Future Energy Needs at a Glance

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I. Introduction

As global energy demand continues to rise, the need for accurate and adaptive load forecasting has become increasingly critical for ensuring energy security, economic stability, and sustainability. Effective forecasting enables grid operators and policymakers to anticipate fluctuations in energy consumption, optimize resource allocation, and integrate renewable energy sources more efficiently. This study provides a comprehensive analysis of key factors influencing future energy demand, including technological advancements, socio-economic trends, and policy interventions. By examining emerging challenges and forecasting methodologies, we aim to develop load forecasting methodologies that will promote sustainability, affordability, and reliability in the evolving energy landscape.

II. Problem Definition

We are generating a choropleth map visualization of 10 year energy demand forecasts to better understand potential grid strain and failure likelihood in the near-future.

III. Literature Review

Load forecasting in the energy sector is a critical task that enables efficient grid management, resource allocation, and operational planning. The literature on forecasting methodologies highlights a range of techniques, from traditional statistical models to modern machine learning and hybrid approaches, each contributing unique advantages and addressing different forecasting challenges.

A. Market Factors

The evolving energy industry is shaped by technological, socio-economic, and environmental factors that significantly impact energy demand forecasting. A key challenge is the increasing complexity of energy systems due to flexible demand technologies like smart meters and distributed generation, alongside growing electrification and intermittent renewable supply [1]. These factors necessitate adaptive forecasting models, though current research lacks detailed exploration of model implementation. Smart grids also play a crucial role in demand shifts, as the study by Tuomela et al. examines their integration in Finnish households, revealing significant variability in energy savings across different regions [2]. This underscores the need for region-specific forecasting models that account for infrastructural and regulatory differences. Similarly, the building sector remains a major contributor to energy consumption, with regulatory, technological, and behavioral factors influencing long-term demand trends [3]. However, reliance on short-term data limits the ability to predict long-term shifts in energy use. Renewable energy integration further complicates forecasting by impacting grid stability. With increasing distributed energy systems, maintaining grid reliability becomes a challenge, as consumers also become producers [4]. This shift requires models that incorporate both energy consumption and production patterns, particularly in residential sectors. On a broader scale, energy demand drivers differ between developed and developing nations. Economic growth, infrastructure, and climate drive demand in developing countries, whereas institutional factors like innovation and governance play a larger role in developed economies [5]. Additionally, long-term studies show that energy consumption in wealthier nations grows more slowly than GDP, highlighting the role of technological advancements [6]. Socio-economic policies, such as energy taxes and demographic shifts, also influence demand, emphasizing the need for policy-driven forecasting approaches [7]. These studies illustrate the complexity of energy demand forecasting in a rapidly changing landscape. As flexible demand, renewable integration, and regional variations reshape consumption patterns, traditional models must evolve to incorporate these emerging variables effectively.

B. Machine Learning and Deep Learning Approaches

Several studies demonstrate the effectiveness of machine learning (ML) and deep learning (DL) methods in improving load forecasting accuracy. Advanced architectures such as long short-term memory (LSTM) networks and convolutional neural networks (CNNs) capture temporal dependencies and nonlinear patterns in energy consumption data [8]–[11]. These approaches are particularly useful for handling large-scale datasets and dynamic load variations, which are crucial for improving demand predictions in real-world applications. Additionally, hybrid models combining deep learning with traditional statistical methods show promise in reducing forecasting errors by leveraging the strengths of both approaches [12], [13].

C. Statistical and Time Series Models

Traditional statistical techniques, such as autoregressive integrated moving average (ARIMA) and exponential smoothing methods, remain foundational in load forecasting [14], [15]. These models provide interpretable and robust predictions, particularly for short-term forecasting where historical patterns are relatively stable. Despite their limitations in capturing complex nonlinear relationships, their integration with ML-based models can enhance overall forecasting performance by providing baseline predictions that ML models can refine [12], [16].

D. Feature Engineering and Data Preprocessing

Several studies emphasize the importance of feature selection and data preprocessing in forecasting accuracy. Methods such as principal component analysis (PCA) and wavelet transformations help in extracting relevant features from raw energy consumption data, thereby reducing noise and improving model efficiency [3], [17]. Additionally, handling missing data and seasonality adjustments play a crucial role in ensuring model reliability [1], [16]. These insights are valuable for optimizing input features in our forecasting framework, enhancing the predictive power of ML-based models.

E. Hybrid and Ensemble Methods

The combination of different modeling techniques has been explored to improve forecasting precision. Hybrid models that integrate statistical methods with deep learning architectures or ensemble approaches, such as boosting and bagging, have been found to outperform individual models by leveraging multiple predictive strengths [9], [13], [16], [18]. These methods provide robustness against fluctuations and uncertainties in energy demand, making them particularly relevant for our research, where high accuracy and adaptability are required.

F. Applications in the Energy Sector

The application of these models to real-world energy demand forecasting has demonstrated their potential in grid optimization, renewable energy integration, and demand-side management. Studies analyzing regional and national-scale energy consumption highlight the importance of incorporating external factors such as weather conditions, economic indicators, and policy changes into forecasting models [2], [3], [17], [19]. These insights will be crucial for refining our approach by integrating external variables that influence energy demand dynamics.

G. Conclusion

The reviewed literature underscores the necessity of adopting a multi-faceted approach to load forecasting, leveraging both statistical and ML-driven methods. While deep learning techniques enhance the ability to model complex patterns, traditional methods provide a solid foundation for interpretable and stable predictions. Hybrid and ensemble techniques further improve forecasting reliability, making them ideal candidates for our research into energy demand prediction. Incorporating feature engineering strategies and external influencing factors will be critical in optimizing our forecasting framework for practical implementation in the energy sector.

IV. Proposed Method

This study aims to enhance energy demand forecasting by leveraging machine learning techniques to analyze US historical data and produce dynamic, geographically mapped projections of future consumption. Unlike traditional forecasting methods that primarily rely on statistical models with near-term forecasts, our approach integrates interactive choropleth maps to illustrate predicted demand shifts over a 10-year time period, aligning with existing grid infrastructure. This choropleth map will allow for regional outlook of consumption by larger state separations, combining both current abilities to meet demand with future consumer energy needs will allow providers to optimize resource allocation, policymakers to make steps towards preventing grid failures, and consumers to better comprehend the near-future load expectations.

A. Data Preprocessing

The data preprocessing phase involved several systematic steps to prepare the Electricity Generation dataset for model development. The dataset comprises historical electricity generation data collected between 2015 and 2024, with each source file containing monthly net generation figures for the corresponding year. Below is a detailed outline of the preprocessing procedures:

- **Data Acquisition and Collection:** Electricity Generation data was acquired for each year from 2015 to 2024. Each dataset contained detailed records of monthly net generation, which served as the foundational element for further analysis.
- **Data Integration:** To facilitate comprehensive temporal analysis, the monthly net generation data from each annual dataset were integrated. This process involved aligning and merging the data across all years to construct a unified dataset. The result was a consolidated time series that represents the monthly net generation values from 2015 through 2024, ensuring that the dataset is chronologically complete and consistent.
- **Data Cleaning and Missing Value Treatment:** The initial integrated dataset was examined for inconsistencies, errors, and missing values. Since the net generation values are inherently numeric, any missing or null entries identified during this inspection were systematically replaced with a value of 0. This imputation strategy is particularly suitable for the domain, as it preserves the numeric integrity of the data and mitigates potential issues during subsequent statistical analysis and model training.
- **Final Dataset Verification:** After the integration and cleaning steps, the final consolidated dataset underwent verification procedures. This ensured that all records adhered to the required format and that no gaps existed in the time series data from 2015 to 2024. The verification step is crucial for maintaining data quality and ensuring that the dataset is ready for advanced analytics and model development.

B. Time-Series Modeling

One of the modeling methodologies to predict the electricity demand is to consider the historic data as a time series dataset. Of the various data elements available in the dataset chosen, electricity generation and storage are key indicators to determine demand. Of course, the assumption is that the electricity generation and storage are keeping up with demand over time.

One of the cleaned datasets consists of generation data for each state in the United States and from various sources the electricity is generated for each month across years. This data is now aggregated and transformed to reflect the total electricity generated per state for each month across years. This transformed data is then ready to be analyzed and modeled as a time series dataset. Fig. 1 shows the sample view of the constructed time series dataset.

Date <date>	State <chr>	Total.Generation <dbl>
2015-01-01	AK	327312.64
2015-02-01	AK	295036.21
2015-03-01	AK	295942.31
2015-04-01	AK	222601.15
2015-05-01	AK	251415.94
2015-06-01	AK	212635.74
2015-07-01	AK	233481.72
2015-08-01	AK	239849.36
2015-09-01	AK	230783.07
2015-10-01	AK	191489.91

Fig. 1. Sample view of time-series dataset

Analysis of the time-series data was performed by plotting to observe trends, seasonality, or cyclical patterns. Fig. 2 shows this for California

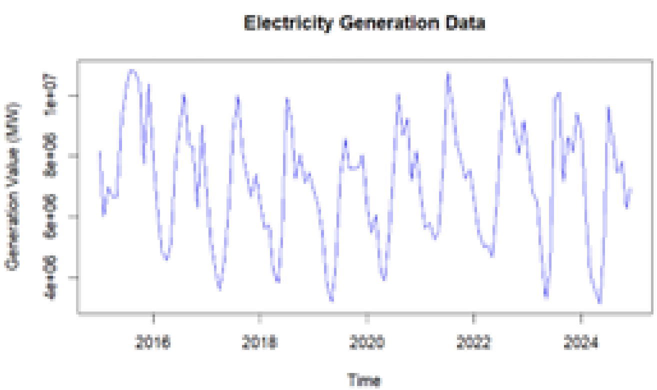

Fig. 2. Electricity Generation Data from 2015 to 2024

An Autocorrelation Function (ACF) plot was then constructed to observe the stationarity behavior of each individual dataset as seen in Fig. 3.

Date <date>	State <chr>	Total.Generation <dbl>
2015-01-01	AK	327312.64
2015-02-01	AK	295036.21
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2015-04-01	AK	222601.15
2015-05-01	AK	251415.94
2015-06-01	AK	212635.74
2015-07-01	AK	233481.72
2015-08-01	AK	239849.36
2015-09-01	AK	230783.07
2015-10-01	AK	191489.91

Fig. 3. ACF Plot of Electricity Generation Data

After splitting into training and test datasets, the ARIMA model was chosen as the previously listed time-series data was univariate. The training data consists of the time periods from 2015-2023, with the training set pulled from 2024, the latest that EIA has energy data for the US.

C. CNN-LSTM Hybrid Architecture

The energy demand data, sourced from U.S. power plants, was first cleaned by converting net generation values to numeric types, handling non-numeric values as NaN. The data was then aggregated by state and year to enable state-level analysis, transforming it from wide to long format using the melt function. The month names were extracted, converted to datetime objects, and the dataset was sorted by state and date for temporal analysis.

To prepare the data for the CNN-LSTM model, the net generation values were normalized using MinMaxScaler, scaling the values between 0 and 1. Sequences of 12 months of past energy generation data were created, where each input sequence consisted of the last 12 months of generation, and the output was the next month's energy generation. The dataset was split into training, validation, and test sets, and saved in .npz format for easy manipulation during model training.

The model architecture combined Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) layers to capture both local patterns and temporal dependencies in the data. The input sequences were passed through several 1D convolutional layers, starting with 48 filters, followed by 32 and 16 filters in subsequent blocks. Each convolutional block was followed by a flattening operation, with dropout layers (rate: 0.25) applied to prevent overfitting. The CNN layers extracted high-level features from the data.

After the convolutional layers, the data was reshaped into the required format for the LSTM layers, which consisted of three layers, each with 20 units. The first two LSTM layers returned sequences, retaining temporal features across time steps, while the final LSTM layer returned only the last output, representing the model's prediction for the next time step. Another dropout layer was applied after the LSTM layers to further reduce overfitting. The final output was produced by passing the concatenated CNN and LSTM features through a dense layer with a tanh activation function, which was appropriate due to the scaled energy generation values.

The model was trained using the Adam optimizer and Mean Squared Error (MSE) loss function. The model was evaluated using Mean Absolute Error (MAE) as the performance metric. After training for 50 epochs, the model achieved a Root Mean Squared Error (RMSE) of 0.022 and an R-squared value of 0.979. These results indicate that the model accurately forecasts energy demand, explaining approximately 97.9% of the variance in the test data.

This CNN-LSTM hybrid model successfully integrates feature extraction and sequence learning, making it well-suited for forecasting future energy generation based on historical data.

D. Visualization

These models can be used to generate energy predictions that, averaged across all models, or chosen from one specific high confidence model, can be visualized in a choropleth map, month by month, across the United States to better understand future states needs as seen in Fig. 4. These were constructed using D3.

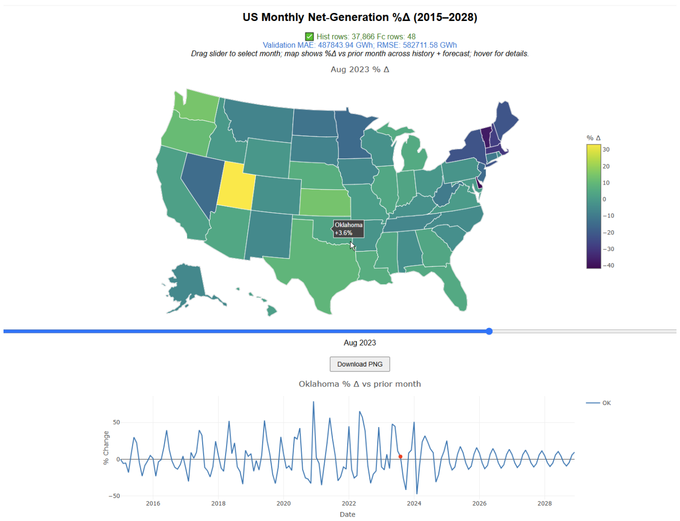

Fig. 4. Past and Future of US Energy Demand

V. Evaluation

The goal of our evaluation was to determine if our models could accurately predict future energy demands using past energy demand data. With that in mind both were trained using the cleaned data from 2015-2023 and then tested against the 2024 data to determine the confidence we could place in said models.

A. *Time-Series Modeling*

The ARIMA model was evaluated using the following metrics:

- MAPE (Mean Absolute Percentage Error): Measures the average percent error between actual and predicted values. A Low MAPE (¡1%) indicates highly accurate predictions (e.g., AL, AZ, FL, TX), while a high MAPE (¿2-3%) indicates less reliable forecasts (e.g., AK at 3.59%).
- Precision Measure (PM): Reflects how consistently close the model's predictions are to actual values, factoring in variability and scale. A lower PM indicates higher precision. An example of these is seen in Table 1.

The forecasts performances were evaluated with a validation set created from 2024 energy demands. An example of these in our modeling predictions is seen in Table 1.

B. *LSTM-CNN Hybrid Architecture*

The performance of the CNN-LSTM hybrid model was evaluated on a held-out test set, representing national-level energy generation patterns. The goal of this evaluation was to determine how accurately the model could forecast monthly energy generation based on prior sequences of historical data.

TABLE I
Example of Accuracy and Precision ranges state-by-state

State	MAPE(%)	PM	Interpretation
TX	0.09	0.0077	Extremely accurate and precise forecast. Has both high accuracy and consistency — very solid ARIMA model performance.
CA	0.32	0.84	Good accuracy; slightly less precision. Shows decent performance, usable with some caution.
AK	3.59	922.96	Weak model fit — forecasts are unstable. Has more irregular or low-volume data, making it hard to model reliably.

To quantify performance, the following regression metrics were computed:

- Mean Squared Error (MSE): Captures the average squared difference between predicted and actual values.
- Root Mean Squared Error (RMSE): Provides an error measure in the same units as the original data.
- Mean Absolute Error (MAE): Reflects the average magnitude of prediction errors, offering a straightforward interpretation of forecast deviation.
- R-squared (R2): Indicates the proportion of variance in the actual data that is explained by the model.

These allowed general error measurements and fit metrics of the model to the data available.

After 50 training epochs, the model achieved the following test results:

TABLE II
Test Metrics of LSTM-CNN Hybrid Architecture

Test MSE (loss)	MAE	RMSE	R2
0.0006231	0.01275	0.02496	0.9743

These metrics suggest the model offers strong predictive performance, capturing approximately 97.4 percent of the variation in the test data. A visual comparison of predicted versus actual energy generation confirms that the model closely tracks real-world trends, with minimal over- or under-estimation. This performance highlights the effectiveness of combining CNN feature extraction with LSTM-based sequence modeling for time series forecasting tasks.

VI. Conclusion and Discussion

The CNN-LSTM model performed excellently as the error values showed low across the board and the R-squared showed excellent fit of the model to the data. ARIMA performed well overall with generally low MAPE values, indicating reliable forecasts across most states. The highest confidence states were TX, CA, FL, AL. There were several with low confidence, due to volatility and lower data volume as seen in AK, WY, and WV. Table 2 outlines some of the larger considerations for ARIMA in the US.

TABLE III
REGIONAL ASSESSMENT OF ARIMA MODEL

Region	MAPE(%)	PM	Interpretation
Northeast	1.80	1.803	Has the highest MAPE, suggesting relatively lower forecast accuracy there
Midwest	0.48	2.393	Has strong accuracy, though slightly more variability (higher PM)
South	0.25	1.336	Shows the best model performance overall (lowest MAPE and PM)
West	0.71	72.935	Has high PM, indicating greater variability or inconsistency in predictions — this is due to states like Alaska and Wyoming

A. Impact

The importance of the models shows that even viewing the data as a stationary, non-volatile set for the purposes of the ARIMA model can have a highly confident predictor of future energy demand.

Accurately forecasting energy generation is a cornerstone of reliable power grid operation and long-term infrastructure planning. Traditional statistical models like ARIMA offer a baseline for prediction by treating energy demand as a stationary or slowly evolving time series. In many cases, this approach can yield reasonable forecasts, particularly when seasonal patterns and trends are stable. However, as the energy landscape becomes increasingly dynamic—driven by factors such as renewable integration, policy shifts, and climate variability—stationarity-based models face significant limitations.

This research highlights the value of adopting more expressive and adaptable models such as CNN-LSTM architectures. While ARIMA assumes linearity and requires manual differencing and parameter tuning, deep learning models can automatically learn nonlinear temporal dependencies and extract complex features directly from raw data. In this study, the CNN layers efficiently captured short-term local patterns in the input sequences, while the LSTM layers modeled long-term dependencies, resulting in a highly accurate national-level forecast with an R^2 of 0.974.

The impact of this modeling approach extends beyond immediate forecast accuracy. By demonstrating the effectiveness of hybrid deep learning models, this work encourages utility providers, policymakers, and researchers to explore advanced forecasting tools that are better equipped to handle the volatility and high dimensionality of modern energy systems. These models not only improve prediction quality but also open the door to more granular forecasts—such as those at the state or plant level—which can enhance operational decision-making, inform investment in renewable capacity, and support grid stability.

Ultimately, the integration of machine learning into energy forecasting represents a shift toward more data-driven and resilient energy planning frameworks. This research serves as a proof of concept for how neural networks, when appropriately structured, can outperform traditional time-series models and meet the evolving demands of the energy sector.

B. Limitations

As this is overall a prediction of future outcomes that solely rely on time to play out, proper validation and testing of our models will require time over the coming years to be fully vetted. The benefit however with our models is that the look at macro market trends in the US that will take longer than 10 years to truly perturb. 10-years is indeed enough to shift total energy demands in a gradual, albeit sometimes still shocking, scale. However 10-years will not see a sharp deviation from budding trends as large scale factories will often still be in place and a large portion of the population will not likely emigrate or sustain increases in such a time period.

One limitation lies in the use of ARIMA, which, while strong for stationary and linear time series, may underperform in capturing the nonlinear dynamics of energy generation driven by policy shifts, renewables integration, or market volatility. Conversely, the CNN-LSTM model is designed to learn such complex patterns but requires large and diverse datasets to generalize well. The use of only a decade's worth of historical data may limit its ability to fully detect long-term cycles or rare but impactful disruptions.

Additionally, while the study incorporated plant-level and state-level regional data to capture more localized patterns in energy generation, the forecasting models did not explicitly model spatial dependencies or inter-regional influences, which could further improve predictive performance. Moreover, the models assumed relative continuity in market and environmental conditions, and thus may not be fully robust against structural breaks such as abrupt policy changes, rapid technological disruption, or unforeseen climate events. These limitations emphasize the need for periodic retraining and refinement of the models as more data becomes available and conditions evolve.

C. Future Considerations

To further enhance the robustness of the time-series analysis, future work should explore benchmarking the CNN-LSTM architecture against a broader suite of models. This includes hybrid statistical models such as ARIMA-GARCH, which can capture both trend and volatility components, especially in datasets with more stochastic or heteroscedastic behavior. Vector Autoregression (VAR) models also present a valuable avenue, particularly for multivariate analysis that includes exogenous factors such as commodity prices, weather data, or economic indicators. These can reveal potential causal relationships or external influences that a univariate model might overlook.

In terms of deep learning, architectural improvements to the CNN-LSTM framework can be investigated. Deeper or wider CNN layers may capture more nuanced local features, while attention mechanisms or Transformer-based layers could be integrated into the LSTM pipeline to better model long-range dependencies. Furthermore, ensemble approaches—such as combining CNN-LSTM with other recurrent models (e.g., GRUs) or even non-neural models—could yield greater predictive performance and resilience across different states or time periods.

The integration of state-level forecasts is another promising direction. With higher granularity, models could account for regional variability in generation capacity, policy environments, and weather patterns. This would enable more targeted forecasting, benefiting utilities and regulators seeking localized insights for planning and grid optimization.

Ultimately, advancing this work involves not only refining model architectures but also expanding the scope of data inputs and temporal horizons, ensuring that forecasts remain both accurate and actionable in an evolving energy landscape.

All Team Members have contributed a similar amount of effort.

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