International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Review Article)

Short term load forecasting analysis using machine learning method: An SVM based study

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International Journal of Science and Research Archive, 2024, 13(01), 864–870

Publication history: Received on 19 July 2024; revised on 16 September 2024; accepted on 19 September 2024

Article DOI: https://doi.org/10.30574/ijsra.2024.13.1.1624

Abstract

Short-Term Load Forecasting (STLF) is crucial for effective energy management, enabling utilities to optimize electricity generation, distribution, and pricing strategies. This study explores the application of three machine learning models—Linear Regression (LR), Artificial Neural Networks (ANN), and Support Vector Machines (SVM)—to predict short-term electrical load demand. Each model was trained using historical load data enriched with temporal features to capture daily, seasonal, and other variations in electricity consumption. The SVM model demonstrated strong predictive capability, achieving a Mean Absolute Error (MAE) of 1887.41 MW, Mean Squared Error (MSE) of 6942.36 GW, Root Mean Squared Error (RMSE) of 2634.83 MW, and an R2 score of 91.95%. In comparison, the ANN model showed slightly higher errors, while the LR model had the highest error rates, indicating its limitations in capturing non-linear relationships. The results suggest that SVM and ANN models are more effective than LR for STLF due to their ability to handle non-linear dependencies and high-dimensional data. This study highlights the potential of machine learning techniques in enhancing the accuracy and reliability of load forecasting, ultimately supporting better decision-making in energy management.

Keywords: Forecasting analysis; Machine learning method; SVM based study

1. Introduction

Short-Term Load Forecasting (STLF) is a critical component of power system management, directly influencing the efficiency of electricity generation, transmission, and distribution processes. With electricity demand patterns continually evolving due to changing consumer behavior, urbanization, and the integration of renewable energy sources, accurately predicting short-term load demand has become a significant challenge. The ability to forecast load demand with precision allows power utilities to optimize their resources, ensure grid stability, and make informed decisions regarding energy generation and distribution, ultimately reducing operational costs and enhancing the overall performance of the power system. Traditional methods such as regression analysis, time series modeling, and pattern recognition techniques have been widely used for load forecasting. However, these approaches often struggle to handle the inherent non-linearity and complexity of modern energy consumption patterns, particularly in large and diverse grids. Consequently, more advanced techniques are needed to improve the accuracy and reliability of load forecasts. In this context, machine learning (ML) methods, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and decision trees, have emerged as effective alternatives. These models are adept at capturing complex, non-linear relationships in data and have shown promise in various applications, including energy forecasting. Among the ML techniques, Artificial Neural Networks (ANN) have been particularly effective due to their flexibility in model structure and ability to learn from data patterns. Different types of ANNs, such as backpropagation networks, Hopfield networks, and Boltzmann machines, offer varied capabilities for building accurate forecasting models. Additionally, other state-of-the-art ML methods, such as SVMs and ensemble techniques, have also been employed for STLF,

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demonstrating improved performance over traditional methods. These advanced models not only enhance forecasting accuracy but also address the limitations of classical statistical methods by effectively modeling complex, non-linear dynamics.

Current work focuses on evaluating and comparing three machine learning models—Linear Regression (LR), ANN, and SVM—for their efficacy in short-term load forecasting. The objective is to identify the most suitable model that can provide accurate and reliable load forecasts, thereby supporting more efficient power system operations. By leveraging historical load data and advanced ML techniques, this study aims to contribute to the ongoing development of effective load forecasting models, which are essential for modern energy management. Short-term load forecasting (STLF) is essential for guaranteeing the optimal operation of power systems, since the accuracy of load prediction has a substantial impact on the industry's performance and expenses. Traditional techniques, such as regression, time series, pattern recognition, and the Kalman filter model, are inappropriate for complicated nonlinear models. Therefore, artificial neural networks (ANN) have emerged as a viable option, employing back-propagation (BP), Hopfield and Boltzmann machines, fed forward or backward models, and optimal weights allocation to build accurate models.

Various researchers in the modern age also employed cutting-edge machine learning techniques in their research. For example, Shahare et al. (2023) compared traditional methods like exponential smoothing with machine learning methods, including SVM, ANN, and a CNN-LSTM hybrid, finding that the hybrid model achieved the highest correlation coefficient for load prediction accuracy. Zulfikar et al. (2023) proposed a hybrid model integrating locally weighted support vector regression with optimization algorithms, showing improved accuracy and stability for load forecasting.

Table 1 Summary analysis of the published literature

Reference	Study Focus	Key Methods/Models Used	Key Findings
Shahare et al., 2023 [1]	Comparison of traditional methods vs. machine learning methods for STLF.	CNN-LSTM hybrid model, ANN, SVM, ensemble methods, deep learning techniques	CNN-LSTM hybrid model achieved the highest correlation (R=95.05%). Hybrid methods outperform traditional methods for load forecasting.
Zulfikar et al., 2023 [2]	Hybrid load forecasting model integrating optimization techniques.	Locally Weighted Support Vector Regression (LWSVR), Adaptive Grasshopper Optimization (AGO), Feature Engineering (FE)	Proposed model enhances stability, accuracy, and convergence rate for STLF in smart grids, outperforming benchmark models with actual load data.
Chen et al., 2022 [3]	Optimal data length for STLF in buildings using machine learning.	LightGBM, k-means clustering, CV(RMSE) analysis	Reduced prediction error by 15% for length-sensitive buildings. Improved performance by optimizing training data length and reducing data noise.
Deng et al., 2022 [4]	STLF model for extreme weather conditions using ensemble methods.	Bagging-XGBoost (BG-XG), weather factor analysis, Mutual Information	The model reduces Mean Absolute Percentage Error by 3-10%, provides accurate load forecasts and early warning information, improves grid stability.
Xiang et al., 2022 [5]	Weight assignment method for improving STLF accuracy in data-driven models.	Sample similarity measurements, weight assignment to training samples, Deep Neural Network (DNN)	Proposed method enhances accuracy without altering model structure or feature selection; demonstrates scalability across various STLF models.
Guo et al., 2021 [6]	Multi-step load forecasting for household electrical data.	LSTNet (long- and short-term time series network), CNN, LSTM, Autoregressive (AR) models	The proposed model outperforms other algorithms, effectively captures time series relationships with higher prediction accuracy.
Li et al., 2021 [7]	Fuzzy theory-based ML model for STLF	Data de-noising, Fuzzy Time Series, Back Propagation Neural Network (BPNN),	The model improves accuracy and stability, better than individual or hybrid

	considering temporal patterns.	Multi-Objective Optimization Algorithm (MODA)	models without preprocessing, provides confidence intervals for predictions.
Panda et al., 2021 [8]	Comparison of GA-based BP and PSO-based BP for STLF using ANN.	Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Back Propagation Neural Network (BP)	PSO-BP is more efficient with a prediction accuracy of 1.40%. Suitable for non-linear problems in STLF and other domains like signal processing.
Sahu et al., 2021 [9]	Modified optimization and learning approach for real-time solar power prediction.	Modified Teaching Learning-Based Optimization (MTLBO), Extreme Learning Machine (ELM)	MTLBO-ELM model outperforms others in accuracy, training speed, and generalization, proving suitable for SPG prediction in power grids.
Singh et al., 2021 [10]	Day-ahead electrical load forecasting model combining wavelet transform with SVM.	Repeated Wavelet Transform-based SVM (RWT-SVM), comparison with models like ARIMA, LSTM, XGBoost	RWT-SVM outperforms other models, with Gaussian kernels yielding better results. Suitable for power system control and planning.

Chen et al. (2022) explored the use of LightGBM and clustering techniques to determine optimal historical data for forecasting multiple buildings, reducing prediction error significantly. Deng et al. (2022) utilized a Bagging-XGBoost approach to address extreme weather impacts on load forecasting, achieving better accuracy than traditional methods. Xiang et al. (2022) introduced a sample-weighted assignment method to enhance the accuracy of STLF models. These studies underscore the growing trend towards leveraging advanced ML techniques to improve load forecasting, identifying gaps and potential future research directions in the field.

2. Support Vector Machine (SVM) Modelling for STLF

Support Vector Machines (SVM) are powerful machine learning models commonly applied in Short-Term Load Forecasting (STLF). SVM, a supervised learning algorithm, aims to find an optimal hyperplane in a high-dimensional space to separate and classify data points. In STLF, SVM is adapted for regression tasks, predicting load values with high accuracy. The basic concept behind SVM regression is to construct a hyperplane that maximizes the margin around the predicted load values. Support vectors, the data points closest to the hyperplane, influence its position and help minimize regression error while maximizing the margin.

The model is formulated as follows:

$$Y\hat{}=b+\sum(\alpha i*K(Xi,X))+\varepsilon$$

Here, $\hat{Y}$ is the predicted load, b is the bias term, α_i are Lagrange multipliers, $K(X_i, X)$ is the kernel function, and ε is the error term. The kernel function is crucial, mapping input features to a higher-dimensional space to capture non-linear relationships. Popular kernel functions in STLF include the Linear Kernel, Polynomial Kernel, and Radial Basis Function (RBF) Kernel. Parameter tuning, involving the selection of kernel type, regularization parameter (C), and kernel-specific parameters (γ, d), is essential for optimal performance. Techniques like grid search and cross-validation are used to determine the best parameter configuration. SVM model performance is evaluated using error metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics, along with visual analysis and cross-validation, help assess the accuracy and generalization capabilities of the SVM model in STLF scenarios.

3. Dataset Selection for Short-Term Load Forecasting (STLF)

The dataset utilized in this study is sourced from ENTSO-E, the European Network of Transmission System Operators for Electricity, a leading association responsible for the efficient and coordinated operation of the European electric power system. This data set, encompassing data from various transmission system operators (TSOs) across Europe, is characterized by its extensive coverage and diverse metrics. It includes detailed records of power consumption, generation, and transmission, providing a comprehensive perspective on the operational dynamics of the European power grid. The dataset spans multiple years and covers numerous European regions, thereby incorporating a wide range of energy sources, from conventional power plants to renewable energy installations. This diversity allows the modeling to capture the inherent variability in energy demand and supply, which is crucial for accurate STLF. The data's temporal granularity ranges from high-resolution intervals, such as 60-minute data points, to more aggregated, longerterm trends. This range enables the application of various forecasting techniques, accommodating both short-term fluctuations and long-term patterns in load behavior.

In this study, the dataset for Great Britain (GB) from 2016 to 2019, recorded at one-hour intervals, is selected for detailed analysis. This dataset, provides a rich source of information, allowing the study to evaluate the performance of different machine learning models, such as Linear Regression, and Support Vector Machines (SVM). By using real-world data, the study aims to offer practical insights into the effectiveness of these models under different operational conditions. The dataset includes critical parameters such as hourly load values, timestamps, country codes, and covariate ratios, which are essential for understanding the underlying patterns in electricity demand. Each entry in the dataset reflects the power consumption recorded at specific time intervals, providing a comprehensive hourly profile of electricity usage across different days and seasons. This extensive dataset not only facilitates a thorough comparative analysis of different STLF modeling techniques but also ensures that the findings are directly applicable to real-world scenarios.

4. Result and Discussion

The Support Vector Machine (SVM) model was evaluated for its effectiveness in Short-Term Load Forecasting (STLF), focusing on predicting electrical load demand over short time intervals. The results of the SVM model's application to the STLF problem are promising, indicating that the model can achieve a high level of accuracy in predicting load values.

4.1. Evaluation Metrics and Performance Analysis

- The SVM model's performance was assessed using several metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics provide a comprehensive evaluation of the model's prediction accuracy and reliability.
- Mean Absolute Error (MAE): The SVM model achieved an MAE of 1887.41 MW, suggesting that the average deviation of the predicted load values from the actual load values is approximately 1887.41 MW. This relatively low MAE indicates that the SVM model can make accurate predictions of the electrical load demand.
- Mean Squared Error (MSE): The MSE value of 6942.36 GW shows the average squared difference between predicted and actual values. The low MSE indicates a good fit between the model's predictions and the actual load values.
- Root Mean Squared Error (RMSE): The RMSE of 2634.83 MW offers an interpretable measure of prediction error. The RMSE value suggests that, on average, the predicted load deviates from the actual load by around 2634.83 MW. The low RMSE value is consistent with the MAE, indicating that the SVM model provides robust predictions with minimal error.
- Mean Absolute Percentage Error (MAPE): The SVM model's average MAPE is 4.8%, while the minimum MAPE observed is 0.0003%. The relatively low MAPE value indicates that the SVM model's prediction errors are minimal compared to the actual load values, further affirming the model's reliability.
- Coefficient of Determination (R^2): The R^2 score of 0.9194 implies that the SVM model explains about 91.95% of the variance in the load data, signifying a strong correlation between the predicted and actual load values.

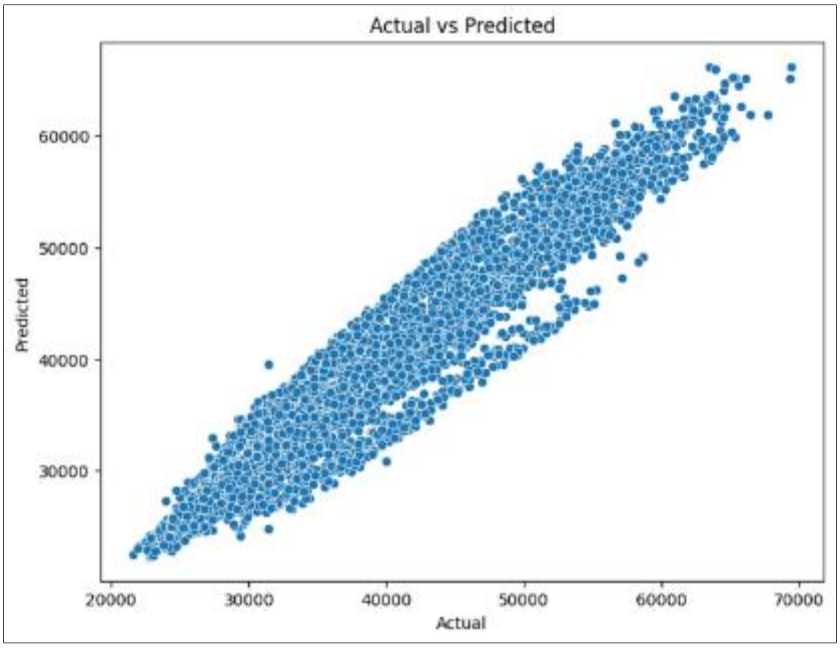

Figure 1 Model comparison using SVM machine learning method

4.2. Comparative Analysis of the Predicted and Actual Values

Present section a comparison of the original and predicted load values using the SVM model. The predicted values closely follow the actual values, with a few exceptions where discrepancies are noticeable. For example, at Time 23 and Time 24, the model exhibited higher MAPE values of 18.16% and 13.78%, respectively, indicating deviations between the actual and predicted loads during specific time intervals. These outliers could be attributed to sudden changes in load demand or other external factors not captured by the model's features.

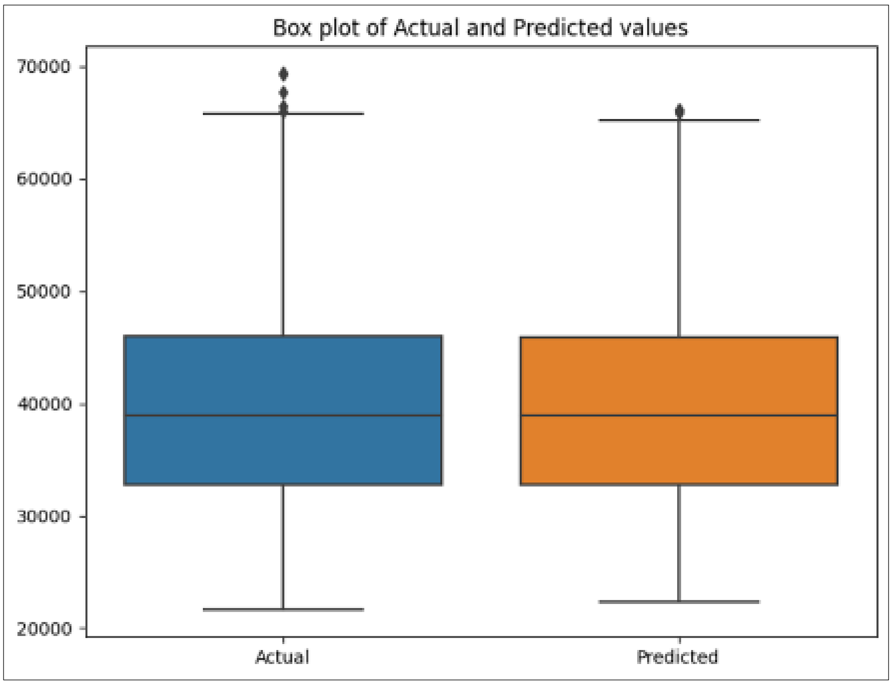

Figure 2 Box plot analysis of the SVM analysis

The findings reveal that the SVM model is highly effective for STLF, achieving a balance between accuracy and computational efficiency. Compared to simpler models like Linear Regression (LR), the SVM model performs better in capturing non-linear relationships and complex load patterns. This is evident from the SVM model's higher R^2 score and lower MAE, MSE, and RMSE values.

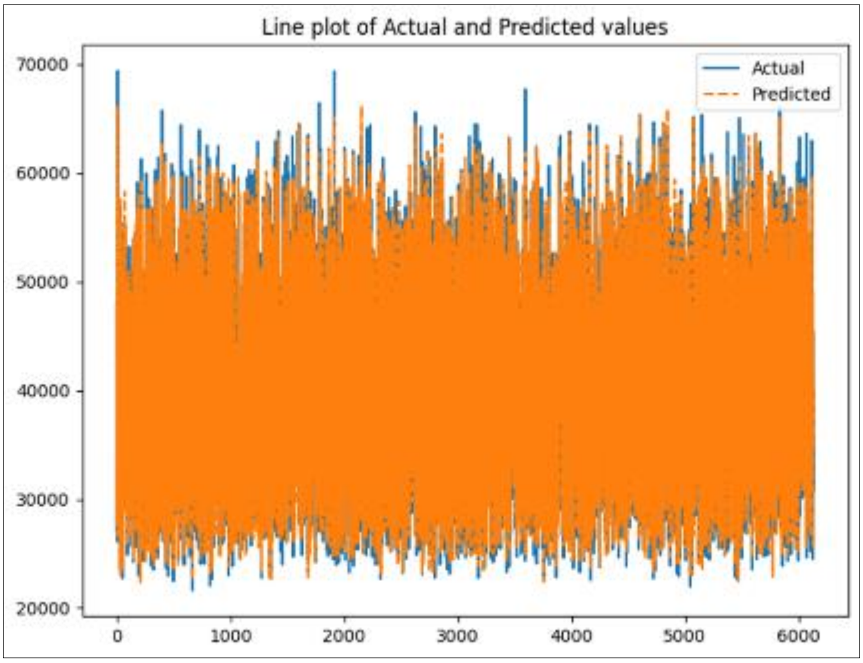

Figure 3 Real data and prediction analysis of the SZTLF modeling

Certain limitations are observed in the model's performance. For instance, the model's prediction errors are more pronounced during specific time intervals, suggesting that additional factors, such as weather conditions, economic activities, or unexpected load shifts, may need to be incorporated into the model to enhance its accuracy further. Additionally, the choice of hyperparameters and kernel functions can significantly influence the model's performance, suggesting a need for careful tuning to achieve optimal results.

5. Conclusion

The research presented a comprehensive analysis of three machine learning models—Linear Regression, Artificial Neural Networks, and Support Vector Machines—for Short-Term Load Forecasting. The SVM model outperformed the other two in terms of prediction accuracy, demonstrating the lowest MAE, MSE, and RMSE values and a high R2 score, thereby validating its effectiveness in capturing complex patterns in load data. The ANN model, while also effective, showed marginally higher errors, suggesting that its performance may depend on hyperparameter tuning and computational resources. Conversely, the LR model, which assumes a linear relationship, exhibited the highest prediction errors, underscoring its limitations in handling non-linear and complex patterns. The findings indicate that SVM and ANN models are better suited for STLF, especially in scenarios where accurate load predictions are critical. However, considerations such as computational complexity, interpretability, and data availability must guide the selection of the appropriate model for practical applications. Future research could explore hybrid approaches combining the strengths of these models and incorporating additional factors, such as weather data, to further enhance forecasting accuracy and utility in real-world scenarios.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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