

Comprehensive Analysis of Energy Demand Prediction Using Advanced Machine Learning Techniques

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Abstract. Energy prediction plays a critical role in maximizing energy usage, reducing costs, and improving the effectiveness of power systems. Machine learning (ML) techniques are increasingly potent for analyzing intricate patterns in energy consumption and providing precise forecasts—both crucial for effective energy management. This study examines the application of ML in forecasting energy usage, focusing on two techniques: Long Short-Term Memory (LSTM) and Support Vector Machines (SVM). LSTM models, known for their ability to capture complex patterns, are evaluated for time-series energy data prediction. SVM, a supervised learning algorithm, is analyzed for its performance in energy forecasting under varying data conditions. The study compares the predictive accuracy, computational efficiency, and generalization capabilities of these models using metrics like R^2 , RMSE, and MAE. Results indicate that LSTM excels with large datasets and non-linear patterns, while SVM is effective for smaller datasets with sensitivity to outliers. This analysis provides insights into selecting appropriate models for specific data characteristics and prediction requirements.

1 Introduction

Machine learning (ML) is a transformative technology capable of creating systems that learn and adapt from data without explicit programming. These systems excel at identifying complex patterns within vast datasets, making ML a valuable tool for energy forecasting.

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The science of machine learning revolves around developing systems capable of autonomously learning from data. This learning involves identifying intricate patterns within vast datasets to make informed decisions or predictions. At its core, a machine learning algorithm is a computational framework designed to process data, recognize patterns, and forecast future outcomes. Over time, these systems adapt and enhance their performance independently, requiring minimal human intervention [18].

In this context, the term "automatic" signifies the self-improving nature of ML systems. They continually refine their accuracy by leveraging feedback from the data itself. For instance, supervised learning models utilize labeled data to make predictions and adjust parameters iteratively, whereas unsupervised models identify hidden patterns without prior annotations. This adaptability positions machine learning as a cornerstone in advancing predictive analytics.

1.1 Economic and Energy Implications

The rapid expansion of global economies has heightened the demand for electrical energy, posing significant challenges to existing energy infrastructures. Sudden surges in energy demand can lead to inefficiencies in power plants and increased emissions, highlighting the critical need for accurate forecasting. Effective energy prediction is particularly vital for developing nations, where resource constraints demand optimal utilization of existing infrastructure [3].

Machine learning provides a solution by utilizing historical data and real-time analytics to predict energy generation and consumption patterns accurately. By analyzing parameters such as weather conditions, economic activities, and consumption habits, ML algorithms enable utilities to balance supply and demand effectively. This proactive approach minimizes wastage, ensures grid stability, and supports sustainable development initiatives [21].

1.2 Importance of Accurate Energy Forecasting

Energy forecasting is foundational to achieving efficient energy management, ensuring grid stability, and promoting sustainable resource utilization. Machine learning excels in both long-term and short-term forecasting by processing vast amounts of historical and real-time data. Its ability to adapt to changing patterns makes it invaluable for:

- **Grid Stability:** By predicting load fluctuations, ML models prevent overloading and under utilization of grid resources.
- **Sustainable Practices:** Forecasting helps integrate renewable energy sources, such as wind and solar, into the grid by accounting for their intermittent nature.
- **Economic Optimization:** Accurate forecasts reduce operational costs by minimizing the reliance on auxiliary power plants and optimizing fuel usage [23].

This article reviews the primary machine learning models utilized for energy forecasting. The review aims to identify which variables exert the most significant influence on energy consumption patterns. By doing so, it provides actionable insights for improving prediction accuracy and selecting appropriate ML techniques for specific scenarios [11][15].

2 Role of Energy Prediction in Economy

Energy prediction plays a crucial role in shaping economies by enabling efficient resource allocation, minimizing costs, supporting sustainable development, and fostering innovation. Accurate energy forecasting ensures that supply meets demand, reduces uncertainties, and optimizes energy use—essential factors for economic stability and growth. Governments and corporations leverage energy forecasts to make informed decisions about energy production, infrastructure development, and resource allocation. By reducing the risk of energy shortages or surpluses, forecasting contributes to the creation of sustainable and efficient energy systems [9][10].

2.1 Resource Allocation

Energy forecasting aids businesses, utilities, and governments in planning resource allocation. For instance, resources such as coal, natural gas, and renewable energy can be distributed effectively based on demand projections. This reduces waste and ensures a reliable energy supply for critical economic activities like manufacturing and services, which are vital for GDP growth [13][24].

2.2 Policy Development

Accurate energy predictions enable the formulation of policies that promote energy efficiency and encourage the adoption of renewable energy sources. By minimizing risks associated with energy interruptions, forecasting strengthens economic resilience. For example, energy providers can adjust production to avoid shortages and surpluses, maintaining market stability and preventing price volatility [9][24].

2.3 Grid and Renewable Integration

Grid upgrades and the incorporation of renewable energy sources heavily depend on accurate energy projections. Forecasting provides insights into the continuous and variable nature of renewables like solar and wind energy. By reducing dependency on fossil fuels, energy forecasting supports the optimization of energy source balances, fostering a sustainable energy future. This is particularly important in rapidly urbanizing areas, where precise forecasts assist in power infrastructure expansion and the integration of renewables [13].

2.4 Infrastructure Investment

Long-term energy projections guide investments in infrastructure, including power plants, renewable energy projects, and grid expansions. These investments are crucial for meeting future energy demands and avoiding bottlenecks that could hinder economic growth. For instance, underestimating future energy consumption may result in power shortages, disrupting businesses and reducing productivity [24].

2.5 Economic Transformation and Job Creation

As economies transition to cleaner energy sources, accurate energy forecasting becomes indispensable for integrating weather-dependent renewables like solar and wind. Forecasting tools maintain grid stability by balancing renewable and conventional energy supplies. This transition drives the creation of environmentally friendly jobs, encourages investment in sustainable technologies, and bolsters long-term economic growth [10][24].

Energy forecasting is vital for economic planning and development. It ensures reliable energy provision, reduces costs, and fosters innovation. As global energy systems shift toward sustainability, the importance of accurate forecasting will grow, influencing policies, investments, and economic trends worldwide [9][10][13][24].

3 Applications of Machine learning models

3.1 Machine Learning in the Energy Sector

ML optimizes energy systems by leveraging large-scale data to improve predictions, integrate renewables, and reduce carbon emissions. Models like Gradient Boosting and LSTM networks excel in short- to long-term energy demand forecasting, enhancing grid reliability and operational efficiency [24].

3.2 Machine Learning in Robotics

ML enables intelligent, adaptable robots capable of performing complex tasks. Applications span autonomous vehicles, industrial automation, and healthcare robotics, with future advancements driving more versatile and efficient solutions [25].

3.3 Machine Learning in Healthcare

In healthcare, ML improves diagnostics, optimizes treatments, and enhances operational efficiencies. By analyzing vast datasets, ML algorithms identify patterns to address healthcare challenges proactively [23].

3.4 Machine Learning Models for Energy Prediction

3.4.1 Long Short-Term Memory (LSTM)

LSTM, a type of recurrent neural network, excels in time-series forecasting by capturing long-range dependencies in sequential data.

Key features include:

- Applications: Energy consumption patterns with seasonality and irregular variations.
- Strengths: Effective for large datasets and non-linear patterns.
- Limitations: High computational cost and significant training time due to complex internal gates [2][17].

3.4.2 Support Vector Machines (SVM)

SVM is ideal for medium-sized datasets with high dimensionality and non-linear patterns.

Key features include:

- Applications: Historical energy data combined with external factors (e.g., weather, occupancy).

- Strengths: Robust against overfitting and noise.
- Limitations: Computationally expensive and memory-intensive for large datasets [23].

3.4.3 XGBoost

XGBoost, a decision-tree-based algorithm, is valued for its speed, scalability, and ability to handle diverse datasets.

Key features include:

- Applications: Regression and classification tasks in energy systems.
- Strengths: High accuracy and efficient parallel computation.
- Limitations: Requires extensive hyper parameter tuning [24].

3.4.4 Random Forest

Random Forest combines multiple decision trees to enhance prediction accuracy.

Key features include:

- Applications: Simple relationships in energy data.
- Strengths: Handles noise well and prevents overfitting.
- Limitations: Difficult to interpret due to the ensemble nature [19].

3.4.5 Decision Trees

Decision Trees are simple yet powerful for energy forecasting, particularly when explainability is essential.

Key features include:

- Applications: Analyzing both numerical and categorical data.
- Strengths: High interpretability and low computational cost.
- Limitations: Prone to overfitting with small changes in data [23].

3.4.6 Metric Parameters for Model Evaluation

Evaluation metrics provide quantitative insights into model performance:

- Mean Absolute Error (MAE): Measures average prediction error magnitude.
- Root Mean Squared Error (RMSE): Highlights larger errors by squaring deviations.
- R² (Coefficient of Determination): Indicates variance explained by the model.
- Mean Absolute Percentage Error (MAPE): Offers error as a percentage for cross-model comparisons.
- Normalized RMSE (NRMSE): Ensures scale-independent evaluations.

Energy prediction is critical for managing resources, enabling sustainable development, and ensuring economic stability. This study highlights the capabilities and limitations of ML models like LSTM, SVM, XGBoost, and Random Forest for energy forecasting. Future

research should explore integrating real-time data streams, ensemble methods, and advanced feature engineering to enhance model accuracy and scalability.

4 Machine learning models for predicting energy consumption

Accurate energy consumption prediction is essential for optimizing energy management, improving power system efficiency, and enhancing resource allocation. This section evaluates key machine learning models used for energy forecasting and examines the variables and systems they are applied to.

4.1 Long Short-Term Memory (LSTM)

LSTM networks, a specialized type of recurrent neural network (RNN), are widely utilized for energy prediction tasks. Their ability to recognize long-range dependencies and capture patterns in sequential data makes them highly effective for forecasting energy consumption. LSTM models are particularly advantageous for time-series data with seasonality, trends, and irregular variations.

- **Advantages:** LSTM's memory cells store pertinent information, while input, forget, and output gates regulate the flow of data, enabling the model to identify relevant historical data for current predictions. This makes LSTMs suitable for both short-term and long-term energy forecasting tasks.
- **Applications:** Forecasting energy demand and supply in scenarios with high data variability and sequential dependencies.
- **Limitations:** High computational cost and training time due to their complex architecture [2][17].

4.2 Support Vector Machines (SVM)

SVM models are highly effective for energy prediction tasks involving high-dimensional data and non-linear patterns. By leveraging historical energy usage data and external factors such as weather and occupancy, SVMs can deliver robust predictions without overfitting.

- **Advantages:** SVM models are resilient to noise and are particularly suited for datasets with small sample sizes. They prevent overfitting while maintaining high prediction reliability.
- **Applications:** Optimizing energy supply, balancing grid loads, and enhancing energy management system efficiency.
- **Limitations:** Computationally expensive and less scalable for very large datasets [23].

4.3 Extreme Gradient Boosting (XGBoost)

XGBoost, a gradient-boosting algorithm, is highly efficient and scalable, making it popular for energy prediction tasks. It incrementally builds an ensemble of decision trees, where each tree addresses the errors of the previous one, leading to a highly accurate predictive model.

- **Advantages:** Combines speed and accuracy, manages complex data structures, and supports regularization to minimize overfitting.
- **Applications:** Regression and classification tasks in energy systems, particularly for datasets with diverse features.

- Limitations: Requires extensive hyperparameter tuning to achieve optimal performance [23][24].

4.4 Random Forest

Random Forest is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reliability. It is effective for both classification and regression tasks.

- Advantages: Handles complex datasets, avoids overfitting, and produces reliable results across various applications. Its bootstrap aggregation approach ensures robustness by training on different dataset subsets.
- Applications: Energy load forecasting and evaluating simple relationships in energy data.
- Limitations: The ensemble nature makes it less interpretable compared to individual decision trees [19].

4.5 Decision Trees

Decision Trees are simple and interpretable machine learning models widely used for energy forecasting. They split datasets into subsets based on feature values, forming a tree-like structure of decisions and outcomes.

- Advantages: Highly interpretable and capable of handling both numerical and categorical data. Decision trees do not require data scaling, relying on relative feature comparisons.
- Applications: Used in fields where model explainability is crucial, such as energy policy development and infrastructure planning.
- Limitations: Prone to overfitting, especially with small changes in data [23].

The machine learning models discussed—LSTM, SVM, XGBoost, Random Forest, and Decision Trees—demonstrate varied strengths and limitations across different energy prediction tasks. Temporal information, such as seasonality and trends, plays a critical role in models like LSTM and SVM. Conversely, ensemble methods like Random Forest and XGBoost excel in handling diverse datasets and improving prediction reliability. Understanding these characteristics is key to selecting the right model for specific energy forecasting requirements.

5 Metric Parameters

The evaluation of energy prediction models relies on statistical metrics to assess their accuracy and reliability. These metrics provide critical insights into how well a model captures energy data patterns and predicts outcomes. Depending on the specific goals—such as minimizing errors or analyzing variability—certain metrics may be prioritized.

5.1 Importance of Metric Parameters

Metric parameters serve as the foundation for quantitatively evaluating the accuracy and dependability of predictive models. By comparing forecasted energy usage (\hat{y}_i) against actual values (y_i), these metrics reveal a model's performance. Common metrics include Root

Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2), each offering a distinct perspective on prediction accuracy [9][10][24].

5.2 Key Statistical Metrics

5.2.1 Terms and Definitions:

- y_i : Actual (observed) value of the i -th data point.
- \hat{y}_i : Predicted value for the i -th data point.
- \bar{y} : Mean (average) of the actual values:

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i \tag{1}$$

- n : Total number of data points.
- Error: The difference between the actual and predicted values:

$$Error = y_i - \hat{y}_i \tag{2}$$

5.3 Metrics

5.3.1 Mean Absolute Error (MAE):

Measures the average magnitude of prediction errors, irrespective of direction.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \tag{3}$$

5.3.2 Mean Squared Error (MSE):

Calculates the average squared difference between actual and predicted values, emphasizing larger errors.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \tag{3}$$

5.3.3 Root Mean Squared Error (RMSE):

The square root of MSE, aligning error units with the original data.

$$RMSE = \sqrt{MSE} \tag{4}$$

5.3.4 R-squared (R^2):

Quantifies the proportion of variance in the dependent variable (y_i) explained by the model.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \tag{5}$$

5.3.5 Mean Absolute Percentage Error (MAPE):

Expresses errors as a percentage of actual values, facilitating cross-scale comparisons.

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{6}$$

5.3.6 Coefficient of Variation of RMSE (CVRMSE):

Normalizes RMSE by the mean of actual values, yielding a unit-less percentage.

$$CVRMSE = \frac{RMSE}{\bar{y}} \tag{7}$$

5.3.7 Explained Variance (EV):

Assesses how much variance in the target variable y_i is captured by the model.

5.3.8 Normalized Root Mean Squared Error (NRMSE):

Adjusts RMSE for comparisons across datasets with varying scales.

5.3.9 Mean Squared Logarithmic Error (MSLE):

Suitable for datasets where predictions span multiple orders of magnitude.

5.3.10 Cross-Validation:

Techniques like k-fold validation evaluate a model's generalization performance by partitioning the dataset into training and testing subsets [15].

5.4 Balancing Factors in Energy Prediction

Effective energy forecasting depends on balancing metrics, input features, hyperparameter optimization, and data quality. Striking this balance ensures models generalize effectively to unseen data while maintaining scalability and interpretability [23].

Metrics such as RMSE, MAE, and NRMSE are vital for evaluating machine learning models in energy prediction. Coupled with robust input features and optimized parameters, these metrics underpin accurate, scalable, and sustainable forecasting systems. Effective evaluation

contributes to optimized energy production, distribution, and consumption, supporting long-term sustainability goals.

6 Conclusion

Energy forecasting plays a critical role in modern life due to its significant financial and operational benefits. This study highlights the application of machine learning methods for predictive analysis of energy usage, demonstrating their ability to improve forecasting accuracy and enable efficient energy management. Traditional approaches often fall short in capturing periodicity and complex patterns in energy data, whereas advanced machine learning techniques have shown superior performance.

Table 1. Comparison of key machine learning models

Criteria	Data Suitability	Types of Data	Capacity Prediction	Training Time	Computational Cost	Limitations
Long Short-Term Memory (LSTM)	High-dimensional data	Voltage, Current, Power Demand	Potential for high accuracy for sequential data	High (hours to days)	High due to time-consuming processes	Requires significant computational resources, long training time; needs large datasets to perform well.
XGBoost	Structured data	Voltage, Current, Temperature	Can achieve high accuracy	Moderate to high (varies with data size)	Low to moderate; memory usage can be high	Extensive hyperparameter tuning needed; high memory consumption with large datasets.
Support Vector Machines (SVM)	High-dimensional	Unstructured data; Voltage, Current, Load	High accuracy for medium-sized datasets	High for large datasets	High with non-linear kernels	Computationally expensive and memory-intensive for large datasets; difficult to interpret results.
Random Forest	Simple relationships	Voltage, Current, Simple relationships	Can achieve high accuracy	Fast (seconds to hours)	Moderate due to multiple decision trees	Harder to interpret than a single decision tree due to the ensemble nature.
GA-PSO-BPNN	Complex, high-dimensional data	Complex datasets: Voltage, Current, Humidity, Temperature	High accuracy for small datasets	High for large datasets (minutes to weeks)	High due to multi-stage optimization	Computationally expensive due to multiple optimization and training stages.
Decision Trees	Numerical and categorical data	Continuous and discrete data	High accuracy	Fast for small datasets	Low for smaller datasets	Sensitive to small data changes, leading to significantly different tree structures.

By comparing various machine learning models, such as XGBoost, Random Forest, Decision Trees, and LSTM networks, this study showcases their distinct strengths and limitations. Table 1 is a comparison of key machine learning models based on their suitability for energy forecasting.

LSTM networks, for instance, excel in identifying non-linear patterns and long-range dependencies in time-series data, making them particularly effective for energy forecasting. Support Vector Machines (SVMs) are highlighted for their robustness in handling high-dimensional data and resilience against overfitting, especially in noisy, real-world datasets. The importance of feature engineering and hyperparameter tuning in optimizing model performance is also emphasized.

Energy forecasting has broader implications, influencing investment, policy decisions, and resource allocation. Accurate predictions support the development of sustainable energy systems, enabling governments and organizations to plan for energy production, infrastructure development, and emergency scenarios. Advanced forecasting methods are particularly critical for integrating renewable energy sources, such as solar and wind, which are highly weather-dependent.

Future research in this domain could focus on integrating real-time data streams, leveraging advanced feature engineering techniques, and employing ensemble methods to further enhance the performance of machine learning models. Machine learning's ability to identify non-linear relationships, process vast amounts of structured and unstructured data, and adapt to dynamic conditions sets it apart from traditional statistical methods. These capabilities enable improved forecasting of energy demand, generation, and consumption, supporting both strategic planning and operational decision-making.

As energy demand continues to rise, the development of precise, scalable, and interpretable forecasting models will become increasingly essential, impacting global economic trends and policy formulation. Future advancements in this field will drive progress toward more efficient, reliable, and sustainable energy systems.

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