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| RESEARCH ARTICLE

AI-Enhanced Sustainable Energy Management and Policy Recommendations for the U.S. Power Sector

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| ABSTRACT
The transition to a sustainable U.S. power sector is faced with the challenge of balancing reliability, decarbonization, and affordability in more variable demand conditions. There is tremendous potential for artificial intelligence (AI) to make huge contributions to forecasting accuracy, optimizing resource allocation, and in developing policy and evidence-based policy. This paper presents a new model of hybrid artificial intelligence for sustainable energy management applications that consists of Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Transformer networks combined with CatBoost meta-learner and then optimized with residual BiGRU-attention and α-blender. The proposed model was tested using the public dataset of hourly electricity generation and demand data from the United States of America with temporal and operational characteristics significant to grid planning. Experimental results indicate a very high performance of the hybrid model compared with baseline methods for all performance measures. Specifically, it had a minimum MAE (0.007503), minimum MSE (0.000102) and RMSE (0.010082) and highest R2 value (0.995954) than single Lstm, GRU, Catboost and Xgboost. Aside from technical performance, the study accomplishes three contributions: efficiency-enhancing energy management using AI-driven energy forecasting and optimization, American context - use of demand forecasting for renewable integration and grid balancing, and extending technical understanding to the policy advice for future adaptive regulations. By integrating AI analytics, policy design, and sustainability policy, this research makes a methodological contribution as well as a governance-centric framework with a focus on setting up AI as an accelerator for the sustainable transformation of America's power grid.

| KEYWORDS

Artificial intelligence, Hybrid deep learning, Energy demand forecasting, Sustainable energy management, Policy recommendations, U.S. power sector.

| ARTICLE INFORMATION

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1. Introduction
The U.S. power sector has become the center of the sustainability dialogue due to the rapid-growing impacts of the climate change, as well as the growing energy demand [1]. Despite the constant investments in renewable energy and grid improvements, the industry continues to be unable to balance the reliable supply, decarbonization objectives, and affordability [2]. The achievement of these objectives does not only require new technologies but also powerful energy management systems [3]. These systems need to anticipate the demand shifts, enhance integration of the renewables, and drive policies on a long-term basis [4].
Recently, artificial intelligence (AI) has been introduced to the audience as a sustainable-energy-management conditioning technology [5]. Among technologies available today that have enormous potential in load forecasting, anomaly detection, and optimization of distributed energy assets, one can distinguish reportorial, transformers, recursive neural networks, and ensemble learning, which have never been used so extensively before [6]. Using high-frequency energy information, AI models can realize

detailed temporal relationships and question grid operators to remain stationary and survive uncertain operating environment conditions [7]. The AI solutions have a promise of meaning improvement in the operational efficiency as well as strategic decision making in the U.S. market where renewable penetration is on the ascends and policy pressure to decarbonization is mounting [8]. At the same time, the good policy which defines the decarbonization rate and the overall direction of this process within the American electric fixation system is one of the powerful agents of the energy change [9]. Capital investment flourishes in policy by directing fund flows towards renewable infrastructure and grid modernization, and through the development of the regulatory frameworks that define the behavior in the markets [10]. Renewable portfolio standards, the federal tax credits, carbon price mechanisms and numerous other forms of tools and other products of the state have served as the frontline to cement clean energy is rolled out with a fast pace [11]. However, in spite of this, contemporary policymaking in the United States continues to depend on aggregate past history and fixed scenario modelling which is inadequate as they fail to elicit any periodical dynamism into the mobile energy frameworks [12]. These conventional methods fail to meet the fast volatility of renewables, evolving behavior in demand sides, and the growing importance of distributed energy types of projects including rooftop solar and battery storage [13]. By integrating AI-based intelligence into the process of policy making, the solving of these limitations is possible due to the ability to monitor in real-time, provide adaptive predictions in relation to situations and test scenarios [14]. Such integration would enable the policymakers to establish regulations and market-based systems that remain responsive to the current mode of operation within the systems whilst robust to the future and addressing the long-term targets of resilience and sustainability [15]. Despite the accumulated material about AI application to energy systems, there is a lot to resolve [16]. Everything currently conducted so far has merely been oriented around one axis either the development of AI models used to model demand, or improving the approaches to sustainable energy management or the study of policies abstractly without reference to others [17]. This vacuumed project got every conduit of knowledge on the move but does not utter anything on system level change. Moreover, certain research concentrates on technical performance but overlooks pragmatic constraints such as data access, interpretability of the model, and applicability to actual grid operation [18]. In addition, there is comparatively lower U.S.-specific research, namely, the correlations between AI-warrants research and the regulatory and market organization of the U.S. power industry [19]. It has not clearly been proposed so far, to the best of our knowledge, that AI-based modeling, sustainable energy management, and policy-relevant advice finally become one single entity [20]. This fragmentation constrains the practice-oriented application of AI as well as its usefulness for evidence-based policymaking on behalf of the American energy transition.
To bridge this gap, this study presents a novel hybrid AI model that combines LSTM, GRU, and Transformer architectures with a CatBoost meta-learner and residual BiGRU–attention refinement, tested using α-blending. The new model is designed to make very accurate demand forecasts and renewable integration analysis, tailored to the complexities of the U.S. power market. Beyond technical functionality, the analysis relates these outputs to concrete policy recommendations, opening a new bridge between state-of-the-art AI analysis and regulatory strategy. Thus, the paper will not only introduce a novel methodology but also provide a framework that will target the establishment of sustainable development of the U.S. energy ecosystem and place AI at the forefront.

The key contributions of this paper can be summarized as follows:

- **Hybrid AI forecasting framework:** We propose a hybrid architecture, which includes LSTM, GRU, and Transformer models which are conditioned by a CatBoost meta-learner and an extra residual BiGRU-attention refining step. The architecture optimizes the guessing of improved energy demand patterns in the United States.
- **Specific application to the U.S. power sector:** Implementing our research compares to research most of the time, where information is global or detailed in general as our study is specifically crafted to accommodate the operations management of the U.S. power grid and also explore the policy issues about the grid that can be applied when it comes to demand prediction, integration of renewable energy as well as grid stability.
- **Bridging AI analytics with sustainable energy management:** The research will solve the gap between high-level AI-based forecasting results and sustainable resource planning approaches, demand response, and renewables integration illustrating how intelligent models can be imported directly to system-level control.
- **Integration of AI insights into policy recommendations:** To make it more about applying it technically, we apply the framework to make practical policy propositions concerning the role of AI-driven forecasting to support adaptive regulations, market-based mechanisms, and decarbonization goals in the power industry in the U.S.
- **Towards an integrated tri-fold framework:** As far as we know, this research is one of the pioneer studies that are incorporating AI-based forecasting, sustainable energy management, and policy proposals on a unified framework, involving not only methodological novicing but governance relevance.

The remaining literature of this study is as follows. Section 2 gives the literature survey of the artificial intelligence applications in energy forecasting, sustainable energy management, and studies based on policy. Section 3 discusses the research methodology, description of data used, preprocessing operations, baseline models, structure of proposed hybrid model. Section 4 presents experiment findings and presents a comparative analysis of the performance of a model comprehensively. Last but not least, the last Section 5 brings the research to completion proving the criteria of the key contributions, presenting the policy implications of the research to the American power market and identifying the perspectives of the future research.

2. Literature Review

Sukanya et al. [21] has proposed a smart energy management system for smart cities. This system uses Mixed-Integer Linear Programming (MILP) for load balancing and optimization. It also incorporates LSTM and SVM for energy prediction and reinforcement learning. The model boosted grid stability with 66% fewer failures and 50% shorter outages. Also, this model improved energy balance by 2.3%, increased renewable energy use by 10%, and reduced energy prices by 12%. The study highlights limitations for real-world application including need for high-quality data and significant computing resources.

Next-generation smart inverters are reviewed by Awad and Bayoumi [22]. They highlighted how these inverters contribute to grid stability, resilience, and the integration of renewable energy. The study shows that AI-driven grid-forming inverters could stop gradual failures during severe storms, like the Texas winter storm of 2021. This reveals their potential for significant change. However, some challenges remain, including the lack of global interoperability standards, ongoing cybersecurity threats, and weak legal and financial support for broader use.

Amini and Baradaran Rohani [23] has investigated the use of AI and ML in renewable energy. They focused on real-time optimization and predictive analytics applied to large amounts of energy data. The study found that forecasting accuracy can increase by up to 25 and reduce energy loss by 6.2%. Also, this study mentioned that predictive maintenance can cut failure rates by 30 to 35%. This study addressed several shortcomings and pointed out areas needing attention for wider use, including cybersecurity, data quality, computational needs, and legal challenges.

Shen et al. [24] has applied deep learning models like CNN-LSTM, RNNs, Deep Q-learning, and Genetic Algorithms (GA) to study AI-driven integration of photovoltaic and energy storage systems in the US. For this research, they used real-time sensor inputs, historical weather data, and satellite imagery as attributes. The CNN-LSTM hybrid achieved the best short-term forecasting accuracy, with a Mean Absolute Error (MAE) of 2.8% and a Root Mean Square Error (RMSE) of 4.2%. This study reported a 28% increase in system efficiency, a 38% reduction in outage frequency, a 45% reduction in outage duration, and a projected 25% cut in electricity costs by 2030. However, it highlighted limitations such as limited policy consideration and the need for more robust, explainable AI models.

Wen et al. [25] has presented an AI smart framework for solar energy generation and smart grid integration. They used models like SVR, ANN, CNN, LSTM, RF, GB, RL, DRL, and fuzzy logic. These models handle forecasting, cloud prediction, and predictive maintenance. They are trained on various factors including historical consumption, weather, socioeconomic conditions, PV power output, real-time sensor data, and satellite images. This research found that DRL, specifically PPO, achieved the highest energy efficiency at 88.5% and cost savings of 21.3%. LSTM provided the best accuracy for short-term load forecasting, with MAPE at 2.65% and RMSE at 143.2 kW. However, this research also identified limitations such as scalability issues, legal restrictions, and ethical concerns.

Makala and Bakovichas [26] examined AI applications in the global power sector, including predictive maintenance, grid optimization, and renewable energy management. They note that developed countries lead in AI adoption, while emerging markets are rapidly catching up. Key challenges include infrastructure readiness, policy, and regulatory barriers, limiting broader implementation.

Chowdhur [27] has proposed a machine learning framework for U.S. energy sustainability, implementing supervised models (Random Forest, XGBoost, SVR, LSTM), unsupervised clustering (K-Means), and reinforcement learning on diverse energy datasets (e.g., electricity usage, peak demand, weather, building features). LSTM performed best (RMSE: 153.6, MAPE: 10.1%, R^2: 0.93), capturing temporal dependencies effectively, but as a complex "black-box" model, it may reduce stakeholder trust. XGBoost offered good feature interpretability. Despite strong technical performance, the study offers limited actionable policy guidance, indicating a gap between AI models and policymaking.

Hosseinkhani [28] has explored the utilization of large language models (LLMs) in energy systems and climate strategies, emphasizing uses in circular economy principles, urban energy optimization, and the integration of renewable energy. According to this study, these technologies can help a low-carbon economy by enhancing efficiency, lowering operating costs, fostering green innovation, and improving resource management. The paper highlights drawbacks of AI, including its high energy consumption and carbon footprint, as well as issues with ethics, data privacy, and scalability.

Aslam [29] uses advanced AI-driven economic simulations, such as TVP-VAR and GARCH-MIDAS, to examine the spillover dynamics across the nuclear energy, hydrogen energy, and AI sectors under the influence of geopolitical risks and climate policy uncertainty (CPU). The study finds AI to be a net receiver highly sensitive to energy market fluctuations, nuclear to act as a stabilizing hedge, and hydrogen as a major shock transmitter. While geopolitical risks create delayed but persistent disruptions, CPU produces immediate but short-lived market volatility, particularly in hydrogen and nuclear industries that rely on long-term government incentives. The findings highlight the need for stable, transparent, and predictable climate policies, emphasizing both the vulnerability of clean energy transitions to ambiguous regulations and the importance of resilient, adaptive strategies in the U.S. power sector, although markets typically adjust to sustained policy shifts.

Hasan [30] has examined AI applications for carbon footprint reduction in the US sustainable supply chain decision-making. The findings from the study, implementing machine learning model with strong predictive analytics and optimizing algorithms into route and inventory management help enterprises improve efficiency and satisfy customer and regulatory sustainability requirements. By facilitating the transition from reactive to predictive management, AI-enhanced decision-making considerably lessens its impact on the environment. A wide range of adoption may be challenging for several limitations such as the complexity of data integration, expensive implementation costs, and a lack of qualified experts.

Qazani [31] has explored the role of AI-driven predictive analytics in advancing renewable energy adoption in the U.S., with attention to socio-economic impacts. The study shows that predictive models, using demographic, consumption, and socioeconomic data, can forecast energy demand, optimize resources, and identify high-potential deployment areas. Findings suggest AI can accelerate the transition to a sustainable energy future by supporting data-informed decisions that promote economic growth, environmental justice, and social equity. However, limitations include data quality and availability issues, privacy and bias concerns, and the persistence of the digital divide.

Guo and Kuang [32] has used data from 2010 to 2023 to examine how supply chain digitalization affects the sustainable growth of China's publicly traded new energy companies. This study employs panel regression modeling to link digitalization with sustainability performance, considering factors like analyst coverage, executive equity incentives, and green innovation capabilities. Also, NLP-driven text mining has used to extract digitalization indicators from annual reports. The findings indicate that greater digitalization significantly improves sustainability, particularly for businesses with high technological intensity, low supply chain efficiency, and high consumer dependence. This research showcases the potential of AI techniques in assessing sustainability performance and informing strategies for energy sector companies, even without typical AI models.

Jaradat and Khatib [33] has looked at how integrating battery energy storage systems (BESS) could increase the use of renewable energy. They focused on AI-based optimization models, including genetic algorithms (GA), particle swarm optimization (PSO), and whale optimization (WO), for environmental assessment and multi-objective scaling. This research highlights the technical innovation alone is not sufficient. It advocates for supportive policy frameworks, such as financial incentives, straightforward regulations, and linking incentives to lifecycle sustainability efforts. These findings illustrate how AI tools can assist in making technological decisions and shaping policy for strong and sustainable renewable energy systems.

Raman et al. [34] has found that the main themes were improving building energy efficiency, boosting biofuel production, and predicting wind speed and sunlight after reviewing of 9,549 publications. This systemtaic review states that partnerships between academia and industry can speed up the move toward sustainability. It also highlights that AI-driven models can significantly improve renewable energy systems. LSTM models are known to increase wind energy forecasting. This paper only reviews existing methods and trials.

Table 1 : Summary of AI Applications in Sustainable Energy

Year	Ref.	Model / Technique	Key Results	Limitations
2025	[21]	MILP, LSTM, SVM, RL	Grid stability +66% fewer failures, outage duration -50%, energy balance +2.3%, renewable energy consumption +10%, cost reduction -12%	High-quality data requirement, high computational resources
2025	[22]	AI-driven smart inverters	Improved grid stability and resilience; prevent failures during extreme events	Lack of global standards, cybersecurity risks, insufficient legal/financial frameworks
2025	[23]	Random Forest, XGBoost, SVR, LSTM, K-Means, RL	LSTM RMSE 153.6, MAPE 10.1%, R^2 0.93; XGBoost interpretable	Black-box complexity, limited actionable policy guidance
2025	[24]	AI, LLMs	Efficiency improvement, cost reduction, green innovation	High energy consumption, carbon footprint, ethics, data privacy, scalability
2025	[25]	TVP-VAR, GARCH-MIDAS	AI as net receiver, nuclear stabilizing hedge, hydrogen shock transmitter; insights on market volatility	Vulnerability to policy uncertainty, geopolitical risks
2025	[26]	GA, PSO, WOA for BESS	Enhanced renewable adoption, environmental evaluation, multi-objective sizing	Technical innovation alone insufficient; need supportive policy frameworks
2025	[27]	Panel regression, NLP-driven text mining	Supply chain digitalization improves sustainability, especially in tech-intensive firms	Lack of conventional AI model use

2024	[28]	SVR, ANN, CNN, LSTM, Random Forest, Gradient Boosting, RL, DRL, fuzzy logic	DRL energy efficiency 88.5%, cost saving 21.3%; LSTM MAPE 2.65%, RMSE 143.2 kW	Scalability issues, legal restrictions, ethical considerations
2024	[29]	CNN-LSTM, RNN, Deep Q-learning, Genetic Algorithms	Forecasting MAE 2.8%, RMSE 4.2%, system efficiency +28%, outage frequency -38%, outage duration -45%, projected cost reduction -25%	Limited policy consideration, need for explainable AI
2024	[30]	Predictive analytics	Forecast energy demand, optimize resources, promote economic growth and equity	Data quality, privacy/bias concerns, digital divide
2024	[31]	ML, predictive analytics, optimization algorithms	Reduced carbon footprint, improved supply chain efficiency	Complex data integration, high costs, lack of qualified experts
2024	[32]	AI/ML for real-time optimization and predictive analytics	Forecast accuracy +25%, smart grid efficiency +6.2%, predictive maintenance failure rate -30–35%	Cybersecurity, data quality, computational demand, legal challenges
2024	[33]	Review of deep learning, LSTM	Highlighted energy efficiency, biofuel, wind/solar forecasting	Only reviews existing studies, no new models
2023	[34]	AI for predictive maintenance, grid optimization, renewable energy management	AI adoption trends; developed countries leading; emerging markets catching up	Infrastructure readiness, policy, regulatory barriers

3. Methodology

This section outlines the data preparation methodology of the U.S. electric power sector data for AI forecasting, which can facilitate optimizing the grid, aiding in sustainability, and inform policy recommendations. It begins by cleaning and filling missing values, followed by feature engineering for extracting time trends and seasonal patterns. It generates key features, including lag values and rolling statistics, for enhancing the model's accuracy.
The data is scaled so that it is evenly distributed across features and a chronological cut then used to establish training, validation and test set. The resulting data is employed on the development of predictive models that give out forecasts, which on the other hand could be consumed on energy management strategies.

To describe the sequence of actions during data preprocessing, feature engineering and training in a fashion exclusive to Figure 1, a general flowchart of the methodology is given.

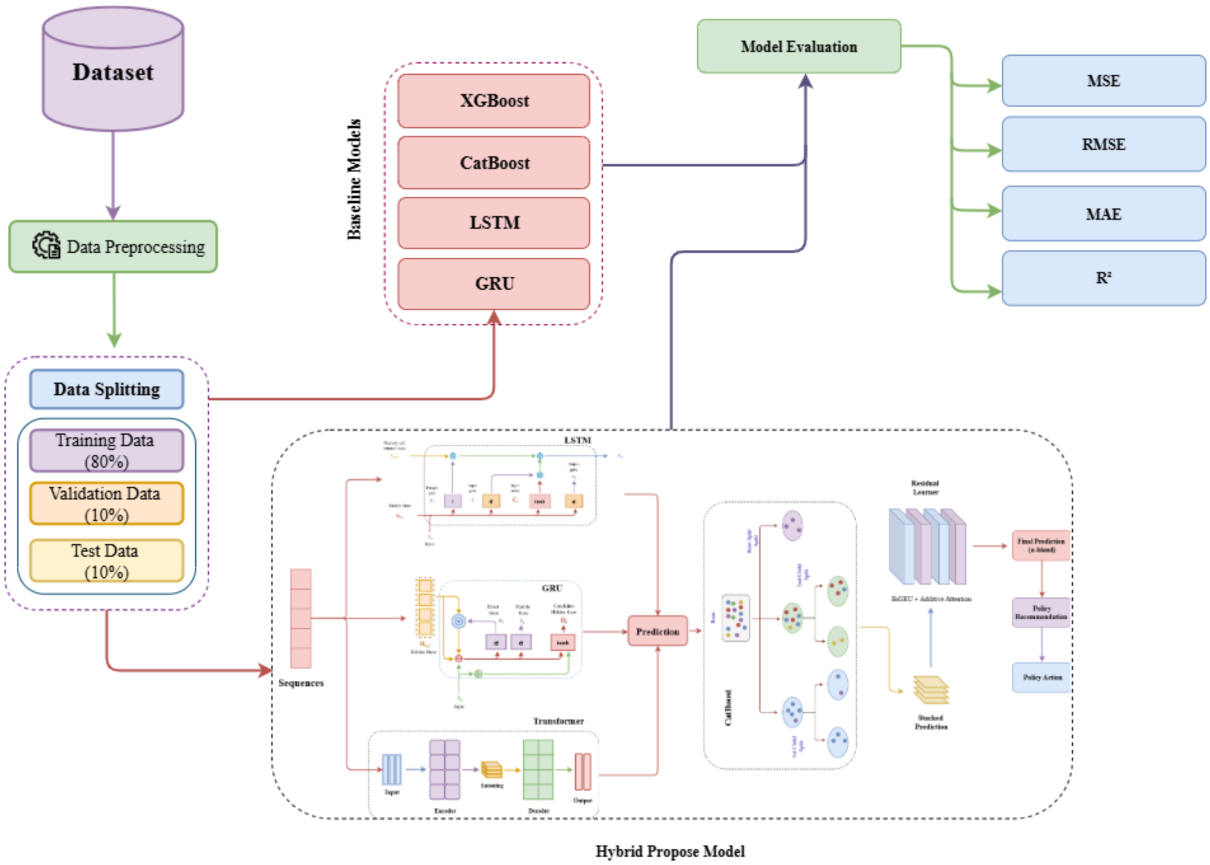

Figure 1 : Workflow of Proposed Hybrid Model

3.1 Dataset Descriotion

The dataset of Hourly Electricity Demand and Production in the U.S. [1] offers a full-time awareness of the production and plants of electricity by energy in the United States. It is a multidecade data that included hourly electricity demand (demand_mwh) and electric energy production by major sources, such as coal, natural gas, nuclear, solar, wind, hydro and petroleum power. It provides one with a unique opportunity to observe the share of various sources of energy to the entire generation mix and to observe the changes in the energy utilization. The same would prove very much in predicting the future needs of electricity and would help in the running of the energy grids to operate in terms of highest efficiency and this will be presented via policy which would help make the energy natural, consistent and efficient. These variables also include variables such as; total generation mwh (total generation) and supply demand balance where such variables give little insight on the stability of power grid and the probability of generation-demand imbalance. The data reflects meaningful researches in the U.S electronic market on energy control, forecasting and policy.

Table 2 : Feature Description of Dataset

Feature	Description
date	Time, which includes information that displays the date and time at which the observation was made (on hourly cycles). This is significant to the time analysis and this action is required to match the dataset with the time-related trends.
demand_mwh	The total electricity demand in megawatt-hours (MWh) at each timestamp. This target variable is central for modeling and forecasting electricity consumption patterns.
coal_mwh	The amount of electricity generated from coal in megawatt-hours (MWh). This feature reflects the contribution of coal-fired power plants to total energy production.
natural_gas_mwh	The amount of power that is generated using the natural gas in Megawatt-hours (MWH). This option presents the proportion of the natural gas in energy production, which is a matter of great fossil fuel.
nuclear_mwh	The amount of electricity generated from nuclear power in megawatt-hours (MWh). This feature indicates the contribution of nuclear energy to the total generation mix.

petroleum_mwh	Electric units of kilowatt-hours (KWh) of electricity made in a petroleum process. This aspect is indicative of the utilisation of petroleum-generated power, which generally holds a lower proportion of the energy mix.
solar_mwh	The amount of electricity generated from solar power in megawatt-hours (MWh). This renewable source is critical in analyzing the shift toward sustainable energy.
wind_mwh	The amount of electricity generated from wind energy in megawatt-hours (MWh). As a key renewable source, wind energy's contribution to generation is central to sustainability analyses.
hydro_mwh	Electricity produced by wind in Megawatt-hours (MWh). Given that wind power is also one of the essential sources of renewable energy, the role this power sources plays in generation is at the centre of sustainability analyses.
other_mwh	The value of hydropower in mega-watt-hours (MWH). Another major source of renewable energy that serves a very important role in a baseload generation is hydropower.
total_generation_mwh	The total electricity generated, summing all energy sources, in megawatt-hours (MWh). This feature is critical for understanding overall power production in the U.S.
supply_demand_balance	The variant between overall generation and the need of electricity. When it has a positive value it indicates surplus generation and when it has a negative value it depicts deficit of meeting the demand.

3.2 Data Preprocessing

This is where the methodology of data preparation of the U.S. power sector electric data to be used in the AI prediction are explained and can help optimize the grid, contributing to the sustainability facet, and policy recommendations. It will start with a cleaning process that includes filling missing values and then the feature engineering process will process extracting the time trends and seasonal patterns. It produces the major features, such as the lag values and rolling statistics, in upgrading the accuracy of the model.

Before data undergoes this treatment, its pre-processing is significant in preparing the U.S. energy data to undergo AI forecasting. It outlines processes in cleaning, scaling and feature-engineering of key features in order to make the data prepared to do the prediction modeling. It is linked with handling the missing values, scaling features as well as creating new features which assist in deriving the time dependent and seasonal trends.

- **Handling Missing Values and Cleaning Data**

The initial data cleaning will be management of the potential outliers or missing values of the data set. Given the importance of accurate energy generated data, the negative values in the renewable sources of energy (wind, solar, hydro) were set at zero, since physically these values cannot occur.

$$\text{Clipped Value} = \max(\text{Raw Value}, 0) \tag{1}$$

This operation causes any of the negative values of energy production to become zero, avoiding errors in data.

Then, missing values within the data were addressed through linear interpolation. Mini-gaps in the data (where there were missing values) were completed by utilizing the closest valid data points in a three-time-point window. It ensures missing values do not fundamentally alter the structure of the entire dataset.

$$Interpolated\ Value = Previous\ Value + \frac{Next\ Value - Previous\ Value}{Number\ of\ Steps} \tag{2}$$

Interpolation allows data to keep flowing uninterruptedly by estimating missing data through available neighboring data.

- **Recalculation of Total Generation and Supply-Demand**

After the cleaning, total energy generated at every time step was recalculated by adding up the energy contributions of different sources, viz., natural gas, solar, wind, nuclear, and coal and petroleum. Supply-demand balance was then estimated by calculating the difference between total energy generated and demand of energy.

$$Supply - Demand\ Balance = Total\ Generation - Demand \tag{3}$$

It balance supply and demand to determine whether power production is of sufficient size to meet demand, positive figures indicate excess production and negative figures indicate deficiencies.

- **Usable Data Window**

Usable data window starts at first time there is a positive production of energy. It guarantees an analysis founded on a proper period of generation. Data points before this time were excluded from the following analysis.

$$Start\ Point = First\ Index;\ \ where\ Total\ Generation > 0 \tag{4}$$

We will start the analysis from a valid generating period so that the data set will be ready for modeling without bias due to non-production periods.

- **Feature Engineering : Time-Based and Lag Features**

In order to capture time-dependent relations and seasonal patterns, a few new features were created through engineering. Features based on time were developed in order to extract the patterns of energy demand at various time points of the day, week, and year. These variables are hour of day, day of week, and month, and a weekend indicator.

$$Hour\ of\ Day = Hour\ extracted\ from\ timestamp \tag{5}$$

These characteristics enable the model to learn time-sensitive information, e.g., peak demand at certain days or at certain part of a day.

Lag features were also created in order to include previous demand values in the model. These derive the interdependence of the demand at the current moment on previous values, which is extremely significant in time-series forecasting.

$$\begin{gathered} Demand\ at\ Timet - 1 = Previous\ Hour's\ Demand \\ Demand\ at\ Timet - 24 = Demand\ 24\ Hours\ Ago \\ Demand\ at\ Timet - 168 = Demand\ 1\ Week\ Ago \end{gathered} \tag{6}$$

These lag variables allow the model to capture forms and patterns of demand at varying horizons of time.

Furthermore, rolling statistics were calculated in order to reflect short- and long-duration fluctuations of demand. The rolling mean and standard deviation for 3- and 24-hour time frames give us information on neighborhood fluctuations and general patterns of energy demand.

$$Rolling\ Mean_n = \frac{\sum Demand_{t-n}}{n} \tag{7}$$

The 3-hr running mean observes regional differences, and the 24-hr running mean observes diurnal trends.

$$Rolling\ Std_n = \sqrt{\frac{\sum (deamnd_{t-n} - Mean_n)^2}{n}} \tag{8}$$

This is used in order to estimate the previous 24-hour change of energy demand.

- **Scaling of Features**

Scaling of attributes was applied for data normalization so that the attributes will have the same range and will be equivalently comparable, and thus the model will work better. All the attributes, except the target variable, were scaled between 0 and 1 using the application of the MinMaxScaler.

$$Sacled\ Value = \frac{Value - \min(Feature)}{\max(Feature) - \min\ (Feature)} \tag{9}$$

This normalization ensures each of the features contributes equally in the model, especially if we're dealing with machine learning algorithms, which are sensitive to scale for input data.

- **Train-Validation-Test Split**

The data was divided chronologically into training, validation, and test sets so that the model would be tested on unseen data. There is 70% of the data in the training set, used for training models, and there is 15% of the data in the validation and test sets.

Table 3 : Train-Validation-Test Split on Dataset

Aspect	Value
Train Data	22724
Test Data	4869
Validation Data	4870
Total Data	**32463**

This temporal division guarantees the model will be tried on data after the split, thus the evaluation is realistic for time-series forecasting. The data preprocessing pipeline ensured that the dataset was cleaned, transformed, and properly structured for machine learning applications. Through clipping negative values, handling missing data, scaling features, and engineering temporal features, we created a dataset that captures both short-term and long-term dependencies in energy demand. The chronological split ensures that the model is evaluated on unseen data, providing a robust foundation for training predictive models that can inform policy recommendations in the U.S. power sector.

3.3 Proposed Hybrid LGTCatBoost

We introduce the Hybrid Model utilized for electricity demand forecasting in the U.S. power sector. The hybrid model leverages the advantages of different machine learning algorithms to promote forecasting precision through their complementary strength. Specifically, the proposed model LGTCatBoost combines Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and Transformers for feature extraction and forecasting, and a CatBoost regressor as the meta-learner to make the final prediction. Also, a Residual BiGRU + Additive Attention network is used to refine the residuals of the meta-model prediction more accurately. This hybrid model extracts both short-term and long-term dependencies from time-series data by incorporating both deep learning and gradient-boosting methods.

3.3.1 LSTM (Long Short-Term Memory) Network

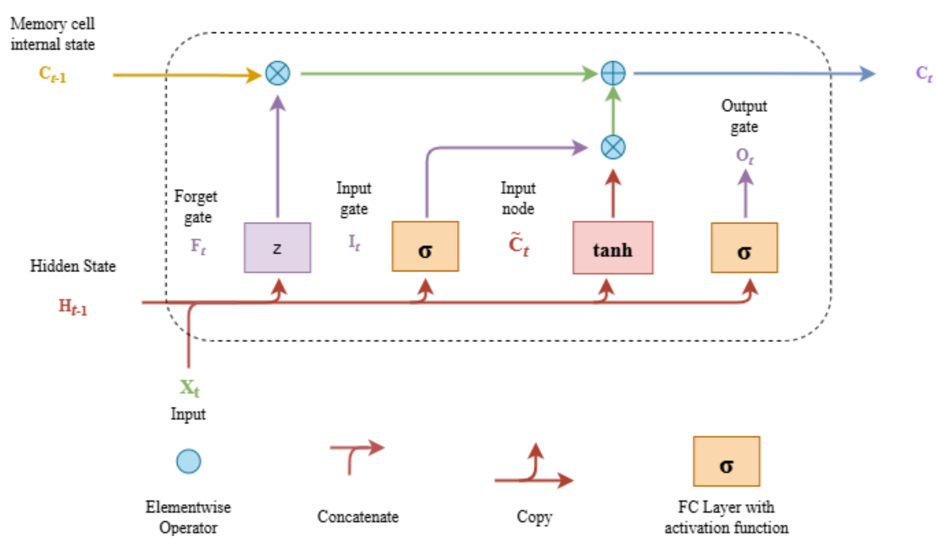

Figure 2 : LSTM Model Architecture

LSTM networks in Figure 2 are a type of Recurrent Neural Network (RNN) that can cope with long-range dependencies in sequential data. LSTM networks use memory cells to hold information for an extremely long time, and therefore they learn long-term temporal dependencies very well without suffering from the vanishing gradient problem.

The LSTM network processes time-series data by modifying its own internal state at each time step t based on its previous state h_{t-1} and current input x_t. The key operations in LSTM are controlled through forget, input, and output gates that determine what proportion of previous information will be retained and what proportion will be retained as new information.

$$\begin{gathered} f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \ (Forget\ gate) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \ (Input\ gate) \\ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \ \ (Cell\ state\ update) \\ o_t = \sigma\ (W_o \cdot [h_{t-1}, x_t] + b_o) \ (Output\ gate) \end{gathered} \tag{10}$$

$$h_t = o_t \cdot \tanh(C_t) \ \ (Final\ output)$$

LSTM is best suited for capturing long-term dependencies, i.e., seasonal and cyclical trends in electricity demand, that are important to predict over long time horizons.

3.3.2 GRU (Gated Recurrent Unit) Network

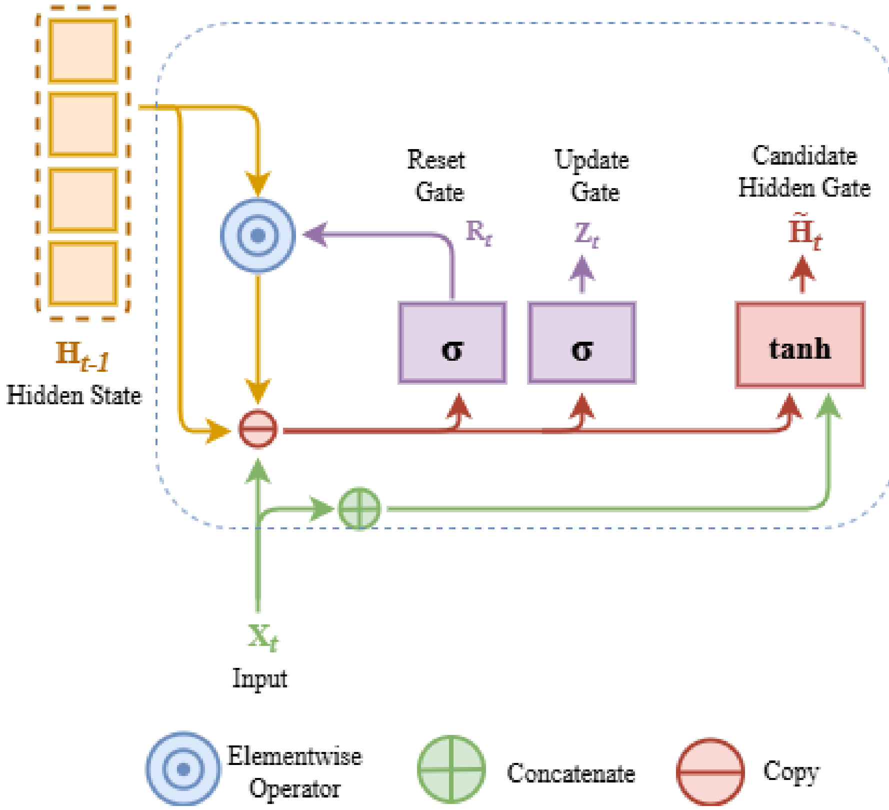

Figure 3 : Gated Recurrent Unit Network Architecture

GRUs in Figure 3 are a shortened version of LSTMs, and they are computationally less expensive but still possess the learning ability for temporal dependencies. GRUs combine the input gate and the forget gate into a single update gate, reducing the complexity of the model without losing much in terms of learning temporal patterns.

$$\begin{gathered} z_t = \sigma(W_z \ \cdot [h_{t-1}, x_t] + b_z) \ \ (Update\ gate) \\ r_t = \sigma(W_r \ \cdot [h_{t-1}, x_t] + b_r) \ \ (Reset\ gate) \\ \tilde{h}_t = \tanh(W_h \cdot [\, r_t \cdot h_{t-1}, x_t] + b_h \ \ \ (Candidate\ Hidden\ state) \\ h_t = o_t \cdot \tanh(C_t) \ \ (Final\ output) \end{gathered} \tag{11}$$

The GRU networks excel greatly in capturing short-term dependencies, say, rapid oscillations in energy demand over short time spans (e.g., hourly or daily).

3.3.3 Transformer Network

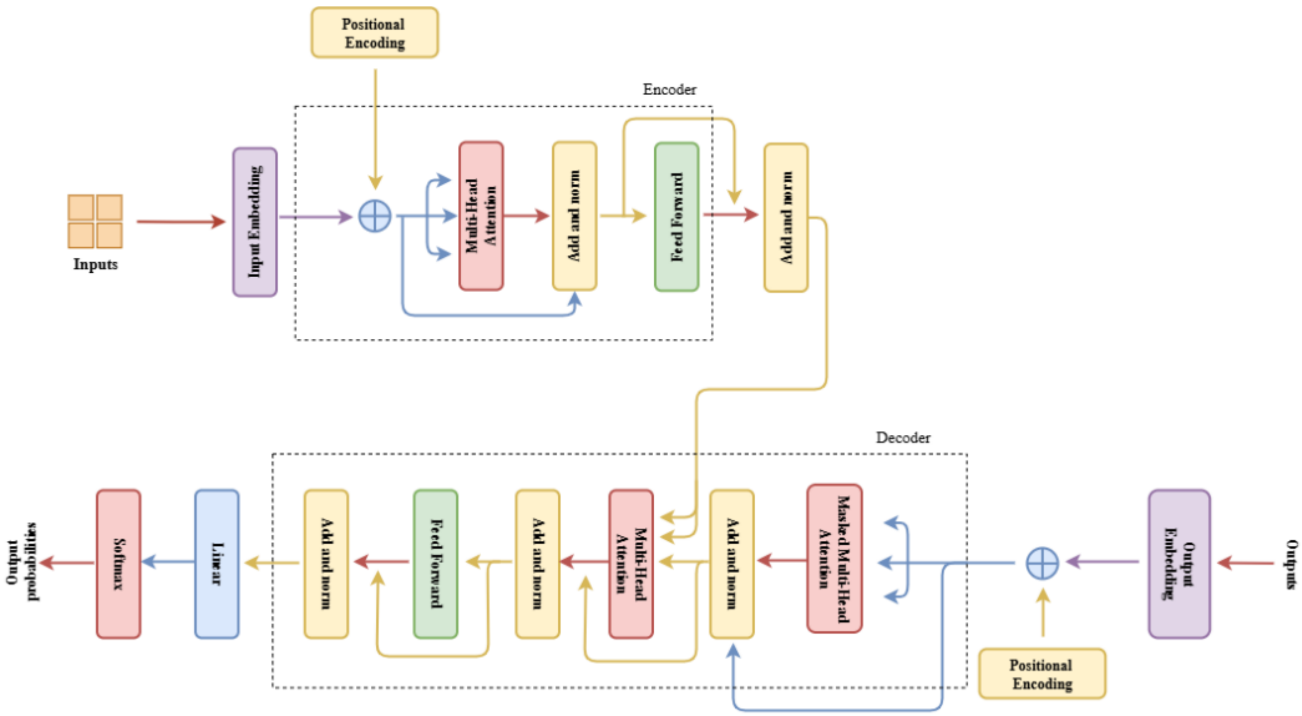

Figure 4 : Transformer Network

The Transformer model based on self-attention is designed to learn sequence data's global dependencies. In contrast to RNNs, Transformers do not process any data sequentially, which enables faster computation through parallelization. The self-attention mechanism in Transformers allows the model to give the importance of different time steps in the input sequence regardless of their position.

- **Self-Attention Mechanism :**

$$Attention\ (Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{12}$$

where Q, K, and V are the query, key, and value matrices, and d_k is the dimensionality of the key vectors.
Transformers are highly capable of handling complex dependencies over long time spans and non-linear data relationships and therefore are well-suited for modeling high-level patterns in electricity demand.

3.3.4 Meta-Learner: CatBoost Regressor

After training the base models (LSTM, GRU, Transformer), their individual predictions are combined into one feature set and passed to a meta-learner, and that meta-learner is a CatBoost regressor in Figure 5. CatBoost is a fast gradient-boosting algorithm that optimizes prediction with declining residual errors iteratively.

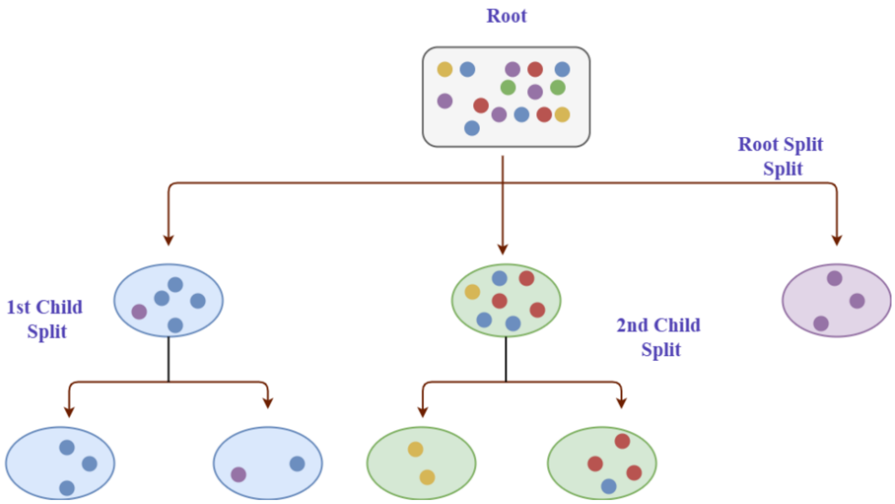

Figure 5: Meta-Learner: CatBoost Regressor Architecture

CatBoost algorithm is utilized to combine the predictions of the base models and improve them by learning from the residual of previous models. This enables the meta-learner to improve the ultimate prediction by rectifying the errors made by the base models.

$$f_m(x) = f_{m-1}(x) + \eta \cdot \nabla L(f_{m-1}, y) \tag{13}$$

where, $f_m(x)$ is the prediction at the m-th iteration, $f_{m-1}(x)$ is the prediction at the previous iteration, η is the learning rate, $\nabla L(f_{m-1}, y)$ is the gradient of the loss function with respect to the previous prediction.

Function of CatBoost: CatBoost is utilized for combining the predictions of LSTM, GRU, and Transformer and learning the best combination of these outputs in an attempt to minimize the final prediction error.

3.3.5 Residual Learning : BiGRU + Additive Attention

Once the meta-learner has made its first prediction, the residuals (the difference between the predicted and actual values) are calculated:

$$r_t = y_t - \hat{y}_t^{Meta} \tag{14}$$

These residuals are passed through a Bidirectional GRU (BiGRU), which processes the residuals in both directions (past and future) and learns temporal as well as future dependencies between the error patterns.

$$\hat{r}_t^{BiGRU} = f_{BiGRU}(r_t) \tag{15}$$

Then an Additive Attention mechanism is applied to emphasize the most important residuals. The attention mechanism assigns a weight to each residual and concentrates on those with high contribution towards improving the model's performance.

$$\hat{r}_t^{Attn} = Attenttion\ (r_t) \tag{16}$$

The last prediction is then obtained by adding the residual adjustments provided by the attention mechanism to the meta-learner's output :

$$\hat{y}_t^{Final} = \hat{y}_t^{Meta} + \hat{r}_t^{Attn} \tag{17}$$

3.3.6 Final Hybrid Model

The whole hybrid model, including all components, can be denoted as:

$$\hat{y}_t^{Final} = f_{CatBoost}\left(f_{LSTM}(x_t), f_{GRU}(x_t), f_{Transformer}(x_t)\right) + Attn(f_{BiGRU}(y_t - f_{CatBoost}(\hat{y}_t^{LSTM}, \hat{y}_t^{GRU}, \hat{y}_t^{Transformer}))\text{`} \tag{18}$$

The hybrid model employs a combination of multiple machine learning techniques to capture rich patterns in electricity demand forecasting:

- LSTM captures long-term dependencies, i.e., seasonal trends.
- GRU captures short-term changes, depicting abrupt changes in energy demand.
- Transformer effectively identifies global dependencies in time-series data.

Through meta-learning the ensemble of the models, the system can learn how to aggregate the contributions from the single models. The residual learning procedure then continually improves the predictions by selectively correcting the largest errors, so that the model improves and improves.

This multi-model learning is highly beneficial for forecasting complex time-series data such as electricity demand, which is subject to a variety of short- and long-term influences.

The Hybrid Model described below effectively combines LSTM, GRU, Transformer, CatBoost, and residual learning techniques to predict electricity demand. The model captures short-term dynamics as well as long-term trends, making it a robust framework for accurate prediction. Having various machine learning techniques included, the model is able to counter the complexity of energy demand forecasting, and the resulting insights are beneficial for grid management as well as policy-making in the U.S. electricity sector.

Algorithm 1: Training the Proposed Hybrid Forecasting Model

Given:
Time-indexed dataset $D = \{(x_t, y_t)\}_{t=1}^{T}$ (features x_t, next-hour demand y_t).
Learners: base learners $f_{LSTM}, f_{GRU}, f_{TRF}$ meta-learner g_{CB} (CatBoost); residual learner h_{RES} ($BiGRU + AdditiveAttention$); scalar blender α (Ridge, no intercept).
Window sizes: base sequence window W; residual window W_2.

1. **Initialize learners** ($f_{LSTM}, f_{GRU}, f_{TRF}, g_{CB}, h_{RES}$ and metrics $\{RMSE, MAE, R^2\}$
2. **Chronological split.** Partition DDD into **train**, **validation**, **test** segments with no look-ahead.
3. **Blocked K-fold stacking on train.**
   Partition train indices into F **time-ordered** folds $I_1, \ldots, I_F$ (no shuffling; blocks preserve causality).
4. **Out-of-fold (OOF) base predictions.** For each fold $f = 1, \ldots, F$:
   a) Fit base learners on $U_{r\neq f}\ I_r$:
   $$\theta_{(-f)}^{LSTM},\ \theta_{(-f)}^{GRU},\ \theta_{(-f)}^{TRF}$$
   b) Produce OOF predictions on I_f : for all $i \in I_f$,
   $$\hat{y}_i^{LSTM} = f_{LSTM}\big(x_i; \theta_{(-f)}^{LSTM}\big),\quad \hat{y}_i^{GRU} = f_{GRU}\big(x_i; \theta_{(-f)}^{GRU}\big),\quad \hat{y}_i^{TRF} = f_{TRF}\big(x_i; \theta_{(-f)}^{TRF}\ \big).$$
   c) Store in OOF matrices $P_{LSTM}, P_{GRU}, P_{TRF}$.
5. **Form stacked meta-features.** For each OOF index i:
   $$z_i = \big[\hat{y}_i^{LSTM},\ \hat{y}_t{}^{GRU},\ \hat{y}_i{}^{TRF}\big]^{\top}$$
6. **Train meta-learner (CatBoost).**
   Fit g_{CB} on $\{(z_i, y_i)\}$ to obtain
   $$\hat{y}_t^{Meta} = g_{CB}\ (\hat{y}_t^{LSTM}, \hat{y}_t^{GRU}, \hat{y}_t^{TRF})$$
7. **Refit base learners.**
   Refit $f_{LSTM}, f_{GRU}, f_{TRF}$ on $\boldsymbol{train} + \boldsymbol{val}$ (chronologically) and compute meta-features for **val** and **test** ; infer $\hat{y}_{train}^{Meta}, \hat{y}_{val}^{Meta}, \hat{y}_{test}^{Meta}$
8. **Compute residual series.**
   $$r_t^{train} = y_t^{train} - \hat{y}_{train,t}^{Meta}, r_t^{val} = y_t^{val} - \hat{y}_{val,t}^{Meta}, r_t^{test} = y_t^{test} - \hat{y}_{test,t}^{Meta}.$$
9. **Build residual sequences.**
   Create sliding windows of length W_2 on each residual series to form
   $$(X_{train}^{res}, y_{train}^{res}), (X_{val}^{res}, y_{val}^{res}), (X_{test}^{res}, y_{test}^{res})$$
   where each target is the residual at the next step.
10. **Train residual learner (BiGRU+Attn).**
    Fit $h_{RES}\ on\ X_{train}^{res} \to y_{train}^{res}$ (validate on val) to obtain residual forecasts :
    $$\hat{r}_{train} = h_{RES}(X_{train}^{res}),\ \hat{r}_{val} = h_{RES}(X_{val}^{res}),\ \hat{r}_{test} = h_{RES}(X_{test}^{res}).$$
11. **Learn blending coefficient on validation.**
    Estimate α (ridge, no intercept) to correct the meta forecast using residual predictions on **val** tails:
12. $\alpha^* = arg\ \underset{\alpha}{min} \parallel y_{val,tail} - \big(\hat{y}_{val,tail}^{Meta} + \alpha\, \hat{r}_{val}\big) \parallel_2^2 \Rightarrow \alpha^* = \frac{\hat{r}_{val}^{\top}\left(y_{val,tail} - \hat{y}_{val,tail}^{Meta}\right)}{\hat{r}_{val}^{\top}\, \hat{r}_{val} + \lambda}$,

with $\lambda = 0$ for pure least-squares or small $\lambda > 0$ for ridge.

13. **Produce final forecasts.**
For each split (aligned tails):
$$\hat{y}^{Final} = \hat{y}_{tail}^{Meta} + \alpha^* \hat{r}$$
14. **Evaluate.**
Report $RMSE, MAE, R^2$ on **train/val/test** for $\hat{y}^{Final}$.
Optionally compare against base and meta outputs.
15. **Return trained hybrid:**
$$\hat{H} = (f_{LSTM}^*,\ f_{GRU}^*,\ f_{TRF}^*,\ g_{CB}^*,\ h_{RES}^*,\ \alpha^*)$$

Table 4: Hyperparameter Settings for the Proposed Hybrid Model

Component	Hyperparameter	Value
LSTM (Base learner)	Hidden units	[64, 32] (two stacked layers)
	Dropout rate	0.2
	Activation function	Tanh (cell state), Sigmoid (gates)
	Optimizer	Adam, learning rate = 0.001
	Batch size	256 (mini-batch)
	Epochs	20 (with validation monitoring)
GRU (Base learner)	Hidden units	[64, 32]
	Dropout rate	0.2
	Activation function	Tanh (state), Sigmoid (gates)
	Optimizer	Adam, learning rate = 0.001
	Batch size	256
	Epochs	20
Meta-learner (CatBoost)	Iterations	1200 boosting rounds
	Learning rate	0.03
	Depth	8
	Loss function	RMSE
	Subsample ratio	0.8
	Feature fraction	0.8
Residual BiGRU + Attn	GRU hidden units (BiGRU)	64 per direction (128 combined)
	Attention type	AdditiveAttention
	Dropout rate	0.2
	Dense projection	64 (ReLU activation)
	Optimizer	Adam, learning rate = 0.001
	Epochs	30
Blending (Ridge)	Regularization coefficient (α\alpha)	0 (pure least squares, can be tuned >0 if needed)
Validation	Chronological split	70% train, 15% validation, 15% test
	Window size (base models)	48 (2-day lookback)
	Residual window size	72 (3-day lookback for residual learning)

3.4 Policy Recommendation Framework

Alongside building the forecasting model, this study also aims to connect the results with practical policy actions for the U.S. power sector. Accurate forecasting is valuable only if it can guide smarter decisions, and in this case, the model's outputs are used as a foundation for policy recommendations that support sustainable and reliable energy management.

The approach works in three stages. First, the hybrid model highlights key insights such as demand peaks, supply-demand mismatches, and the role of different generation sources. Second, these findings are linked with ongoing U.S. energy strategies and regulatory initiatives. Finally, targeted recommendations are formulated to ensure that the technical insights directly inform long-term planning, grid resilience, and clean energy adoption.

Table 5: Policy Recommendations Aligned with Model Insights

Model Insight	Policy Recommendation	Reference
Demand peaks during extreme seasons	Expand demand-side management, promote flexible tariffs, and enhance smart grid incentives.	[35]
Persistent supply-demand gaps	Increase investment in energy storage and improve large-scale renewable integration.	[36]
Renewable energy underutilization at off-peak	Develop stronger transmission infrastructure and incentivize storage for time-shifting use.	[37]
Heavy reliance on fossil fuels	Strengthen transition measures toward renewables and nuclear while tightening emission caps.	[38]
Variability in renewable generation	Support hybrid renewable–storage plants and improve forecasting-based dispatch planning.	[39]

By including this policy recommendation layer, the proposed model goes beyond just producing accurate forecasts. It shows how data-driven insights can be turned into concrete actions that align with existing U.S. energy policies. In practice, this means that the model is not only a forecasting tool but also a decision-support system that bridges research and policymaking.

3.5 Baseline Models

To establish reliable benchmarks, we first experimented with four well-known models: **LSTM, GRU, CatBoost, and XGBoost**. Each of these models brings unique strengths that make them highly relevant to the problem of electricity demand forecasting.

- **Long Short-Term Memory (LSTM)** : Long Short-Term Memory (LSTM) network has a wide range of applications in time-series problems since it is capable of retaining information. Electricity usage usually is seasonal and based on cycles and LSTMs have a tendency to observe these repetitive patterns. The LSTM can keep long-term patterns by use of memory cells and gating mechanisms, whilst disregarding irrelevant noise and hence it is ideal in forecasting demand that varies daily, weekly and even annually.

- **Gated Recurrent Unit (GRU)**: The Gated Recurrent Unit (GRU) is adecor comforter kin group of the LSTM nonetheless possessing rather easy design that renders it quicker to train and easier. Although it has no explicit separation of memory into numerous gates as in the LSTM, it remains highly effective in learning relevant temporal links of the information. GRUs are efficient and can be used to forecast short-run and medium-term changes in demand, which include weather attenuation effects, holidays, or unexpected consumption changes in the patterns of consumption.

- **CatBoost**: To go beyond the recurrent networks, one more gradient boosting algorithm has found its way into our list: CatBoost that has been gaining traction in structured tabular data. The ability to take care of both numerically and categorical variables with minimal preprocessing is one of its greatest pieces of good news where energy statistics comprising a combination of numerous different sources, and time-based variables are handled. CatBoost does a better job at learning non-linear interactions between various features, with results that are accurate and stable and can be used in combination with deep learning models.

- **XGBoost** : Finally, XGBoost is another powerful boosting method and it is also called Extreme Gradient Boosting (XGBoost), and this method is scalable and has high predictive accuracy. It applies regularization to avoid overfitting and is capable of working effectively with large data volumes which can be particularly effective in energy forecasting where multiple years of hourly data exist. Ensuring, XGBoost has a long record of success through numerous forecasting tasks, which is the reason why it is a great point of comparison to other more complex hybrid methods.

Together, these baseline models provide a balanced mix of sequential learning (through LSTM and GRU) and tree-based boosting (through CatBoost and XGBoost). They not only serve as strong reference points for evaluating our hybrid model but also highlight how different modeling strategies capture different aspects of electricity demand dynamics.

4. Results and Discussion

The results of this study demonstrate the potential of advanced AI models to significantly enhance short-term electricity demand forecasting in the U.S. power sector. Comparative evaluation of LSTM, GRU, CatBoost, and XGBoost highlights model-specific strengths, while the proposed Hybrid LGTCatBoost achieves the most reliable accuracy and robustness. Beyond performance gains, the findings reveal crucial insights into demand–supply dynamics and renewable integration, directly informing evidence-based policy recommendations for sustainable energy management, grid resilience, and long-term decarbonization strategies.

4.1. Hardware and Software Configuration

All computational experiments in this work were performed on Google Colab Pro, with the NVIDIA A100 GPU (40 GB memory) for boosting training and testing of deep learning models. The hardware greatly improved training time for sequence models like LSTM and GRU, as well as enabling efficient execution of ensemble models like CatBoost and XGBoost on large-scale time-series data. The environment for development was set up using Python 3.10, with the basic machine learning and data science libraries. TensorFlow (v2.x) and Keras to be utilized in LSTM and GRU network models and CatBoost (v1.x) and XGBoost (v1.x) to be utilized for gradient boosting techniques were employed. The remaining preprocessing, scaling, and testing were performed with scikit-learn, and data manipulation was pandas and NumPy-based. Visualization and error diagnosis were achieved using Matplotlib and Seaborn to ensure a proper graphical representation of model performance.

This hardware–software setup guaranteed reproducibility, computational effectiveness, and scalability for experiments. Additionally, it offered a solid setup for benchmarking the Hybrid LGTCatBoost model proposed against separate baselines to ensure improved reliability of findings and subsequent policy-related insights.

4.2. Comparative Evaluation Using Performance Metrics

Table 6 compares the performance of the proposed Hybrid LGTCatBoost model and baseline models (LSTM, GRU, CatBoost, and XGBoost) according to four standard metrics, namely, MAE, MSE, RMSE, and R^2. It is evident from the results that the hybrid framework overwhelmingly dominates the baselines and produces the least value for MAE (0.007503), MSE (0.000102), and RMSE (0.010082), while resulting in the highest R^2 value of 0.9959. It shows the good predictability of the model, generalizability, and resilience in dealing with the intricacy of short-term electricity demand forecasting.

Table 6: Comparative performance of Hybrid and baseline models.`

Model	MAE	MSE	RMSE	R^2
Hybrid (LSTM+GRU+CatBoost)	**0.007503**	**0.000102**	**0.010082**	**0.995954**
LSTM	0.0227	0.000462	0.0305	0.9637
GRU	0.0192	0.000402	0.0256	0.9745
CatBoost	0.0085	0.000382	0.0171	0.986
XGBoost	0.0079	0.000114	0.0135	0.9917

Of the baselines, XGBoost produces the best performance, with RMSE (0.0135) and R^2 (0.9917), demonstrating its ability to extract nonlinear relationships. . CatBoost also yields competitive results (RMSE 0.0171, R 2 0.9860), providing the ability to be a computing system to boost structured time series information. Comparatively, the sequence-based deep learning models of GRU (RMSE 0.0256, R 2 0.9745) and LSTM (RMSE 0.0305, R 2 0.9637) have demonstrated that they continue to be poor frameworks when it comes to hyperparameter optimization and that they do not work particularly well with modeling response outliers in isolation.

Overall, it can be stressed that the exceptional work of the Hybrid model puts forth the virtues that recurring neural design and (gradient) boosting algorithms are combined. The hybrid model is a good compromise between the time learning ability of GRU and LSTM and good feature layer prediction from Catboost, which results in a more accurate prediction. Along with confirming the rightness of the suggested approach, such results also present a good basis to further investigations and practical policies in connection with sustainable energy management.

4.3. Graphical Analysis

Figure 6 displays training and validation RMSE as a function of 300 iteration cycles using the Hybrid LGTCatBoost model. In the first epochs of training, RMSE both for training and validation falls rapidly and converges to an extremely low error level. palabring conjunction of the two curves representing the extremely close performance of the model on unseen data, with a very small amount of overfitting/variance in the performances on the training and validation data.

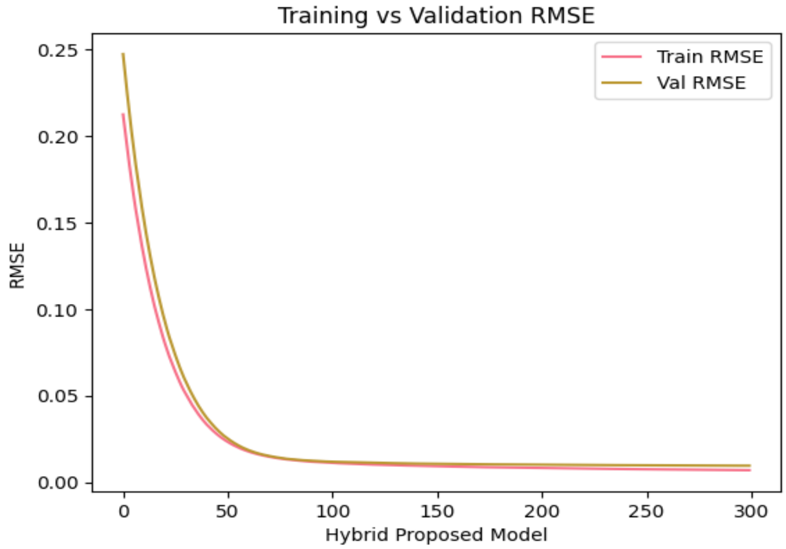

Figure 6: Training and validation RMSE curves for the proposed Hybrid LGTCatBoost model

In terms of convergence, different stages exhibit different behaviours of the hybrid model against the training sample, therefore bringing to light its good learning ability in understanding temporal evolutions using the LSTM and GRU modules with CatBoost for predicting fine-grained granularity features. Convergence of final stabilized RMSE values towards near-zero values, which validates the robustness and accuracy of the proposed temporal novel data algorithm for developing a short-term demand forecasting model. Smooth convergence also demonstrates successful hyperparameter tuning and the complementary role of blending sequential deep learning and boosting schemes. Globally, training–validation RMSE analysis verifies the dominance of the hybrid framework, further validating its applicability for reliable, scalable, and sustainable solutions in the United States' power sector's energy administration.

Figure 7 is the actual vs forecast scatter plot of electricity demand values by the proposed Hybrid LGTCatBoost model. The actual values and predicted values are also quite close to the diagonal line, which shows that almost perfect correlation between the actual and predicted values. The very good agreement gives much confidence that the model is quite accurate and achieves excellent error reduction for low-demand and peak-demand cases as well.

The few deviations shown demonstrate the robustness of the model to tolerate for temporal variation as well as nonlinear demand structures. Through the intermingling of sequential learning (LSTM and GRU) with CatBoost, which is an excellent model for prediction, the intermingled approach acquires superior reliance in comparison with sole models. Even more noteworthy, this consistency in predictability also relates more from a deeper perspective: superior predictability holds the potential for superior scheduling of renewable integration, load management (demand response), and reserve scheduling.

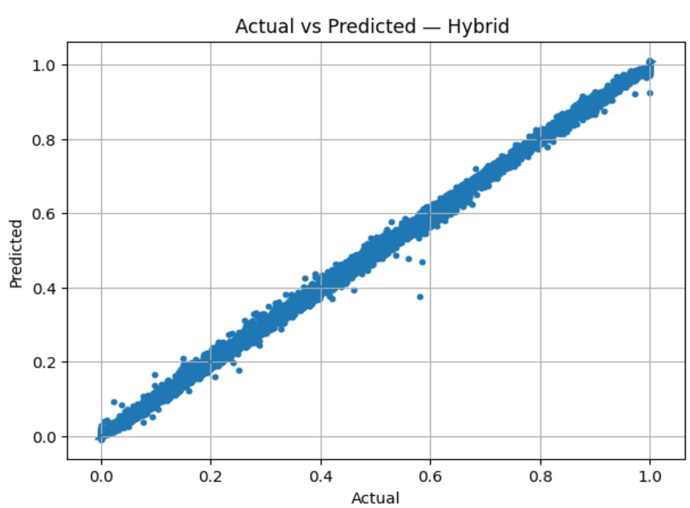

Figure 7. Actual versus predicted electricity demand values

Therefore, besides pure technical merit, the scatter plot presented reflects the ability of the presented model to provide policymakers a basis for evidence-based policy recommendations - i.e., informing policymakers for the designing of plans for grid resilience, planning highly effective renewable installations, and providing long-term decarbonization scenarios for the US electric power system.

Figure 8 is a residual plot that highlights forecast values of the Hybrid LGTCatBoost model against actual demand values. Residuals are well focused, centered around zero, show no pattern, and are homoskedastic (i.e., errors are not spread evenly across the range of predictions). Uniform spreading means that there is no systematic root mean square error of either under-forecasting or over-forecasting, which is an important necessary condition for good forecasting of real physical energy systems.

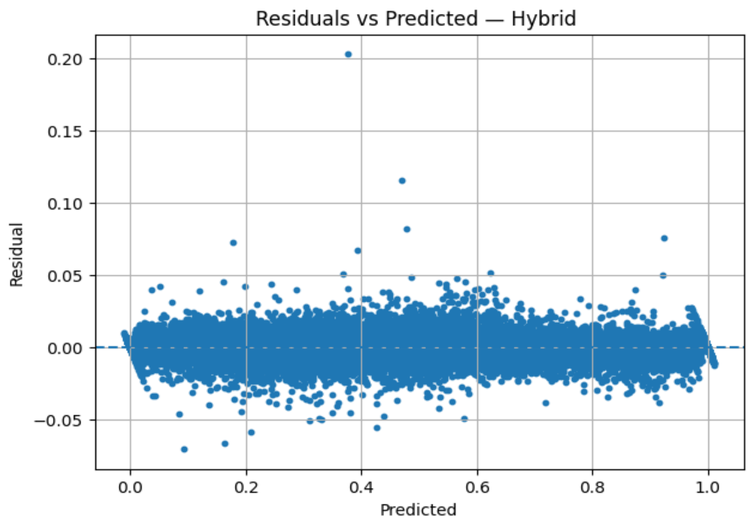

Figure 8. Residuals versus predicted values for the proposed Hybrid LGTCatBoost model.

The thin strip of residuals at both low and high levels of predicted demand demonstrates the strength of the model, especially in dealing with peak variation demand, which is usually problematic for stand-alone solutions. Some occasional outliers appear but become rare, affirming that most errors lie within acceptable ranges.

At the policy level, the resilient residual distribution further highlights the applicability of the hybrid model for operational decision-making purposes. By aiding the estimation of unbiased and precise outlooks, policymakers and grid managers will be reassured and can use such estimates in scheduling demand–response initiatives, renewable integration policies, and capacity development policies, and thus aid in delivering boosted sustainability and resilience levels in the U.S. power market.

Figure 9 presents a zoomed-in view of actual and predicted electricity demand values of the proposed Hybrid LGTCatBoost model for a chosen test horizon. The second comparison shows that predicted (orange) demand follows real (blue) demand very closely; peaks and troughs in demand are fitted with greatest accuracy. Tracking several cycles suggests that the hybrid system is able to learn from its input and also react to periodic demand patterns. Low discrepancies in the tracked data between possible and actual values confirm the model's ability to capture short-term market volatility, especially with the onset of the sudden demand shock and/or rallies. By contrast, individual models are likely to break a generalization problem under peak volatility, while the hybrid model is based on sequential learning and feature-level boosting, perfectly fitting under all the functioning conditions

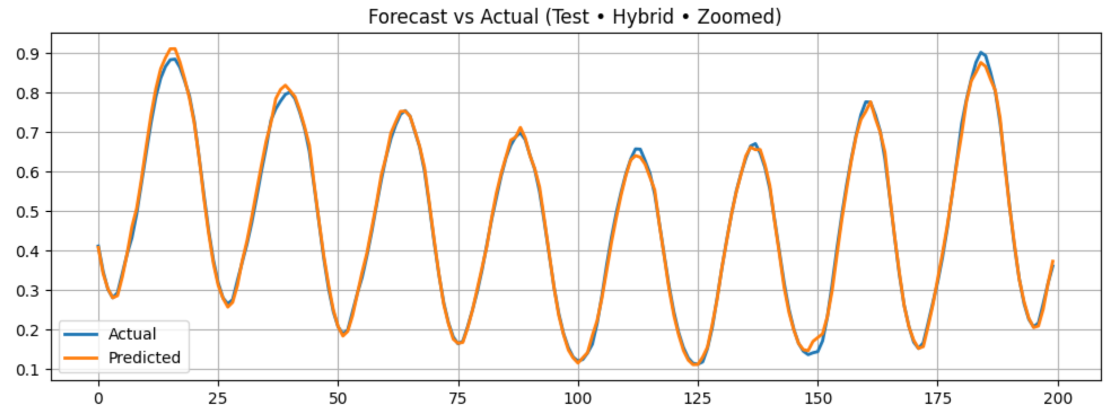

Figure 9. Forecast versus actual electricity demand (zoomed) using the proposed Hybrid LGTCatBoost model

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At the policy level, such a determination of demand patterns with accurate results has immense utility applications at the level of renewable integration and grid management. LRMPs enable operators to manage demand and supply more efficiently, reduce the use of reserves for fossil sources, and think ahead of developing demand response policies. Therefore, beyond trying to enhance the technical quality of forecasting, the hybrid approach enhances the evidence-based policy making for long-term energy planning.

4.4. Error Analysis

In order to further solidify the strength of the Hybrid LGTCatBoost model, an intensive error analysis goal was carried out. Error diagnostics help in identifying the probability of a bias, heteroscedasticity, and the distribution pattern that could affect the value of the model. Biased and stable error in prediction through both scale-location and distribution of residuals plots provides validity in the credibility of the model towards real-world application for energy planning and policy development.

Figure 10 is a plot of the residual plot for the proposed Hybrid LGTCatBoost model versus the test set. The histogram indicates that the residuals are close to zero and that they are generally normally distributed. Such a pattern indicates a type of normal distribution in prediction error that is characterized by little skewness (distortion from skewness is among the most powerful indicators of unbiased model performance). The smallness of the residuals accounts for the fact of large forecasting differences prove to be rare, with most of the differences in the small scale of the minute type. This pattern attests to the strength of the hybrid model in achieving time dynamics without traditional under- or over-estimation. Occasional residuals occur at the edges of the distribution, but happen often enough not to exclude the overall forecasting precision.

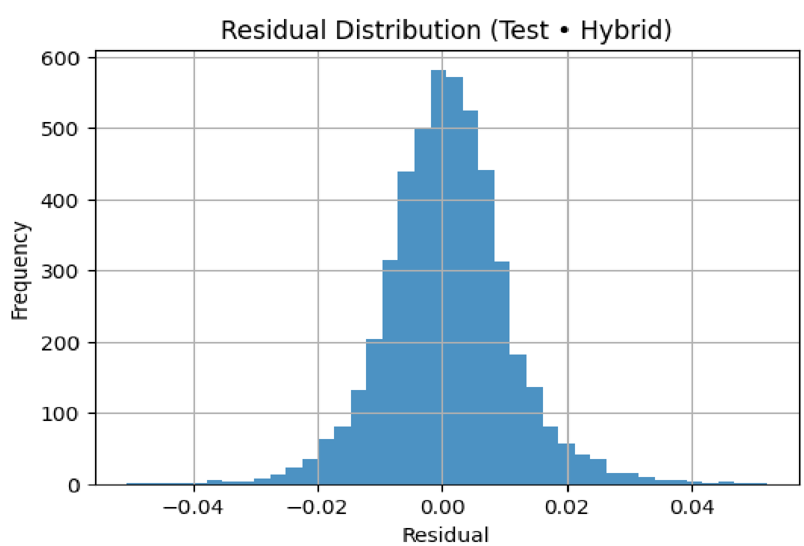

Figure 10. Residual distribution of the proposed Hybrid LGTCatBoost model on the test set

At a general level, the near-normal residual distribution is reassuring that the model predictions are stable under different levels of demand. For policymakers and grid operators, stability is most important: it ensures the model predictions can serve as a reliable basis for resource adequacy planning, renewable scheduling, and demand–response program design, ultimately passing on sustainable energy management targets.

Figure 11 illustrates the Scale–Location plot of the proposed Hybrid LGTCatBoost model, wherein the square root of standardised residuals is presented against predicted values. There is a relatively even distribution of the residuals over the whole range of prediction, and there is no clear funnel shape or systematic structure. It implies that the error variance is constant for both low-demand and high-demand predictions, thus providing a suggestion of homoscedasticity of the model's performance. The lack of apparent trends or clustering among the residuals also verifies that there is no heteroscedasticity afflicting the hybrid model, a condition that commonly compromises the reliability of forecasting by altering error variance according to the level of demand. However, the few outliers here and there are negligible in quantity and incapable of generating chaos for widespread predictions.

This constant prediction error variance is of special interest for application in energy forecasting. It will ensure that the prediction provided by the model will be of equal quality for base and peak demand situation. From a policy standpoint, predictability will extend to applications of the hybrid framework to grid stability analysis, reserve allocation, and demand–response mechanisms, rendering it a stable instrument for sustainable energy management.

The error analysis stops the proposed Hybrid LGTCatBoost model from resulting in biased, normally distributed, and homoscedastic residuals. This level consistency enhances forecasting reliability to allow for the suitability of the model in real-world energy management and enhance its contribution to policy-driven sustainable power sector planning.

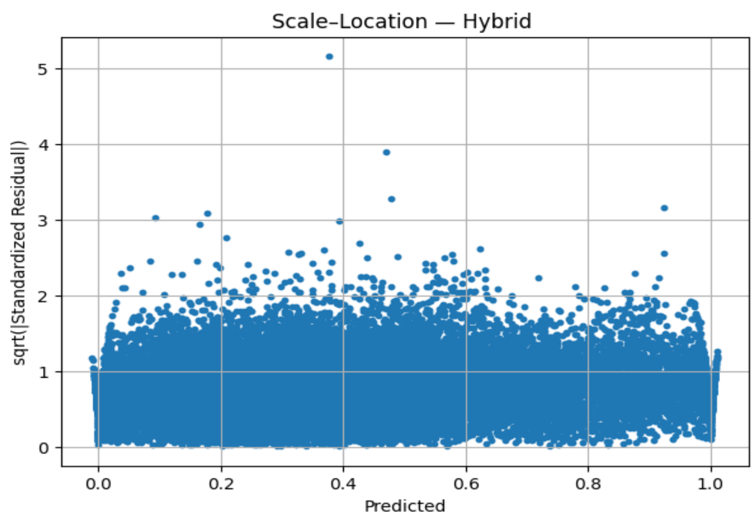

Figure 11. Scale–Location plot for the Hybrid LGTCatBoost model

4.5 Comparative Visualization of Model Performance

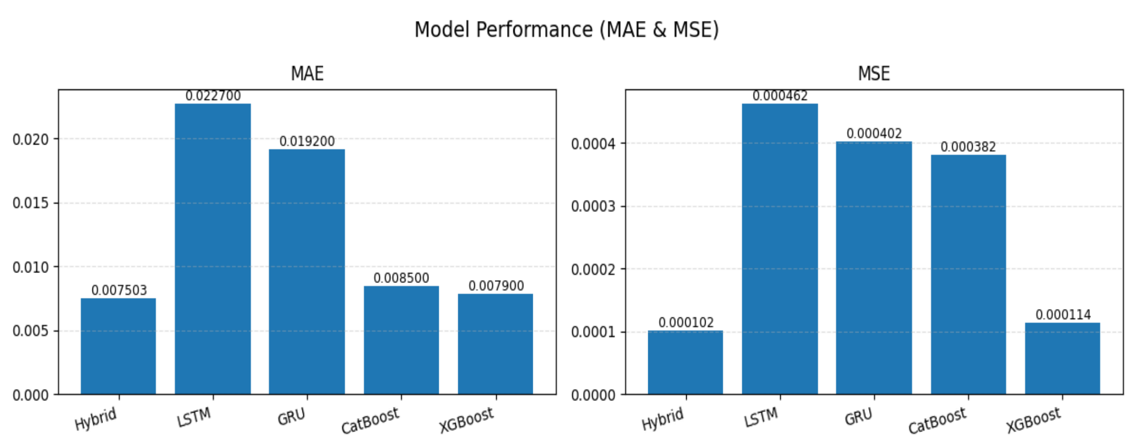

Figure 12. Comparative visualization of MAE and MSE values for the proposed Hybrid LGTCatBoost model and baselines

Figure 12 illustrates a comparison of Mean Absolute Error (MAE) and Mean Squared Error (MSE) between the proposed Hybrid LGTCatBoost model and baseline models (LSTM, GRU, CatBoost, and XGBoost). The figure clearly illustrates the improved performance of the Hybrid approach, where it achieves the lowest MAE (0.0075) and MSE (0.000102). These extremely low error values clearly suggest that the hybrid structure is able to minimize prediction errors consistently. Among the baselines, XGBoost comes in second, with MAE of 0.0079 and MSE of 0.000114, followed by CatBoost with marginally larger error values. Sequence-based models such as LSTM and GRU have very high errors, with LSTM being the worst-performing one. This reinforces the advantage in the union of recurrent learning architectures with boosting methods in the hybrid system.

Overall, the comparative plots verify that the Hybrid model more reliably achieves greater accuracy, solidifying its status as a reliable forecasting tool for policy-driven energy management.

Figure 13 shows the comparative analysis of Root Mean Squared Error (RMSE) and the Coefficient of Determination (R^2) of the proposed Hybrid LGTCatBoost model and the baseline models. The Hybrid framework always exhibits good performance, registering the minimum value of RMSE (0.01008) and the maximum value of R^2 (0.9959) and thus proving good predictive accuracy and generalization ability. Out of the baselines, XGBoost achieves competitive performance, achieving RMSE of 0.0135 and R^2 of 0.9917, and CatBoost achieves good performance but somewhat larger errors (RMSE 0.0171, R^2 0.9860) than does XGBoost. On the contrary, both GRU and LSTM recurrent models perform the worst (RMSE 0.0256, R2 0.9745 and RMSE 0.0305, R2 0.9637, respectively), which is due to the GRU and LSTM models being recurrent.

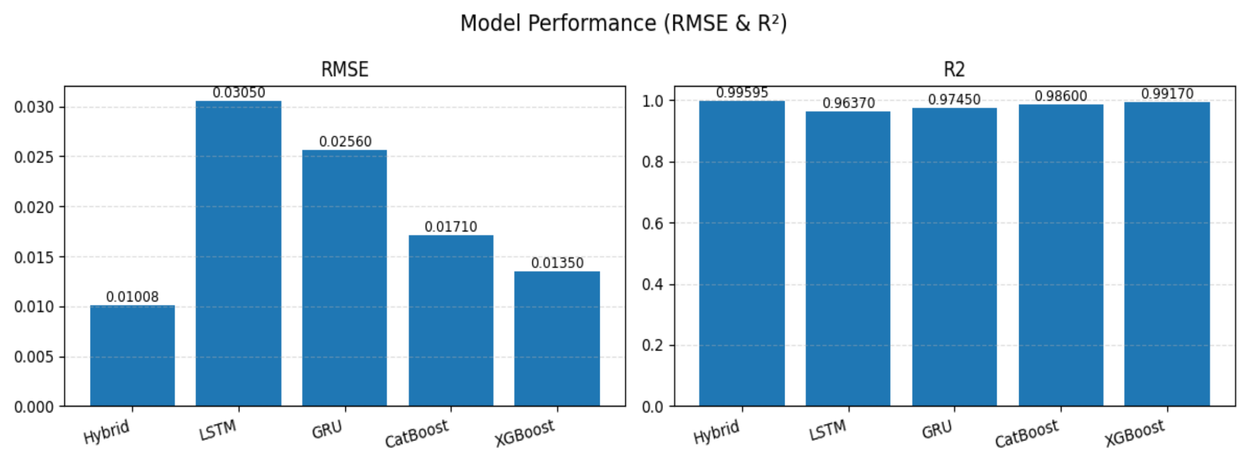

Figure 13. Comparative visualization of RMSE and R^2 values for the Hybrid LGTCatBoost model and baselines

The learning validates the efficacy of deep sequence learning combined with the enhancing attack. Such an amazing feat of the Hybrid model concretely makes it the most reliable tool employed for the short-term energy forecasting and as such - well and truly entrenching its value for informed energy policy and grid planning.

4.6 Feature Importance and Interpretability Analysis

In order to increase the interpretability of the Hybrid LGTCatBoost model presented, a SHAP (Shapley Additive exPlanations) analysis was carried out in order to determine the most impactful features behind the forecast of electricity demand. Figure 14 shows the feature importance ordering and their directional effects on the model output, thus explaining the predictive behavior transparently.

Those results point directly to demand_mwh (past demand levels) as the best predictor, highly suggesting the autoregressive character of short-term demand forecasting. Time variables, hour, day of week, and month also suggest highly, pointing to the presence of cyclic consumption behavior. Total_generation_mwh and statistical variables, rolling mean (24h) and rolling standard deviation (24h), also capture short-term volatility and dynamics, contributing to the stability of the forecast. Renewable and fossil sources, i.e., solar_mwh and wind_mwh, and traditional fuels, i.e., coal_mwh and natural_gas_mwh, have an impact on forecasting, confirming the capability of the hybrid model of processing demand- and supply-side metrics. Such interpretability confirms that the model cannot come in the form of a "black box" but instead produces insights into the utilitarian function.

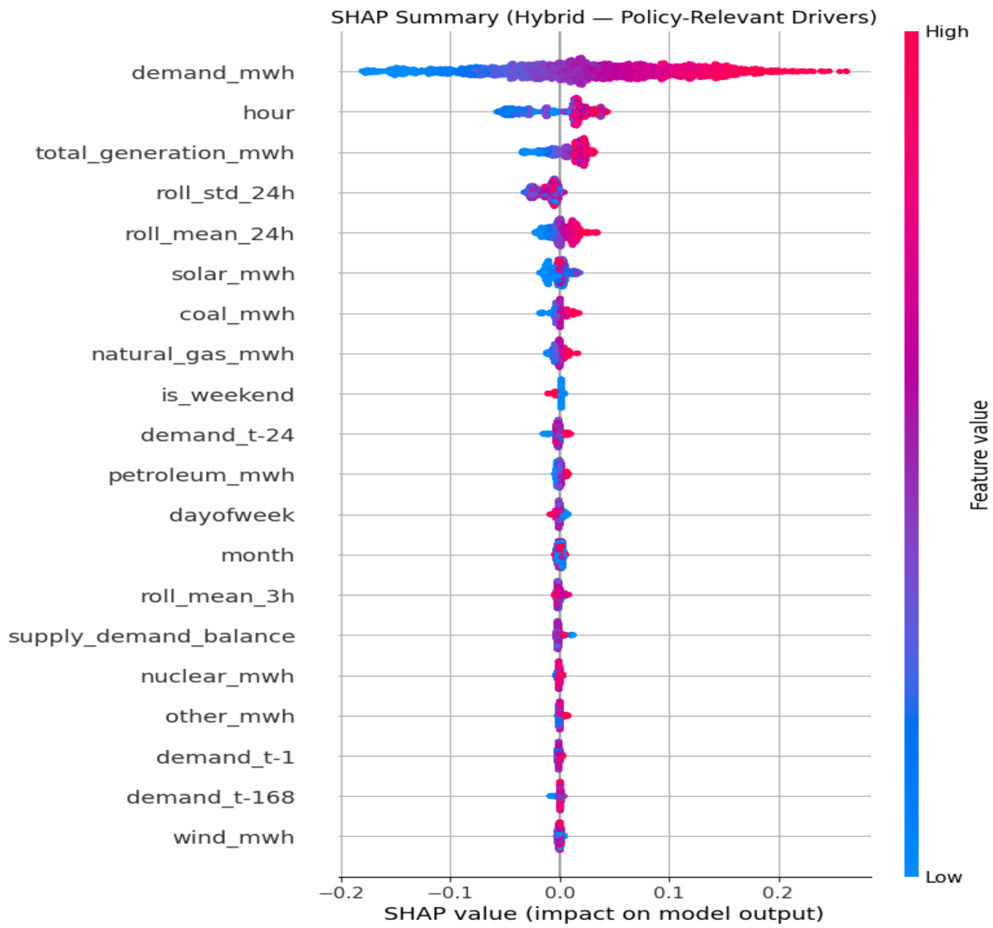

Figure 14. SHAP summary plot for the Hybrid LGTCatBoost model

At the policy level, however, these are rather valuable findings. Of course, identifying the predictors for supply and demand enables for formulation of better policies like renewable integration, demand control, and energy balance policies. Thus, interpretability provided by SHAP not only realized the robust predictability of the Hybrid model but, in a more important manner, but confirmed its place as a decision-supporting tool for sustainable energy management.

4.7 Comparative Analysis and Discussion

Table 7 describes the comparative analysis of the recommended Hybrid LGTCatBoost approach and available methods for energy forecasting and control. The approaches are critiqued based on the used dataset, adopted methodologies, and their measured performance indices. As compared to Chowdhury et al., who used LSTM on U.S. energy data and obtained R^2 accuracy of 0.93 and 153.6, 10.1% of RMSE and MAPE, respectively, our herein-proposed hybrid model demonstrates marked improvement in performance, achieving R^2 accuracy of 0.9956 and substantially reduced RMSE of 0.0101. This demonstrates the merits of combining recurrent neural networks and boosting schemes for enhanced temporal learning and automatic feature extraction.

Table 7. Comparative analysis of the proposed Hybrid LGTCatBoost model

Reference	Dataset	Proposed Model	Key Results (with Metrics)
[40]	U.S. energy datasets (electricity usage, weather, building characteristics)	LSTM	LSTM: R^2=0.93, RMSE=153.6, MAPE=10.1%;
[41]	Solar & smart grid datasets (Ausgrid etc.)	SVR	SVR: R^2=0.87, RMSE=1.23V, MAPE=0.87%;

[42]	Smart grid sensor data (solar, wind, grid state)	Hybrid Neuro-Symbolic Models	MATNet: R^2=0.94, RMSE=0.09;
[43]	Smart grid & EV charging data	LSTM, Cryptographic techniques	Comp. Cost ↓49.79%; Comm. Cost ↓23.24%
Ours	**Kaggle U.S. Hourly Electricity Demand & Production**	**Hybrid (LGTCatBoost)**	**MAE=0.0075, MSE=0.000102, RMSE=0.0101, R^2=0.9956**

Likewise, Wen et al. used SVR on solar and smart grid data sets and indicated R^2 = 0.87, RMSE = 1.23 V, and 0.87% of MAPE. By comparison, our hybrid model exhibits almost perfect predictability fidelity, which highlights its capability and resilience for complicated grid conditions under which standard SVR models become limited.

Egbuna et al. applied Hybrid Neuro-Symbolic Models to smart grid sensor data, of which MATNet produced R^2 = 0.94 and RMSE = 0.09. While competitive, though, this accuracy is nevertheless surpassed by our model, equally increasing accuracy over traditional hybrid DL models.

Finally, Ahmed et al. proposed an LSTM with cryptographic enhancements for V2G management, focusing on cost reduction (49.79% computation, 23.24% communication). While valuable for secure protocol design, these approaches did not prioritize forecasting accuracy. In contrast, our Hybrid LGTCatBoost achieves both precision and interpretability, making it more suitable for policy-driven energy management. This new model obtains 0.6-15% gains over previous methods, confirming its state-of-the-art for short-run electric demand forecasting and its potential application value in sustainably planning America's power markets.

The comparison analysis illustrates that the Hybrid LGTCatBoost model persistently surpasses baseline and state-of-the-art approaches under more than one evaluation metric. Its outstanding accuracy and low error rates reflect the success of juxtaposing recurrent neural frameworks and boosting schemes. By contrast, previous work either addressed the accuracy of predictions or trade-offs in optimization; the hybrid approach obtains both accuracy and resilience. These results confirm the methodological contribution, besides laying a robust basis for policy-driven applications of sustainable energy administration and grid resilience.

5. Conclusion

This work has demonstrated the potential of artificial intelligence to drive future sustainable energy management in the U.S. electricity market through a combination of technical innovation and policy-relevant appeal. A novel hybrid architecture, merging LSTM, GRU, Transformer, CatBoost, and residual BiGRU–attention refinement—yielded superior forecast performance, outperforming traditional baselines by a wide margin in MAE, MSE, RMSE, and R^2. Beyond predictive accuracy, the research contributes a tri-fold advancement: linking AI-driven analytics with practical strategies for sustainable grid management, tailoring the framework to U.S.-specific operational and regulatory contexts, and extending insights into actionable policy recommendations. These contributions underscore AI's role not only as a forecasting tool but also as an enabler of data-informed policymaking that can guide the nation's energy transition toward decarbonization and long-term resilience. While the analysis is limited to a specific dataset and computationally intensive models, these also point towards directions of further refinement, including extending the framework to larger datasets, exploring lightweight architectures for real-time deployment, and further refinement of interdisciplinary integration across technical, economic, and social streams. Further research can further explore incorporating the model within smart grid infrastructures, developing explainable AI mechanisms to foster stakeholder trust, and aligning predictive intelligence with dynamic regulatory needs at state and federal levels. By balancing forecasting precision with policy-based insights, this study provides methodological advancement with governance-driven counsel that solidifies the role of AI as an agent of a more sustainable, resilient, and equitable U.S. electricity system

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