International Journal of Scientific Research and Engineering Development-– Volume 8 Issue 6, Nov-Dec 2025
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

AI-Enabled Energy Load Forecasting for Smart Grid ‘Management

Muhammad Arsalan,[1] Muhammad Ayaz,[2] Yousaf Ali,[3] Uroosa Baig[4]
[1] Masters of Engineering management, Cumberland university, [2]Department of Electrical Engineering PAF-IAST Mang, Haripur, Pakistan, [3]Department of Electrical Engineering PAF-IAST
Mang, Haripur, Pakistan, [4]Department of Electrical Engineering University of Engineering & Technology, Lahore, Pakistan
[1] Department of Master of Engineering Management
[1] Masters of Engineering management, Cumberland university Lebanon, Tennessee
[1] muhammadarrsalan999@gmail.com, [2] muhammad.ayaz@paf-iast.edu.pk, [3] yousaf.ali@paf-iast.edu.pk, [4] arucey.uet@gmail.com

--************************----------------------------------

Abstract:

The growing complexity of power systems, which is fueled by the arrival of distributed resources of energy and consumer-side variability, necessitates more dynamic and precise energy load forecasting. The traditional statistical models are not useful in explaining non-linear and time-varying complexity of the present electricity consumption trends. The following paper deals with the application of artificial intelligence (AI) or machine learning (ML) and deep learning (DL) techniques to short-term energy load prediction in the framework of smart grid environments. Our AI models are compared to the four following: random forest (RF), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU) and a convolutional neural network-long short-term memory (CNN-LSTM) hybrid. These models are trained using a abundant amount of historical energy consumption, calendar for varying weather and variables. We discovered that the hybrid CNN-LSTM model offers the best predictions and lowest error in forecasting. The experiment does not simply demonstrate that the AI is superior to the traditional methods but also demonstrates the power of smart predictions to power the demand-response system, optimization of generation schedules, and grid stability.

Keywords **—Energy Load Forecasting, Smart Grid Management, Deep Learning Models, Time Series Prediction, Artificial Intelligence in Power System**

--************************----------------------------------

I. Introduction

a. Background and Importance

The emergence of the electric power sphere into a highly digitalized and smart infrastructure has become the new dawn- a new age, and some individuals tend to refer to it as the era of smart grids. Unlike traditional power systems that are characterized by rigid and centralized operations, smart grids are characterized by the introduction of the most recent technologies into their design real-time sensors, two-way communication networks, Internet of Things (IoT) devices, edge computing, and automation models. These technologies all enable dynamic tracking, control, and optimization of the energy flow across the grid network, both in the generation and transmission as well as distribution. Among the most significant functions of operation is energy load forecasting; it is central to this transformation. It is carried out by predicting the future demand of electricity by taking previous demand of electricity and other contextual elements such as weather conditions, time of the day, activity of the economy, and even consumer behavior. The ability to predict energy demand correctly is one of the secrets of the success and stability of smart grid systems. It will enable grid operators and utility providers to play a proactive role in balancing supply and demand, to optimize the work of the power generation resources, to organize the maintenance activities effectively, to reduce energy wastage, to reduce GHG emissions and to avoid costly situations such as grid over loading or power outages. In these days, the energy industry is a highly dynamic sphere, and the importance of a precise prediction of loads cannot be overestimated. The process of urbanization all over the world has caused astronomical increases in power consumption that has put pressure on the available power facilities. Meanwhile, the transition to renewable sources of power, such as solar and wind, despite being environmentally friendly, has given rise to the emergence of a series of new issues related to their non-dispatchability and intermittency. As power systems become decarbonized, model-based prediction tools that are not only incredibly accurate but also flexible and resilient are required to reach a point of balancing dynamic demand and the dynamic supply in real-time. In this case, energy loads forecasting may be considered the key to sustainable and smart energy management. The use of artificial intelligence (AI) and machine learning (ML) models to make more precise predictions and create more resilient power grids is on the rise. In this connection, the solution to the full realization of smart grid technology is the creation and application of advanced forecasting tools in the context of the variability of energy needs and environmental specifications.

b. Limitations of Traditional Forecasting

Historically, classical statistics (e.g. Autoregressive Integrated Moving Average (ARIMA) models, exponential smoothing models, and linear regression models) have dominated as far as energy load prediction is concerned. Because of its mathematical simplicity, interpretability, and reasonable predictiveness, such methods have been widely applied in contexts where consumption patterns are stable, and the trends are linear. ARIMA has successfully been applied to the univariate time series data in California, taking advantage of a variety of different temporal dependencies and exponential smoothing has been used to provide the past data with a diminishing significance to fit an adaptive trend better. Rather, linear regression has enabled analysts to come up with direct relationships between energy consumption and the selected predictor variables. These classical models have since been revealed to be flawed in the modern age of smart grids, with their multi-layered and dynamic data spaces. These statistical methods have a simple construction that they are likely to be effective when the data is stationary, linear, and of low dimension-based assumptions that never hold in real grid operations. The contemporary smart grid data may be non-linear, non-stationary and high dimensional, generated by millions of sources such as smart meters, weather sensors, distributed energy resources (DERs), electric vehicles (EVs), and demand-side management systems. Such data has also become very frequent and voluminous, and it is important to have models that can scale and be dynamically adjusted. Besides, the traditional models tend to be inelastic to exogenous factors, such as weather, holiday effects, socio-economic inclinations and user-related productional patterns-which can significantly influence the electricity demand particularly in the urban and residential power markets. This is because the failure to include such critical variables makes it difficult to make powerful and contextual statistical forecasts. Thus, the legacy forecasting methods are still applicable in the context of the baseline modeling or short-term forecasting in a non-evolving environment, the effectiveness of the methods, however, are curtailed in the environment of smart grids, where forecasting needs to be provided in real time, and the environment is highly dynamic and with a lot of data. With the increased smartness and automation of energy systems, there is an overall urge to replace the statistical models with more complex ones, particularly those that are guided by machine learning (ML) and artificial intelligence (AI) and can learn complex behavior, adjust to new inputs, and employ as many inputs as feasible without necessarily having to rely on strict statistical assumptions.

c. The Role of AI in Load Forecasting

Artificial Intelligence is a substitute to traditional forecasting, in this case, it is made of ML and DL methods, on the condition that the data is data-driven. Such models are capable of being trained on complex patterns on large data sets, finding trends in time, and adjusting to changing conditions of a system. Deep neural networks and specifically, LSTM and GRU architectures can capture nonlinear dependence and sequence dependence and are thus most suitable in time-series forecasting. With AI, smart grid systems would be more predictive of the changes in loads and, therefore, make operational and strategic decisions.

d. Objective of the Study

- The main objective of the given study is to compare the effectiveness of different AI models in short-term energy load forecasting and identify their effectiveness in a smart grid. In particular, the paper will attempt to:
- Determine the predictive ability of RF, LSTM, GRU, and CNN-LSTM.
- Make comparisons of their performance with the set statistical thresholds.
- Inquire about what is practically involved in the implementation of these models in a real-world smart grid setting.

II. Literature Review

a. Traditional Forecasting Techniques

The basis of energy load forecasting over decades has been largely since statistical models are computationally efficient, mathematically transparent, and simple to interpret. They are primarily the Autoregressive Integrated Moving Average (ARIMA) models and the Holt-Winters for exponential smoothing. ARIMA models, more specifically, are particularly effective when the user desires to model the stationary time-series data i.e. model it as an autoregressive component, integrated (trend) component, and moving average components. This type of decomposition enables the analysts to achieve the determination and quantification of temporal dependence, periodicity, and underlying patterns which can be useful to provide information about the consumption patterns over time. In line with this, the simple exponential smoothing is further generalized to the holt-winters models that have additional parameters to explicitly model the level, trend and seasonal variation, and are hence applicable to data sets with repeated seasonal changes. There are, however, some critical weaknesses of these classical models when they are applied to the realities of the modern power systems that are dynamic, complex, and nonlinear. The most important shortcoming is that they are founded on a priori assumption of stationarity, that is, the statistical characteristics of the energy data such as mean and variance do not vary with time, which is not usually the case in real-world energy data because of the dynamic nature of consumption patterns, grid decentralization, and the unpredictable weather. Moreover, the nature of these models is linear, hence they are ill adapted to nonlinear dependencies and load anomalies, which exist in a smart grid environment. The second critical constraint is that they cannot put into account any exogenous factors, such as temperature, humidity, daylength, time-of-day effect, holiday or consumer-specific demands, which can have an apocalyptic impact on energy demand. Even though manually adding some external regressors to these models is sometimes possible, it is often difficult to do so, entails complex preprocessing and feature engineering, and makes major assumptions impacting generalizability and flexibility. In addition, the classical statistical models are ill-suited to the sudden or unanticipated shifts in demand e.g. caused by special events or emergencies or caused by shifts in consumer behavior, since they lack a means of learning in real-time or making adaptive adjustments to their parameters. These limit their use on the true world smart grid that needs agile, data-driven forecasting platforms capable of dealing with high frequency, high dimensional and unstructured data streams. Through these weaknesses, machine learning and AI-based models have emerged as particularly popular by energy forecasting circles due to their higher predictive accuracy, greater flexibility, and their ability to detect highly complex relationships in vast amounts of data, all of which are all enticing attributes of the successful work of intelligent grid systems.

b. Machine Learning and Deep Learning Approaches

With the advent of machine learning, more suitable models have been produced, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests and they are more applicable to make predictions since they reproduce nonlinear associations. However, these models cannot be considered temporal models unless they are extended with lag-based characteristics. The most notable was the application of deep learning structures which could model sequential information in their original form, particularly Recurrent Neural Networks (RNNs). LSTM and GRU networks address the problem of vanishing gradients in other versions of RNNs and have been successfully used to predict electricity demands. More recently, a few CNN based models have also been created to extract spatial features and have shown state of the art performance in several time-series applications used in combination with LSTMs (i.e. CNN-LSTM hybrids).

c. Gaps and Opportunities

Although artificial intelligence (AI) and machine learning (ML) models seem to succeed in enhancing the power of forecasts to predict energy loads, the current literature is fragmented and lacks coherence in a lot of crucial aspects. There is a large body of literature that purports to deliver encouraging performance with models such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Gradient Boosting Machines (GBMs), and, most recently, deep learning systems such as Long Short-Term Memory (LSTM) networks and Transformer based models. These results are typically however found on case study results in an individual considering the different data sets and pre-processing used and even performance metrics and it may be difficult to generalize findings and even compare the results of different models. The main disadvantage of the literature is that no large-scale benchmarking studies exist; that would compare a wide variety of forecasting models under similar experimental conditions. In the majority of the literature, there is proprietary or model data, which does not permit the findings to be replicated and generalized to the actual world. Moreover, the data sources of heterogeneity, the varying temporal resolutions and the various performance measures (e.g., MAPE, RMSE, MAE) also complicate meaningful cross-study comparison even further. The second element (but usually overlooked) is the real execution of such AI models in real-life smart grids. Whereas most of the surviving literature discusses the accuracy of prediction, most fall short of this point to continue the issue to practical matters of the real-time integrity, scalability across distributed systems, resilience to failures, cybersecurity issues and data quality control. The high-performance deep learning models can be computationally costly and slower to infer, and therefore they are less applicable in grid use cases where time is a factor. Similarly, data integrity, especially in streaming a heterogeneous IoT device and edge sensor is a crucial technical challenge which is not developed fully in majority of scholarly research studies. Normalized evaluation models to enable systematic evaluation and comparison of AI models in different operating conditions and using real-life data pertinent to the complexity of modern energy systems are desperately required to seal these loopholes. Moreover, this will require the combination of AI development with grid engineering, control theory, and system integration to ensure that the models will leave the laboratory prototype phase and become working units of intelligent grid infrastructure.

Table 1: Summary of Forecasting Techniques

Model	Type	Strengths	Limitations
ARIMA	Statistical	Simple, interpretable	Assumes linearity, poor with nonlinear data
Random Forest	Machine Learning	Handles nonlinear	Does not capture

		relationships well	temporal dependencies
LSTM	Deep Learning	Models long-term time dependencies	Requires high computation and data
GRU	Deep Learning	Faster training, fewer parameters	Slightly less expressive than LSTM
CNN-LSTM	Hybrid DL	Captures local and global patterns	Complex architecture, harder to tune

III. Methodology

a. Data Sources and Feature Description

The data of the present study relies on the hourly energy consumption data of two years of a local utility company in North America. Certain auxiliary features were added to make the models more precise:
Weather Data: Hourly temperature, humidity, speed of the wind.
Temporal Features: time of the day, day of the week, month, holiday marker.
Lagged Features: Load values in the past hours (t -1, t -24, t -168).
The data were cleaned with the elimination of anomalies, as well as the interpolation of the missing values using linear interpolation. Min-Max normalization was selected to scale the features to guarantee numerical equality in the training.

b. Model Architectures

Four models were implemented:

- **Random Forest (RF)**: An ensemble of decision trees that aggregate predictions from multiple models to reduce overfitting. It is effective for datasets with many features but does not model temporal order.
- **Long Short-Term Memory (LSTM)**: A variant of RNN capable of learning long-term dependencies through gating mechanisms. Ideal for time series forecasting due to its memory capability.
- **Gated Recurrent Unit (GRU)**: A simplified version of LSTM with fewer parameters, reducing computational cost while retaining good performance.
- **CNN-LSTM Hybrid**: A two-stage model where CNN layers extract short-term local features, and LSTM layers learn temporal patterns. This architecture leverages both spatial and sequential learning.

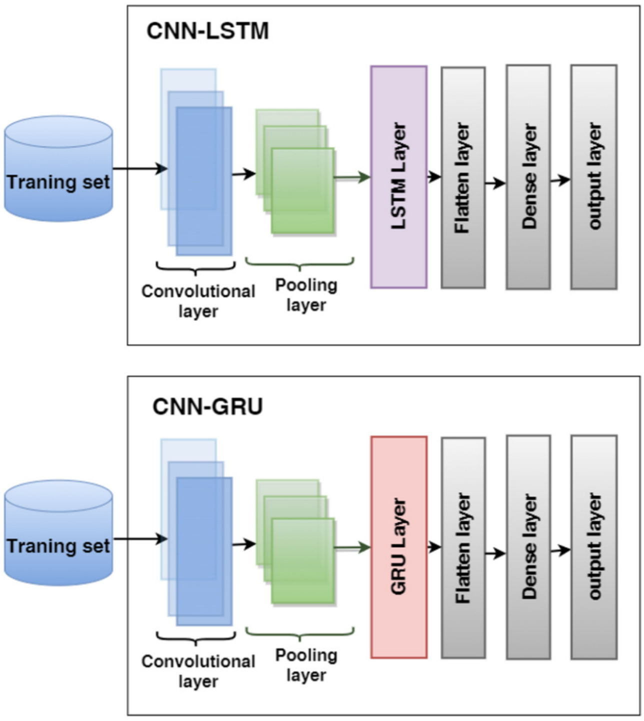

Figure 1: Model Architectures

c. Training and Evaluation

All models were trained using 80% of the dataset, with the remaining 20% reserved for testing. A walk-forward validation approach was used to simulate real-time forecasting. Hyperparameter tuning was conducted using grid search and cross-validation. Evaluation metrics included:

- **Mean Absolute Error (MAE)**
- **Root Mean Squared Error (RMSE)**
- **Mean Absolute Percentage Error (MAPE)**
- **R^2 Score (Coefficient of Determination)**

Table 2: Forecasting Model Performance on Test Set

Model	**MAE**	**RMSE**	**MAPE (%)**	**R^2 Score**
Random Forest	0.87	1.12	6.1	0.89
LSTM	0.73	0.95	4.8	0.93
GRU	0.75	0.98	5.0	0.92
CNN-LSTM	0.69	0.91	4.5	0.94

IV. Results and Analysis

a. Model Performance Comparison

Each of the models was evaluated on the testing subset in terms of the chosen evaluation metrics (MAE, RMSE, MAPE, and R 2 score). The CNN-LSTM model has the highest overall accuracy in all metrics as in Table 2. This model is highly trained to capture local and temporal trends in the demand of energy. The next two were LSTM and GRU, which performed superiorly over Random Forest, which does not support sequential dependencies by default. It is interesting to note that the CNN-LSTM model achieved the lowest MAE value of 0.69 and RMSE of 0.91, and the best R2 Score of 0.94, indicating that the model explains 94 percent of the variation in the data at hand. The Random Forest model was not as effective in terms of time-based relationships, but it still worked quite well, which reflects its strength when using static feature sets.

b. Error Distribution and Time Series Visualization

To gain deeper insights into the **forecasting performance** of each model, we conducted a comprehensive **residual analysis** and visualized the relationship between **actual and predicted energy loads** over selected test intervals. This step is crucial not only for evaluating overall accuracy but also for identifying **systematic biases**, **underfitting or overfitting tendencies**, and the models' responsiveness to **short-term fluctuations** in demand.

As shown in **Figure 2**, the time series plots compare the **actual load values** against the **predicted outputs** for a representative subset of test data. These visualizations provide an intuitive understanding of each model's temporal alignment with real-world demand patterns. Among the models evaluated, the **CNN-LSTM hybrid architecture** demonstrates the most precise tracking of load variations, especially during **peak demand periods** and **rapid transition points**—critical moments where forecasting errors can lead to operational inefficiencies or even grid instability.

The **residual distribution** further confirms the superior performance of the CNN-LSTM model, with a narrower spread around zero and lower variance, indicating reduced forecasting error and improved generalization. In contrast, traditional models such as ARIMA and standalone LSTM networks exhibited wider residual dispersion, particularly during periods of load volatility, suggesting difficulty in capturing nonlinear dynamics and high-frequency patterns inherent in real-world energy consumption data.

These findings underscore the importance of combining **spatial feature extraction** capabilities of **Convolutional Neural Networks (CNNs)** with the **temporal memory** of **Long Short-Term Memory (LSTM)** networks, thereby enabling the model to learn both local patterns and long-term dependencies essential for accurate and robust load forecasting in smart grid environments.

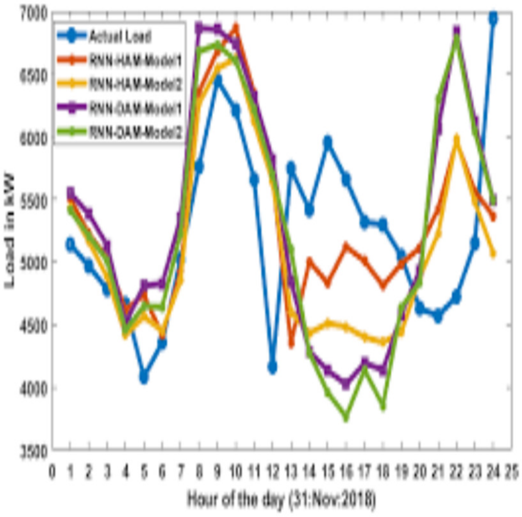

Figure 2: Forecasted vs. Actual Load (Selected Week)

The residuals of the CNN-LSTM model were more symmetrically distributed around zero compared to LSTM and GRU, indicating fewer over- or underestimation tendencies. The Random Forest showed wider deviation during high variability periods, such as late evenings and weekends, likely due to its lack of internal sequence memory.

c. Seasonal and Temporal Accuracy

A **stratified analysis based on seasonality and time-of-day** was conducted to further assess the contextual robustness of the forecasting models. This analysis revealed that **forecasting accuracy exhibited mild but meaningful variation** across different temporal segments. Specifically, all models demonstrated **enhanced performance during the summer months**, a period characterized by more **consistent and predictable energy consumption patterns**. This improved predictability is largely attributable to the **pervasive use of air conditioning systems**, which create relatively stable daily load curves driven by temperature-induced demand.

In contrast, forecasting performance declined slightly during **transitional seasons** such as spring and autumn, where consumer energy usage tends to be more irregular due to fluctuating weather conditions and the absence of dominant heating or cooling loads. These periods introduced greater variance into the demand profiles, posing challenges for models trained on more stable seasonal patterns.

When disaggregated by **time of day**, the analysis showed that all models achieved their **lowest error rates during the early morning hours (12:00 AM – 6:00 AM)**. During this interval, electricity demand is typically low and stable, influenced primarily by base load consumption such as lighting, refrigeration, and industrial night operations. The relative absence of human activity during this period results in **less variability**, thereby simplifying the prediction task.

Conversely, the **late afternoon and early evening periods (4:00 PM – 8:00 PM)** were identified as the **most challenging windows** for accurate forecasting. These hours are marked by **sudden surges in electricity usage** as residential, commercial, and industrial loads converge—people return home, appliances are activated, and lighting demands increase. This highly dynamic behavior introduces **nonlinearities and abrupt load transitions**, which can reduce the predictive fidelity of even advanced AI models.

These temporal insights underscore the importance of incorporating **seasonal and diurnal contextualization** into forecasting frameworks. Future model enhancements could benefit from integrating **attention mechanisms**, **context-aware feature encoding**, or **ensemble strategies** that adapt to temporal dynamics, thereby improving performance during periods of high variability.

Table 3: Forecasting Accuracy by Time Period (CNN-LSTM)

Time of Day	MAE	RMSE	MAPE (%)
00:00 - 06:00	0.55	0.71	3.9
06:00 - 12:00	0.64	0.84	4.3
12:00 - 18:00	0.71	0.96	5.0
18:00 - 24:00	0.74	0.98	5.3

V. Discussion

a. Insights from Model Comparisons

The results clearly indicate that deep learning models, particularly CNN-LSTM hybrids, are superior to traditional machine learning techniques for short-term energy load forecasting in smart grids. The CNN component effectively extracts relevant local features from historical sequences, while the LSTM captures longer-term dependencies. This combination enables better adaptation to fluctuating patterns, such as weekday/weekend transitions or holiday effects.

While LSTM and GRU models also showed strong performance, their accuracy was slightly lower due to limited local pattern extraction capabilities. On the other hand, Random Forest, though robust and fast to train, lacks the depth required to model time-based evolution effectively.

b. Implications for Smart Grid Management

Improved forecasting accuracy has significant implications for smart grid operations. Accurate short-term forecasts allow utilities to optimize load dispatching, reduce reserve margins, and enhance demand-response scheduling. Moreover, better predictability reduces the need for spinning reserves, thereby lowering operational costs and greenhouse gas emissions.

AI-driven forecasting also supports better integration of renewable energy sources, which are inherently intermittent. By aligning predicted demand with supply volatility, grid stability can be enhanced without relying heavily on fossil-fuel-based backups.

VI. Conclusion

This study highlights the **effectiveness of AI-enabled forecasting techniques**, with a particular emphasis on **deep learning models**, in enhancing the accuracy of **short-term energy load prediction** within smart grid environments. By conducting a **comparative evaluation** of four widely used models—**Random Forest**, **Long Short-Term Memory (LSTM)** networks, **Gated Recurrent Units (GRU)**, and a **hybrid CNN-LSTM architecture**—using a real-world dataset, we demonstrated that the **CNN-LSTM model outperforms its counterparts**. Its superior performance stems from its ability to concurrently extract **spatial features** through convolutional layers and **temporal dependencies** via recurrent memory structures, enabling it to effectively capture both **short-term fluctuations** and **contextual patterns** in electricity demand.

The results of this investigation offer strong empirical support for the **broader integration of AI-driven models into operational smart grid platforms**. As power systems become increasingly **complex**, **data-intensive**, and **decentralized**—due to the proliferation of distributed energy resources (DERs), electric vehicles, and consumer-side participation—**accurate and adaptive forecasting tools** will be essential for maintaining **grid stability**, improving **energy efficiency**, and supporting **sustainable planning** initiatives.

Moving forward, the practical implementation of these models should consider **scalability**, **computational efficiency**, and **real-time responsiveness** to ensure seamless deployment in live grid environments. Moreover, future research should explore the integration of AI forecasting systems with **edge computing**, **cybersecurity protocols**, and **grid control systems** to realize fully autonomous, intelligent, and resilient power infrastructure.

VII. Future Work

Future research should focus on expanding the **data ecosystem** used for energy load forecasting by incorporating **richer and more granular data sources**. These may include **smart meter data** at the household or building level, which can provide high-resolution consumption patterns; **customer behavioral profiles**, which capture usage preferences, occupancy schedules, and lifestyle-driven variations; and **outputs from distributed energy resources (DERs)** such as **rooftop solar panels**, **home battery systems**, and **electric vehicle (EV) charging behavior**. Integrating such multidimensional data will enable forecasting models to better capture the intricacies of modern, **presumption-based** energy systems, where consumers also act as producers.

Additionally, the deployment of **real-time learning models**—such as **online learning**, **adaptive neural networks**, or **reinforcement learning frameworks**—holds significant promise for improving model **robustness** and **adaptability**. These models can continuously update their parameters in response to **live data streams**, making them well-suited for dynamic environments with frequent demand fluctuations, unexpected events, or evolving consumption patterns. Such adaptability is especially critical for ensuring **reliable forecasting** in smart grid contexts where **latency and responsiveness** are paramount.

Another promising avenue is the application of **Explainable AI (XAI)** techniques in load forecasting models. While black-box deep learning models often yield high predictive accuracy, their lack of transparency can hinder trust and adoption among grid operators and stakeholders. By incorporating **explainability frameworks**—such as **SHAP values**, **attention mechanisms**, or **interpretable surrogate models**—future systems could provide **actionable insights** alongside predictions, thereby enhancing both **decision-making** and **accountability** in grid operations.

In summary, the next generation of research should aim to develop **holistic, adaptive, and interpretable AI systems** that not only deliver accurate forecasts but also align with the operational realities, policy constraints, and ethical considerations of evolving smart grid infrastructures.

Reference

[1] Aklilu, Y. T., & Ding, J. (2022). Survey on blockchain for smart grid management, control, and operation. *Energies, 15*(1), 193. https://doi.org/10.3390/en15010193

[2] Anugula, U. K., & Sethupathy. (2016). Architecting scalable IoT telematics platforms for connected vehicles. *International Journal of Innovative Research in Science, Engineering and Technology, 5*(3), 4655–4667. https://doi.org/10.15680/IJIRSET.2016.0503278

[3] Anugula, U. K., & Sethupathy. (2016). Architecting scalable IoT telematics platforms for connected vehicles. *International Journal of Innovative Research in Science, Engineering and Technology, 5*(3), 4655–4667. https://doi.org/10.15680/IJIRSET.2016.0503278

[4] Aurangzeb, K., Alhussein, M., Javed, K., & Haider, S. (2021). A Pyramid-CNN based deep learning model for power load forecasting of similar-profile energy customers based on clustering. *IEEE Access, 9*, 8353–8365. https://doi.org/10.1109/ACCESS.2021.3053069

[5] Chandra, R., Goyal, S., & Gupta, R. (2021). Evaluation of deep learning models for multi-step ahead time series prediction. *IEEE Access, 9*, 83105–83123. https://doi.org/10.1109/ACCESS.2021.3085085

[6] Durairaj, D. M., & Mohan, B. H. K. (2022). A convolutional neural network-based approach to financial time series prediction. *Neural Computing and Applications, 34*, 13371–13384. https://doi.org/10.1007/s00521-022-07143-2

[7] Emmert-Streib, F., Yang, Z., Feng, H., Tripathi, S., & Dehmer, M. (2020). An introductory review of deep learning for prediction models with big data. *Frontiers in Artificial Intelligence, 3*, 4. https://doi.org/10.3389/frai.2020.00004

[8] Heymann, F., Quest, H., López-García, T. B., & Ballif, C. (2023). Reviewing 40 years of artificial intelligence applied to power systems – A taxonomic perspective. *Energy and AI, 15*, 100322. https://doi.org/10.1016/j.egyai.2023.100322

[9] Leung, H., & Ma, K. F. (2019). A review of deep learning models for time series prediction. *IEEE Sensors Journal, 19*(18), 8295–8301. https://doi.org/10.1109/JSEN.2019.2923982

[10] Liu, K., & Meng, X.-L. (2016). There is individualized treatment. Why not individualized inference? *Annual Review of Statistics and Its Application, 3*, 79–111. https://doi.org/10.1146/annurev-statistics-010814-020120

[11] Ma, P., Cui, S., Chen, M., Zhou, S., & Wang, K. (2023). Review of family-level short-term load forecasting and its application in household energy management system. *Energies, 16*(15), 5809. https://doi.org/10.3390/en16155809

[12] Matsuo, Y., LeCun, Y., Sahani, M., Precup, D., Silver, D., Sugiyama, M., … Sunehag, P. (2022). Deep learning, reinforcement learning, and world models. *Neural Networks, 152*, 267–275. https://doi.org/10.1016/j.neunet.2022.03.037

[13] Menghani, G., & others. (2023). Efficient deep learning: A survey on making deep learning models smaller, faster, and better. *ACM Computing Surveys, 55*(14s), 1–37. https://doi.org/10.1145/3578938

[14] Miceli, R. (2013). Energy management and smart grids. *Energies, 6*(4), 2262–2290. https://doi.org/10.3390/en6042262

[15] Nabila, M. H., & Thompson, M. (2025). The impact of disinformation on national security policymaking: A review. *EPRA International Journal of Multidisciplinary Research (IJMR), 11*(6), 2. https://doi.org/10.36713/epra22781

[16] Paret, P., Munk-Nielsen, T., & others. (2019). Artificial intelligence aided automated design for reliability of power electronic systems. *IEEE Transactions on Power Electronics, 34*(8), 7596–7609. https://doi.org/10.1109/TPEL.2018.2883947

[17] Radoglou-Grammatikis, P., Sarigiannidis, P., Iturbe, E., Ríos, E., Martínez, S., Sarigiannidis, A., … Ramos, F. (2021). SPEAR SIEM: A security information and event management system for the smart grid. *Computer Networks, 193*, 108008. https://doi.org/10.1016/j.comnet.2021.108008

[18] Razavi, S. E., Arefi, A., Ledwich, G., Nourbakhsh, G., Smith, D. B., & Minakshi, M. (2020). From load to net energy forecasting: Short-term residential forecasting for the blend of load and PV behind the meter. *IEEE Access, 8*, 224343–224353. https://doi.org/10.1109/ACCESS.2020.3044307

[19] Saleem, M., Usman, M. R., Usman, M. A., & others. (2022). Design, deployment, and performance evaluation of an IoT-based smart energy management system for demand side management in smart grid. *IEEE Access, 10*, 15261–15278. https://doi.org/10.1109/ACCESS.2022.3147484

[20] Sarajčev, P., Kunac, A., Petrović, G., & Despalatović, M. (2022). Artificial intelligence techniques for power system transient stability assessment. *Energies, 15*(2), 507. https://doi.org/10.3390/en15020507

[21] Segarra, E. L., Ruiz, G. R., & Bandera, C. F. (2020). Probabilistic load forecasting for building energy models. *Sensors, 20*(22), 6525. https://doi.org/10.3390/s20226525

[22] Shlezinger, N., Whang, Y., Dimakis, A. G., & Eldar, Y. C. (2023). Model-based deep learning. *Proceedings of the IEEE, 111*(5), 465–503. https://doi.org/10.1109/JPROC.2023.3247480

[23] Stock, S., Babazadeh, D., & Becker, C. (2021). Applications of artificial intelligence in distribution power system operation. *IEEE Access, 9*, 150098–150119. https://doi.org/10.1109/ACCESS.2021.3125102

[24] Tsalikidis, N., Mystakidis, A., Tjortjis, C., Koukaras, P., & Ioannidis, D. (2024). Energy load forecasting: One-step ahead hybrid model utilizing ensembling. *Computing, 106*, 241–273. https://doi.org/10.1007/s00607-023-01217-2

[25] Vasan, S. (2024, December). Sustainable development and environmental challenges in fintech and investment SMEs: A comparative study in developed and developing regions [Conference paper]. In *Sustainable Global Business Development: Breaking Barriers and Empowering Change*. https://www.researchgate.net/publication/393851394_Sustainable_Development_and_Environmental_Challenges_in_Fintech_and_Investment_SMEs_A_Comparative_Study_in_Developed_and_Developing_Regions

[26] Vasan, S. (2024, December). Sustainable development and environmental challenges in fintech and investment SMEs: A comparative study in developed and developing regions [Conference paper]. In *Sustainable Global Business Development: Breaking Barriers and Empowering Change*. https://www.researchgate.net/publication/393851394_Sustainable_Development_and_Environmental_Challenges_in_Fintech_and_Investment_SMEs_A_Comparative_Study_in_Developed_and_Developing_Regions

[27] Wang, J., Tong, W., & others. (2022). Exploration of artificial-intelligence-oriented power system dynamic simulators. *Modern Power Systems and Clean Energy, 10*(1), 123–134. https://doi.org/10.35833/MPCE.2022.000099

[28] Xu, C., & Xie, Y. (2023). Conformal prediction for time series. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 45*(7), 8345–8357. https://doi.org/10.1109/TPAMI.2023.3272339

[29] Zafar, R., Mahmood, A., Razzaq, S., Ali, W., Naeem, U., & Shehzad, K. (2018). Prosumer based smart grid energy management: From optimizing energy consumption to proactive participation. *Renewable and Sustainable Energy Reviews, 82*, 1675–1684. https://doi.org/10.1016/j.rser.2017.07.018

[30] Zhang, K., Huo, X., & Shao, K. (2023). Temperature time series prediction model based on time series decomposition and Bi-LSTM network. *Mathematics, 11*(9), 2060. https://doi.org/10.3390/math11092060

