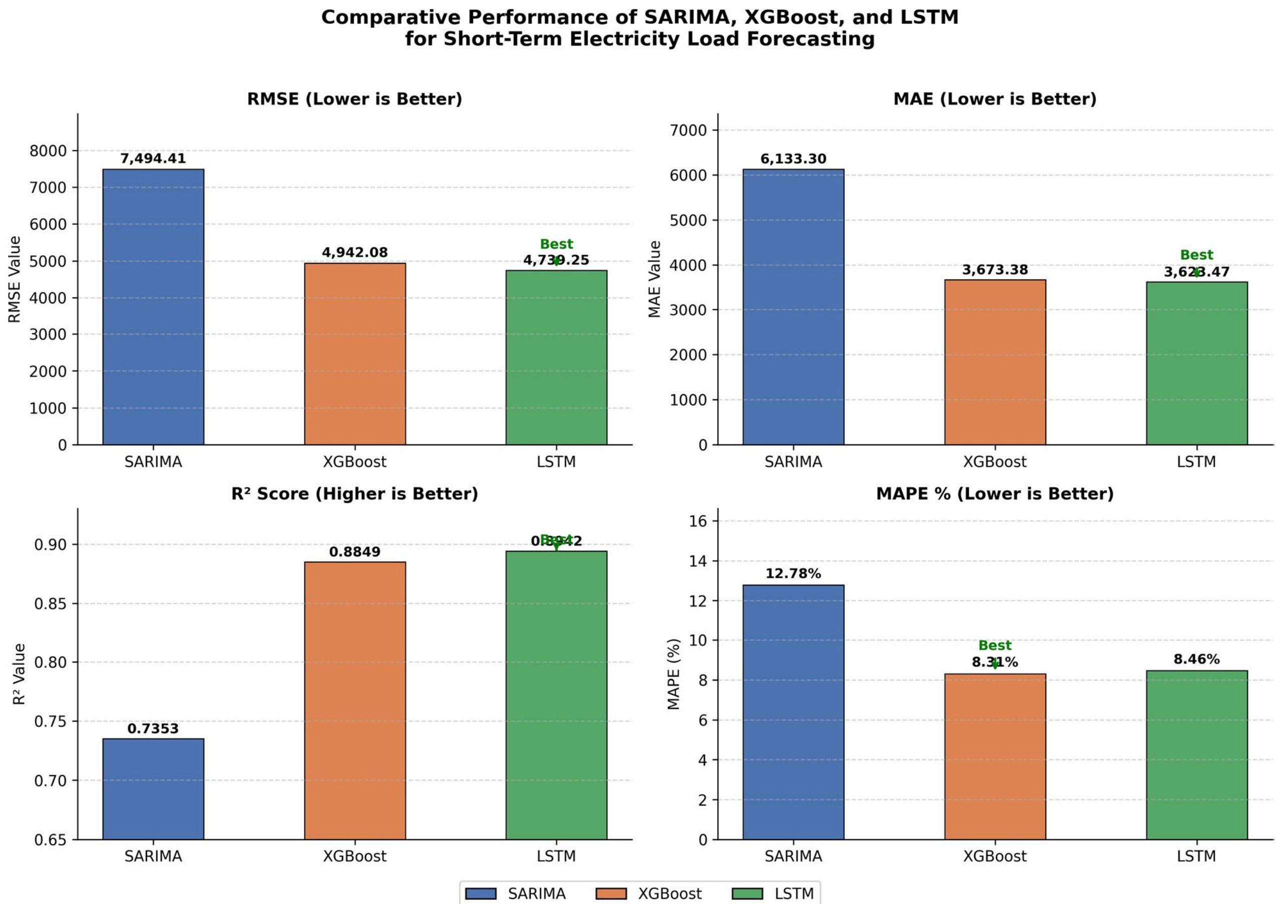

Fig. 9. Performance comparison of RMSE, MAE, R^2, and MAPE for all three models.

The performance hierarchy LSTM > XGBoost > SARIMA is completely consistent with recent benchmarks in the load forecasting literature. In particular, it is worth noting that the performance gap between LSTM and XGBoost is much smaller than the gap between either of these models and SARIMA, indicating that gradient-boosted tree methods could be considered a practically relevant alternative to DL models

V. LIMITATIONS AND FUTURE WORK

The proposed VMD-LSTM model has good forecasting performance, there are some limitations. The most important one is to select the number of VMD decomposition modes (K) and the look-back window size. In this study, different combinations of K and look-back were systematically assessed to understand their combined influence on forecasting accuracy. The initial setting was $K = 5$ with a look-back of 5 time steps, but this configuration resulted in poor peak load tracking. In peak regions, the VMD-LSTM predictions did not closely follow the actual load, which was due to under-decomposition and insufficient temporal context.

Increasing K to 8 and the look-back window to 24 time steps yielded a considerable improvement, with the model showing significantly better alignment with the actual load profile, particularly at peak and trough transitions. These results validate that mode selection and look-back window size are important hyperparameters that directly govern the accuracy of peak forecasting. Nevertheless, peak load predictions can be further improved by incorporating exogenous features such as temperature, humidity and day-of-week indicators. Future work should investigate adaptive mode selection techniques to automatically determine the optimal K for different power systems.

Future work can focus on more advanced architectures such as Bidirectional LSTM, attention-augmented LSTM or Transformer-based models, LLM based, including weather and calendar features as additional inputs, and extend the framework to multi-step probabilistic forecasting to provide uncertainty quantification for practical grid operations.

VI. CONCLUSION

In this paper, we present a reproducible comparative assessment of SARIMA, XGBoost, LSTM and VMD+LSTM for short-term electricity load forecasting under similar experimental settings. The SARIMA model was the least accurate from all the models with RMSE (7494.41), MAE (6133.30), R^2 (0.7353) and MAPE (12.78%) respectively. However,it is still a competitive choice for near-stationary processes with stable seasonality. The XGBoost model came in second place with RMSE (4942.08), MAE (3673.38), R^2 (0.8849), and MAPE (8.31%).due to its balance of high accuracy and computational efficiency. The LSTM model achieved the high accuracy with RMSE (4739.25) , MAE (3623.47) , R^2 (0.8942) , and MAPE (8.46%). This is because LSTM can exploit temporal dependencies due to its recurrent structure. Furthermore, the time series signal was decomposed by the concept of Variational Mode Decomposition combined with LSTM (VMD+LSTM) before modeling. This hybrid approach obtained the highest overall forecasting accuracy with RMSE (2731.95), MAE (2190.34), R^2 (0.9641) and MAPE (5.15%), outperforming all other models substantially.

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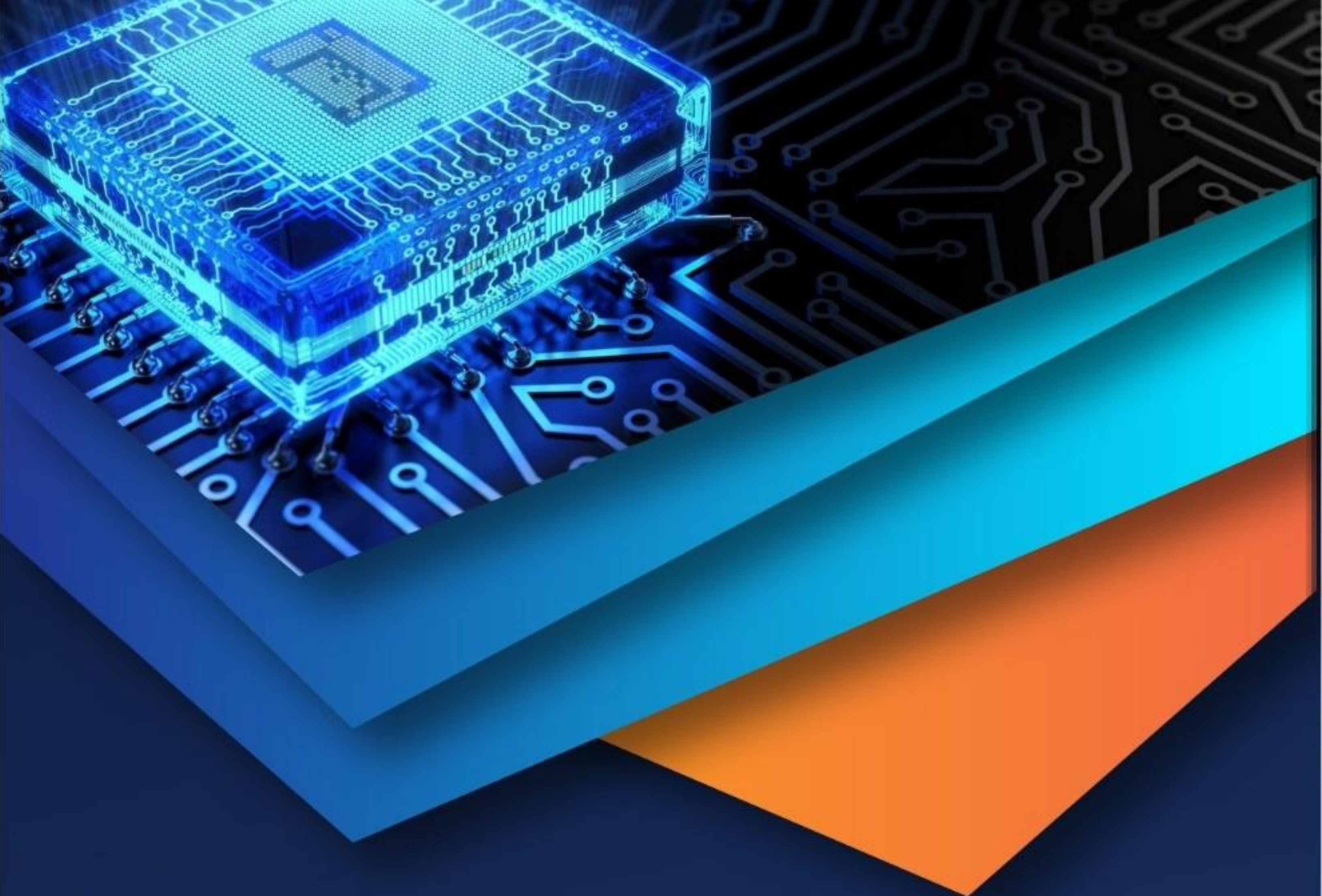

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