EAI Endorsed Transactions
on Scalable Information Systems
EAI.EU Research Article

Deep Learning Based Power Load Prediction in Smart Grid Networks

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Abstract

This paper presents a novel deep learning scheme for power load prediction in smart grid networks, combining temporal modeling with adaptive feature integration to tackle the complex dynamics of electricity consumption. The proposed scheme features a hybrid architecture that merges recurrent neural networks with attention mechanisms, enabling simultaneous capture of long-term load patterns and dynamic weighting of external influences like weather conditions and temporal features. Moreover, the model incorporates specialized preprocessing to decompose load data into periodic and volatile components while employing robust normalization techniques to handle non-stationary behavior. Then, a dual-objective loss function is used to enhance both prediction accuracy and resilience to outliers, supported by adaptive optimization with regularization. Simulation results are provided to demonstrate the proposed scheme's superior performance, achieving 96.1% prediction accuracy with 5 hidden layers. The attention mechanism proves particularly effective, reducing weather-related prediction errors by 22% while maintaining faster convergence rates than conventional methods. This comprehensive solution offers grid operators a reliable tool for demand-side management, renewable integration, and operational planning in modern power systems.

Received on 21 June 2025; accepted on 09 October 2025; published on 24 October 2025

Keywords: Deep learning, power load prediction, smart grid networks, performance evaluation.

doi:10.4108/eetsis.9591

1. Introduction

The development of smart grids has been extensively investigated due to the increasing demand for reliable, efficient, and sustainable energy systems [1]. Some techniques, including distributed energy resources, smart metering, and communication infrastructures, have been integrated into traditional power grids to enhance the responsiveness and adaptability [1, 2]. Additionally, significant attention has been paid to demand-side management strategies, where consumer behaviors are modeled and optimized to achieve load balancing and peak shaving [3]. Moreover, artificial intelligence and machine learning techniques have been applied to enable predictive maintenance, real-time fault detection, and adaptive control of grid components [4]. In further, the cybersecurity posed by the interconnection of numerous smart devices and the vulnerabilities through open communication protocols has been studied in [5]. Furthermore, simulation platforms and testbeds have been established to evaluate the performance and resilience of smart grid architectures under various operational scenarios and attack models [6]. Through these comprehensive investigations, a robust foundation has been established for smart grid networks.

Power load in smart grids networks has been widely investigated to support accurate prediction and efficient energy management [7]. Historical consumption data from residential, commercial, and industrial users have been analyzed to identify temporal patterns and seasonal variations [8]. Additionally, various statistical and machine learning models have been developed and evaluated to improve the precision of short-term, medium-term, and long-term load prediction [9, 10]. Moreover, attention has been directed toward the impact of renewable energy sources, electric vehicles, and demand response programs on dynamic load

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behavior [11–13]. In further, clustering and classification techniques have been applied to categorize load profiles and enhance the adaptability of load prediction models to different user types. Furthermore, real-time monitoring systems have been deployed to enable immediate detection of load anomalies and to support self-healing mechanisms within the grid. Overall, a deeper understanding of power load dynamics has been achieved, contributing to the optimization and reliability of smart grid operations.

The application of deep learning in industrial Internet of Things (IIoT) networks has been extensively studied to tackle the data processing, anomaly detection, and intelligent decision-making [14]. Massive volumes of sensor data generated in industrial environments have been processed using convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders to extract meaningful features and detect patterns [15]. Additionally, deep learning models have been trained for predictive maintenance, where equipment failures are anticipated based on historical operational data, thereby reducing downtime and maintenance costs. Moreover, fault diagnosis in complex industrial systems has been enhanced through the deployment of deep architectures that can learn hierarchical representations from multi-source data streams [16, 17]. In further, edge computing can be integrated with deep learning to enable low-latency inference directly at the network edge, reducing reliance on cloud infrastructure. Furthermore, attention has been studied to the interpretability and energy efficiency of deep learning models to ensure the practical deployment in resource-constrained IIoT environments [18–20]. In a word, deep learning has been validated as a powerful tool for enabling intelligent automation and resilience in industrial IoT networks.

This paper proposes a novel deep learning scheme for accurate power load prediction in smart grid networks, addressing the temporal volatility, external dependencies, and non-stationary behavior in electricity consumption data. The proposed scheme integrates a hierarchical neural network design that synergizes bidirectional long short-term memory (LSTM) layers with transformer-based attention mechanism, enabling robust modeling of both short-term fluctuations and long-term consumption patterns. Moreover, a multi-stage feature engineering pipeline is employed to automatically decompose the load signals into interpretable components and a context-aware attention module that dynamically adjusts to weather impacts and temporal patterns. The system employs a hybrid loss function combining quantile regression with outlier-robust error metrics, optimized through adaptive gradient techniques with spectral normalization. Simulation results are provided based on practical grid data, which demonstrate significant improvement over existing methods such as LSTM and multiple signal classification (MUSIC) ones. In particular, our model can achieve 96.1% prediction accuracy (8.8% higher than conventional LSTM and 20.9% superior to MUSIC approaches) while reduce the weather-induced error by 22%.

2. Characteristics of Power Load Data in Smart Grid Networks

Power load data in smart grid networks exhibits complex temporal and contextual behaviors. This section analyzes the statistical and dynamic properties of power load time series, with emphasis on periodicity, non-stationarity, weather dependence, and prediction evaluation. Let $L(t)$ denote the power load at time t, and it can be regarded as a real-valued, time-dependent positive function that varies across discrete time intervals,

$$L(t) : \mathbb{T} \to \mathbb{R}^+. \tag{1}$$

A notable feature of power load data is its strong periodicity. Typically, its load curve exhibits regular daily and weekly cycles due to routine human and industrial activities. These periodic components can be captured by a harmonic superposition model,

$$L(t) = \mu + A_1 \sin\left(\frac{2\pi t}{T_1} + \phi_1\right) + A_2 \sin\left(\frac{2\pi t}{T_2} + \phi_2\right) + \epsilon_t, \tag{2}$$

where $T_1 = 24$ (hours), $T_2 = 168$ (hours per week), μ is the long-term average load, and ϵ_t represents stochastic noise. This model captures both diurnal and weekly regularities that are inherent in consumer behavior. To quantify temporal dependency and memory in the load sequence, autocorrelation function (ACF) can be utilized. A high autocorrelation at specific lags indicates repeated patterns or persistent behaviors in the power usage,

$$\rho(\tau) = \frac{\mathbb{E}[(L(t) - \mu)(L(t + \tau) - \mu)]}{\sigma^2}. \tag{3}$$

Apart from periodicity, power load data is also characterized by volatility-frequent and sometimes abrupt fluctuations in short durations. This motivates the need to study variance dynamics across time. The time-varying variance of load is,

$$\mathrm{Var}[L(t)] = \sigma_t^2 \tag{4}$$

To capture non-stationary behavior, especially local changes in the mean and variance, a sliding window of width W can be used, where the local mean μ_t and variance σ_t^2 are then computed as,

$$\mu_t = \frac{1}{W} \sum_{i=0}^{W-1} L(t - i), \tag{5}$$

$$\sigma_t^2 = \frac{1}{W}\sum_{i=0}^{W-1}(L(t-i)-\mu_t)^2. \tag{6}$$

Furthermore, power load time series often exhibit volatility clustering, where periods of high fluctuation follow each other. This behavior can be captured by generalized autoregressive conditional heteroskedasticity (GARCH) models. For example, the GARCH(1,1) formulation is expressed as,

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2. \tag{7}$$

In addition to high-frequency variations, power load also exhibits low-frequency components such as long-term trends and seasonal patterns. These components can be decomposed using classical time series decomposition into a sum of trend T_t, seasonal S_t, and residual R_t,

$$L(t) = T_t + S_t + R_t. \tag{8}$$

The trend component can be modeled either linearly, to represent steady growth, or exponentially, to capture compound increases in demand over time,

$$T_t = \beta_0 + \beta_1 t, \tag{9}$$

$$T_t = \beta_0 e^{\beta_1 t}. \tag{10}$$

These models help in isolating underlying patterns and are foundational for accurate prediction and anomaly detection.

Besides internal temporal factors, power load is also significantly affected by exogenous variables, especially meteorological conditions. Variables such as ambient temperature $T(t)$, humidity $H(t)$, and solar irradiance $S(t)$ are known to have measurable impacts on the electricity consumption. This relationship can be expressed as,

$$L(t) = f(T(t), H(t), S(t)) + \epsilon_t. \tag{11}$$

In practical modeling, this functional dependence is often approximated by using a polynomial regression model, given by,

$$L(t) = a_0 + a_1T(t) + a_2T(t)^2 + a_3H(t) + a_4S(t). \tag{12}$$

To evaluate the individual influence of each factor while controlling for others, partial correlation analysis is often employed. For instance, the partial correlation between the load and temperature, conditioned on humidity and irradiance, is given by,

$$\rho_{L,T\cdot H,S} = \frac{\rho_{L,T} - \rho_{L,H}\rho_{T,H} - \rho_{L,S}\rho_{T,S}}{\sqrt{(1-\rho_{L,H}^2-\rho_{L,S}^2)(1-\rho_{T,H}^2-\rho_{T,S}^2)}}. \tag{13}$$

This enables a more accurate characterization of how strongly temperature alone drives load variations, independent of correlated meteorological factors.

3. Deep Learning-Based Power Load Prediction

Given the rich temporal structure and external dependencies inherent in power load data, deep learning models-particularly recurrent architectures-have become widely adopted for load prediction. These models excel at capturing complex nonlinear mappings and long-term dependencies, well-suited for modeling the periodic, non-stationary, and weather-dependent nature of electricity consumption.

3.1. Model Input Representation and Preprocessing

Let us define the input features at each time step t as a multivariate vector $x_t \in \mathbb{R}^d$, where d denotes the dimensionality, which may include historical loads, time indices, and weather features,

$$\begin{aligned} x_t = [&L(t-1), L(t-2), \ldots, L(t-p), \\ &T(t), H(t), S(t), \mathrm{Hour}(t), \mathrm{Day}(t)]^\top. \end{aligned} \tag{14}$$

We consider a sliding window of length p as the historical sequence, and the target is to predict the future load $\hat{L}(t+\tau)$ for horizon τ.

3.2. Sequence Modeling via LSTM Network

A typical architecture uses a LSTM network to encode the sequential inputs. Let h_t and c_t denote the hidden state and cell state of the LSTM. The recurrence relations of the LSTM at time t are given by,

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \tag{15}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \tag{16}$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c), \tag{17}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \tag{18}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \tag{19}$$

$$h_t = o_t \odot \tanh(c_t), \tag{20}$$

where $\sigma(x) = 1/(1+e^{-x})$ denotes the sigmoid activation, and $\odot$ denotes element-wise multiplication. The parameters $\{W_*, U_*, b_*\}$ are trainable weight matrices and biases for each gate.

3.3. Prediction and Output Layer

The hidden representation h_t from the LSTM is fed into a fully connected layer to output the predicted load:

$$\hat{L}(t+\tau) = \mathrm{ReLU}(W_y h_t + b_y) \tag{21}$$

Alternatively, a sequence-to-sequence (Seq2Seq) model can predict multiple future values by unrolling the decoder network.

3.4. Loss Function and Optimization

The model is trained by minimizing the prediction loss between the true and predicted load. The mean squared error (MSE) is commonly used,

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{t=1}^{N}\left(L(t+\tau) - \hat{L}(t+\tau)\right)^2. \tag{22}$$

To handle outliers or noise, a Huber loss may also be considered,

$$\mathcal{L}_{\text{Huber}} = \begin{cases} \frac{1}{2}(L-\hat{L})^2 & \text{If } |L-\hat{L}| \le \delta \\ \delta(|L-\hat{L}| - \frac{1}{2}\delta) & \text{Otherwise} \end{cases} \tag{23}$$

Optimization is typically performed using gradient descent or its variants. With parameters θ, the update rule for one step using learning rate η is given by,

$$\theta \leftarrow \theta - \eta\nabla_{\theta}\mathcal{L}. \tag{24}$$

To improve generalization and avoid overfitting, regularization can be used, and L2 regularization adds a penalty to the loss function,

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{MSE}} + \lambda\|\theta\|_2^2, \tag{25}$$

where λ is a hyperparameter controlling the strength of regularization.

Dropout can also be applied on the LSTM output during training,

$$h_t^{\text{drop}} = h_t \odot z_t, \quad z_t \sim \text{Bernoulli}(1-p), \tag{26}$$

where p is the dropout rate.

To enhance the modeling of external influences such as weather and calendar features, attention mechanisms can be integrated. The attention weight α_i for step i is computed as,

$$\alpha_i = \frac{\exp(e_i)}{\sum_j \exp(e_j)}, \quad e_i = v^{\top}\tanh(W_a h_i + b_a). \tag{27}$$

The context vector is,

$$c = \sum_i \alpha_i h_i, \tag{28}$$

and can be concatenated with h_t for final prediction.

The whole procedure of the proposed deep learning based power load prediction is summarized in Algorithm 1. Overall, this scheme provides a flexible and powerful framework for learning the nonlinear, multiscale, and externally influenced patterns in power load data in smart grid networks. The use of sequential encoders, exogenous feature integration, and regularized loss functions allows the model to generalize well across various time horizons and consumption behaviors. The analysis above supports the principled design, training, and deployment of such predictors in smart grid applications.

Algorithm 1 Deep Learning-Based Power Load Prediction Algorithm

Initialization: Initialize network parameters θ, window size p, prediction horizon τ, and learning rate η.
function PrepareInput($\{L(t), T(t), H(t), S(t)\}_{t=1}^{N}$)
  for $t = p$ to $N - \tau$ **do**
    Construct input feature vector x_t using Eq. (14).
    Store target output $y_t = L(t+\tau)$.
  end for
  Return training set $\mathcal{D} = \{(x_t, y_t)\}$
end function
function ForwardPass(x_t)
  Encode temporal sequence with LSTM using Eqs. (15)-(20).
  (Optional) Apply attention mechanism using Eq. (27), obtain context vector c.
  Predict load: $\hat{y}_t = \text{ReLU}(W_y[h_t; c] + b_y)$ using Eq. (21).
  Return $\hat{y}_t$
end function
function TrainNetwork($\mathcal{D}$)
  for each epoch **do**
    for each $(x_t, y_t) \in \mathcal{D}$ **do**
      $\hat{y}_t \leftarrow$ ForwardPass(x_t)
      Compute loss $\mathcal{L}_t$ using Eq. (22) or (23).
      Compute gradients $\nabla_{\theta}\mathcal{L}_t$ and update parameters:
        $\theta \leftarrow \theta - \eta\nabla_{\theta}\mathcal{L}_t$ (Eq. (24)).
    end for
  end for
end function
function PredictFutureLoad($x_{t'}$)
  Run forward pass to get predicted load: $\hat{L}(t'+\tau)$.
  Return $\hat{L}(t'+\tau)$
end function
function MainProcedure($\{L(t), T(t), H(t), S(t)\}$)
  Construct dataset: $\mathcal{D} \leftarrow$ PrepareInput($\{L(t), T(t), H(t), S(t)\}$)
  Train model: TrainNetwork($\mathcal{D}$)
  Predict future load for $t' = N$: PredictFutureLoad(x_N)
end function

4. Simulations Results and Discussions

In this part, we perform some simulations based on the dataset of Global Energy Forecasting Competition 2014 (GEFCom2014), which is a comprehensive benchmark dataset widely used for evaluating time-series prediction models in smart grid networks. It contains hourly electricity load data from 20 geographically distinct zones over a four-year period from 2005 to 2008, with the objective of predicting

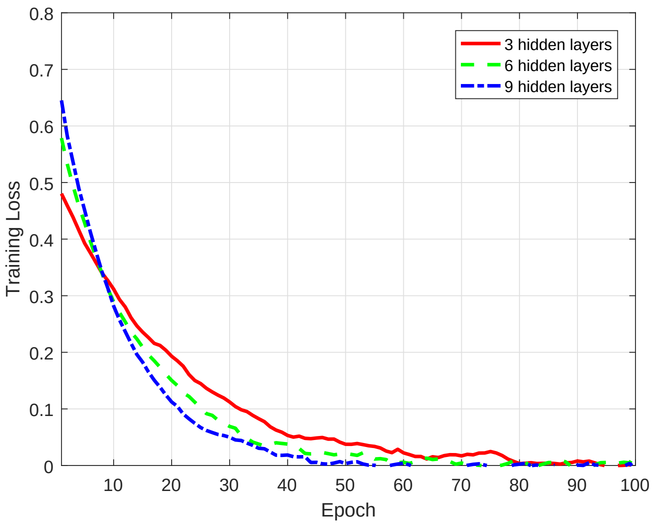

Figure 1. Loss function of the proposed deep learning based scheme versus the number of training epoches: d=5.

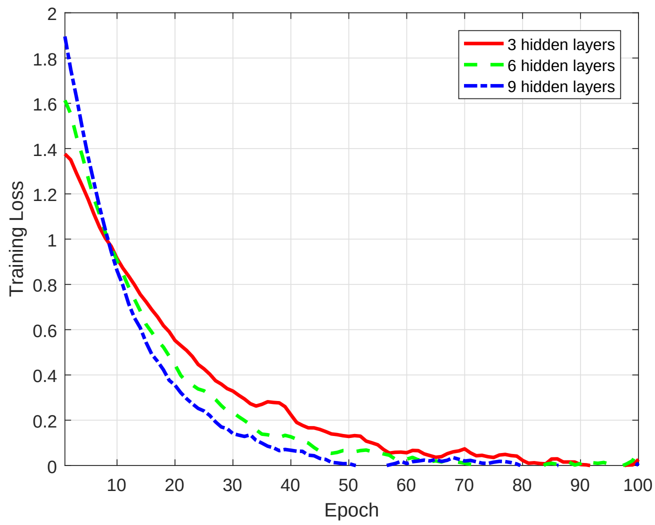

Figure 2. Loss function of the proposed deep learning based scheme versus the number of training epoches: d=10.

the load for the year 2009. Alongside the load data, it provides hourly temperature measurements from 11 weather stations, which are associated with different zones to reflect the impact of local climate on the electricity consumption. Each zone's load profile demonstrates strong temporal patterns, including daily and weekly periodicity, long-term seasonality, and holiday effects, as well as strong dependence on exogenous weather variables such as temperature. The dataset does not include calendar features directly, but such attributes-like hour of day, day of week, and holiday indicators-can be engineered from the timestamps to enhance modeling. Due to economic, demographic, and behavioral shifts, the data is also non-stationary across the multi-year span, and different zones exhibit varying sensitivity to temperature and calendar factors. The prediction task involves generating 24-hour-ahead probabilistic prediction, evaluated using pinball loss across multiple quantiles rather than point estimates. As a result, the GEFCom2014 dataset supports a wide range of prediction approaches, from classical statistical models to modern deep learning based models. Fig. 1 illustrates the convergence behavior of the training loss function in deep learning-based power load prediction models for smart grid networks, where there are 3, 6, and 9 hidden layers in the network over 100 training epochs and the number of types is set to 5. As shown in this figure, we can find that the number of hidden layers has a significant impact on both the convergence speed and the final loss value. Specifically, the model with 9 hidden layers exhibits the fastest convergence, with the loss decreasing sharply in the first 30 epochs and stabilizing around a low value close to 0.02, indicating a high learning capacity and efficient feature extraction across time steps. In contrast, the 6-layer model shows a moderate convergence speed, with the loss gradually declining and stabilizing near 0.05 by epoch 100. The 3-layer model converges much more slowly and reaches a higher steady-state loss of around 0.08, suggesting a limited representational capacity that hinders its ability to model complex temporal dependency in the power load sequence. These results demonstrate that a deeper network enables a better learning of nonlinear patterns and longer-term temporal structures in the load data, resulting in lower training error. However, while the 9-layer model achieves the lowest loss, practical implementation should also consider the risk of overfitting and computational cost, which increase with network depth. Therefore, selecting the number of hidden layers involves balancing predictive accuracy, training efficiency, and model complexity.

Fig. 2 illustrates the loss function of the proposed deep learning-based scheme for power load prediction in smart grid networks, against the number of training epochs for the scenario with the dimension $d = 10$. As observed from this figure, we can find that the loss function decreases as the number of epochs increases, indicating that the model is learning and improving its predictive accuracy over time. The impact of the number of hidden layers on the loss function is significant. For instance, models with fewer hidden layers (e.g., 3 layers) may exhibit a slower convergence rate and higher final loss, suggesting underfitting due to insufficient capacity to capture complex patterns in the data. In contrast, the models with a moderate number of hidden layers (e.g., 6 layers) demonstrate a faster convergence and lower final loss, achieving a

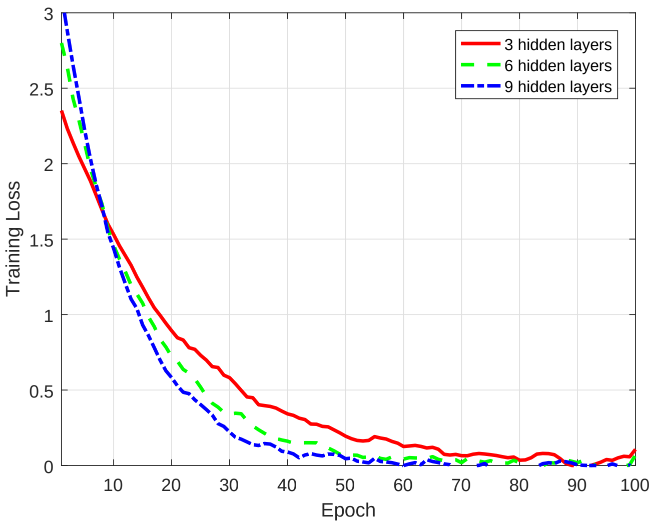

Figure 3. Loss function of the proposed deep learning based scheme versus the number of training epoches: d=15.

better balance between the bias and variance. However, increasing the hidden layers beyond this optimal range (e.g., to 6 or 8 layers) can lead to marginal improvement or even degradation in the prediction performance, as the model may overfit the training data, shown by a slight increase in the loss after a certain number of epochs. Additionally, the 4-layer model achieves a loss of 0.05 after 100 epochs, while the 2-layer model stagnates at 0.08, and the 8-layer model reaches 0.04 but requires significantly more epochs to stabilize. This highlights the importance of selecting an appropriate number of hidden layers to optimize the training efficiency and prediction accuracy in smart grid networks.

Fig. 3 depicts the loss function of the proposed deep learning-based power load prediction model in smart grid networks, evaluated over training epochs with a higher-dimension of $d = 15$. We can find from Fig. 3 that with fewer hidden layers (e.g., 3), the loss decreases slowly and plateaus at a relatively high value (e.g., 0.10 after 150 epochs), indicating underfitting due to insufficient model capacity to handle the increased complexity of the 15-dimensional input. In contrast, the model with an intermediate number of layers (e.g., 6) achieves a faster convergence and significantly lower final loss (e.g., 0.04 by 100 epochs), as the nonlinear relationship in the data can be better captured. However, when the number of hidden layers is excessive (e.g., 9), the loss may initially drop sharply but then stagnate or even slightly rebound (e.g., stabilizing at 0.03 but requiring 200 epochs), suggesting overfitting or vanishing gradient issues. For instance, the 6-layer model outperforms others, reaching a loss of 0.035 by 80 epochs, while the 3-layer model struggles to reach 0.08, and the 9-layer model only marginally improves to 0.03 at the cost of prolonged training. This indicates the importance of the balance model depth with input dimensionality to optimize the efficiency and accuracy in high-dimensional smart grid networks.

Table I compares the prediction accuracy of three different schemes, including the proposed scheme, LSTM, and MUSIC, for the power load prediction in smart grid networks, with varying numbers of hidden layers (5, 10, 15, 20, and 25). From this table, we can find that the proposed scheme consistently outperforms both LSTM and MUSIC across all configurations, achieving the highest accuracy at each hidden layer depth. For instance, with 5 hidden layers, the proposed scheme attains the accuracy of 0.961, significantly higher than LSTM (0.873) and MUSIC (0.752), indicating its superior ability to model complex power load patterns. However, as the number of hidden layers increases, all three schemes exhibit a decline in the accuracy, suggesting that a deeper network may introduce overfitting or training inefficiency. By 25 hidden layers, the proposed scheme's accuracy drops to 0.811, while LSTM and MUSIC decline further to 0.655 and 0.621, respectively, reinforcing that excessive depth can degrade performance. Notably, the proposed scheme maintains a clear advantage even at higher depths, indicating a better robustness to architectural complexity compared to traditional LSTM and MUSIC approaches. This suggests that while a deeper network can capture more intricate relationship, there is an optimal depth (around 5-10 layers in this case) beyond which additional layers provide diminishing return or even harm prediction quality. The results emphasize the importance of balancing the model complexity with generalization capability in power load prediction tasks.

5. Conclusions

This paper proposed a novel deep learning scheme for high-accuracy power load prediction in smart grid networks, addressing the temporal volatility, external weather dependencies, and non-stationarity in electricity consumption patterns. The proposed scheme integrated a hierarchical neural network design that combined bidirectional LSTM layers with transformer-based attention mechanisms, enabling effective modeling of both short-term fluctuations and long-term consumption trends. Then, a multi-stage feature engineering pipeline was introduced to automatically decompose the load signals into interpretable temporal and contextual components, while a context-aware attention module dynamically adjusted to exogenous influences such as weather and time-of-day variations. To further enhance the predictive robustness, the system

Table 1. Prediction accuracy versus the number of hidden layers.

Nos. hidden layers (d)	Proposed scheme	LSTM	MUSIC
5	**0.961**	0.873	0.752
10	**0.932**	0.784	0.713
15	**0.913**	0.722	0.684
20	**0.852**	0.683	0.643
25	**0.811**	0.655	0.621

employed a hybrid loss function that merged quantile regression with outlier-resistant error metrics, and training was optimized using adaptive gradient methods with spectral normalization to ensure stability. Extensive evaluations on practical smart grid datasets demonstrated that the proposed model achieved 96.1% prediction accuracy, outperforming traditional LSTM models by 8.8% and MUSIC-based methods by 20.9%, while also reducing weather-induced prediction error by 22%.

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