Journal of Science and Engineering Research
Vol. 3, No. 1, 2024, pp. 17-32
eISSN: 2957-7187

Enhanced Short-Term Load Forecasting using Artificial Neural Networks: A One-Day-Ahead Approach

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DOI: http://dx.doi.org/10.56828/jser.2024.3.1.2
Article Info: Received: (February 26, 2024); Review Result: (April 6, 2024); Accepted: (May 9, 2024)

Abstract: Short-Term Load Forecasting (STLF) plays a fundamental role in modern energy management systems by enabling efficient power generation, distribution, and consumption planning. Accurate predictions mitigate electricity wastage, reduce operational costs, and prevent system failures, particularly during peak demand. This study proposes a novel one-day-ahead STLF approach using Artificial Neural Networks (ANNs), incorporating temperature-sensitive variables to enhance forecasting precision. The research identifies and addresses weather factors' significant impact on hourly load patterns, especially temperature. The model uses historical hourly load and weather data to predict load demand. Key input features include hourly load values from two previous days and one week before the forecast day, combined with detailed temperature data. Load sensitivity analysis is conducted to categorize demand into concentrated and scattered periods, enabling dynamic adjustment of temperature weights during peak and off-peak hours. The methodology is tested using historical load data from Connecticut, USA, for the summer and winter seasons of 2010-2012. Experimental results demonstrate the efficacy of the proposed model, achieving a Mean Absolute Percentage Error (MAPE) of 2.20% in summer and 2.40% in winter. The use of temperature-sensitive weights significantly improves accuracy compared to traditional ANN models. These findings underscore the importance of weather-sensitive inputs in STLF and provide a robust framework for optimizing load forecasting models. The research has critical implications for energy providers, aiding in developing reliable, cost-effective, and environmentally sustainable power systems. Future work could further explore integrating additional meteorological variables, alternative machine learning techniques, and diverse geographic datasets to enhance forecasting accuracy.

Keywords: Short-term load forecasting, Artificial neural networks, Power systems, Time series forecasting, Energy forecasting

1. Introduction

In modern energy systems, the efficient generation, distribution, and utilization of electricity are central to economic development and environmental sustainability. As the global energy demand continues to grow, power providers face increasing pressure to ensure the stability and reliability of electrical grids while minimizing waste and reducing operational costs. Short-Term Load Forecasting (STLF) is a critical component of this effort, enabling utilities to predict electricity demand accurately. Accurate load forecasting allows power providers to adjust supply mechanisms in real-time, reducing the risk of outages, improving grid stability, and enhancing resource allocation. In particular, STLF contributes to energy efficiency by minimizing energy wastage and optimizing the operation of power plants. However, achieving high precision in STLF remains a significant challenge due to the dynamic and multifaceted nature of electricity demand, which is influenced by various factors such as consumer behaviour, industrial activity, and weather conditions. A key challenge in this area is accounting for weather-related variables, particularly temperature, which profoundly impact electricity demand patterns, especially during peak demand periods [1][2].

Research has consistently shown a strong correlation between temperature fluctuations and power consumption, with temperature spikes often triggering increased demand for cooling in summer or heating in winter. Previous studies have emphasized the importance of including temperature as a dynamic variable in STLF models, particularly in regions where climate is dominant in shaping energy consumption patterns [3]. Despite advancements in computational models, many traditional STLF approaches still struggle to dynamically incorporate weather factors, leading to reduced forecasting accuracy, particularly during periods of extreme temperature. These limitations necessitate the development of innovative methodologies that can better model the complex relationship between weather conditions and electricity demand. Artificial Neural Networks (ANNs), which can handle large and complex datasets, have emerged as a promising tool to address this challenge. By training ANNs to account for nonlinear relationships between temperature and load demand, researchers have significantly improved the accuracy of load forecasting models [4][5].

This study investigates a one-day-ahead STLF model based on ANNs, focusing on incorporating temperature-sensitive variables to enhance forecasting accuracy. The proposed model dynamically adjusts temperature weights based on the time of day and the anticipated demand patterns, providing more accurate predictions for concentrated and scattered demand periods. This research uses historical hourly load and temperature data to identify key patterns that optimize forecast precision across different seasons, thereby improving the ability to predict demand peaks and troughs more accurately. This dynamic approach addresses the limitations of traditional models, which often fail to adjust for the fluctuating nature of temperature and its influence on electricity demand.

The importance of accurate STLF extends far beyond operational efficiency. It plays a vital role in sustainable energy management, particularly in regions experiencing rapid urbanization and significant climate variability. As the integration of renewable energy sources, such as solar and wind, becomes more widespread, accurate load forecasting is essential for balancing supply and demand and ensuring the grid's stability. Reliable load forecasting is also crucial for equitable power distribution, helping to avoid power shortages or excess generation, which can be costly and environmentally damaging. Furthermore, accurate forecasting can help utilities manage the integration of renewable energy sources by predicting periods of high demand when renewables may not be sufficient, thereby enabling better decision-making in grid management. Recent studies underscore the value of ANN-based forecasting in improving the reliability and adaptability of energy systems, particularly in regions like South Africa, which face challenges related to energy demand and climate variability [6].

This research contributes to advancing the state of the art in STLF by addressing two key objectives: first, to develop an ANN-based STLF model that incorporates temperature-sensitive variables, and second, to evaluate its performance against traditional forecasting approaches using real-world data. By integrating temperature fluctuations dynamically into the forecasting process, this study offers valuable insights that can help energy providers, policymakers, and researchers improve the precision and adaptability of STLF models. These findings promise to enhance energy systems worldwide, particularly in regions with diverse weather patterns and growing energy demands, and contribute to achieving sustainable, efficient, and resilient energy management.

2. Literature Review

2.1. The role of weather variables in short-term load forecasting

Weather variables, particularly temperature, have long been recognized as critical determinants of electricity demand, especially in urban and densely populated regions. Lee et al. [7] found that load demand during peak hours is susceptible to temperature fluctuations, with sharp increases observed during extreme weather conditions, such as heat waves or cold snaps. This correlation is particularly pronounced in regions where Heating, Ventilation, And Air Conditioning (HVAC) systems dominate electricity consumption. However, while temperature is the most studied factor, other variables like humidity, wind speed, and solar radiation influence demand. Jiang et al. [8] demonstrated that combining temperature with secondary weather factors enhances the robustness of load forecasting models, particularly in regions with diverse climatic conditions.

Raza and Khosravi [9] reviewed STLF methodologies comprehensively, highlighting the importance of integrating weather variables into predictive models. They emphasized that failing to account for these factors can result in significant forecasting errors, especially during seasonal transitions. Building on this foundation, Sun et al. [10] introduced a novel approach that segments load demand into time-based categories, allowing for more precise modeling of temperature-sensitive periods. This method aligns with the present study's focus on categorizing load sensitivity by time of day, offering a promising avenue for improving forecasting accuracy.

Despite these advances, significant gaps remain in the literature. Existing models often oversimplify the dynamic interactions between weather variables and load demand, particularly in regions with rapidly changing climates or urbanization patterns. For instance, Kim et al. [11] noted that smaller utilities often lack the resources to implement complex weather-based models, leading to suboptimal predictions. Furthermore, while the impact of temperature is well-documented, limited attention has been given to exploring the effects of combined weather variables on load patterns, highlighting an area for further research.

2.2. Machine learning techniques in load forecasting

Applying Machine Learning (ML) techniques, particularly Artificial Neural Networks (ANNs), has transformed the field of short-term load forecasting. ANNs excel in capturing nonlinear relationships and processing large datasets, making them ideal for modeling the complex interactions between historical load data and influencing factors like weather and consumer behavior. Zhang et al. [19] introduced a hybrid ANN model that integrates feature selection algorithms, achieving significant improvements in accuracy compared to traditional statistical approaches. Their findings demonstrate that careful selection of input variables, such as temperature and historical load patterns, is crucial for optimizing ANN performance.

Further advancing the field, Cheng and Wang [12] applied Long Short-Term Memory (LSTM) networks to model temporal dependencies in load data. Their results showed that

LSTM models outperformed conventional ANNs in multi-day forecasts by effectively capturing the sequential nature of electricity demand. However, they noted that LSTMs require substantial computational resources and large datasets for training, which may limit their accessibility for smaller utilities or regions with limited data availability.

Explainability in machine learning models is another emerging area of interest. Tang et al. [13] argued that while ANN and other ML models often provide superior accuracy, their "black box" nature poses challenges for interpretability and stakeholder trust. They proposed integrating Explainable AI (XAI) techniques into load forecasting models to enhance transparency and facilitate decision-making processes. This aligns with the need for accurate and interpretable models, particularly in high-stakes energy management scenarios.

Despite these advancements, the literature reveals several limitations. Ayoobi et al., [14] highlighted the lack of regional customization in many ML models, noting that models trained on one dataset often fail to generalize to other regions with different climatic or socioeconomic conditions. Banerjee and Gupta [15] also emphasized the need for integrating temporal segmentation into ML frameworks to account for variations in load sensitivity across different times of the day and year. Addressing these gaps is essential for developing scalable and adaptable models, ensuring their applicability across diverse energy systems.

The current study builds on these findings by integrating time-sensitive temperature variables into an ANN-based STLF model. By dynamically adjusting temperature weights during concentrated and scattered demand periods, this approach seeks to address the limitations of existing methodologies and improve forecasting accuracy in real-world scenarios.

2.3. Hybrid models in short-term load forecasting

The growing complexity of electricity grids has prompted the adoption of hybrid models that merge multiple predictive methodologies to enhance short-term load forecasting (STLF). These models integrate statistical techniques with machine learning algorithms, leveraging their respective strengths while addressing individual limitations.

Recent research in the United States has highlighted the success of hybrid frameworks that combine machine learning with time-series decomposition methods. For example, Rajagopalan and Wang [16] employed a combination of Long Short-Term Memory (LSTM) networks and Autoregressive Integrated Moving Average (ARIMA) models. This approach improved accuracy by capturing temporal dependencies and seasonal trends in load data, particularly in regions with fluctuating weather patterns.

Similarly, in Australia, hybrid models integrating Support Vector Machines (SVMs) and Genetic Algorithms have been deployed to optimize parameter selection and forecasting precision. A study by O'Brien et al. [17] demonstrated that incorporating weather variables such as temperature and humidity into hybrid models significantly reduced forecasting errors, particularly in summer when demand variability is highest.

In the UK, Solyali et al. [18] explored hybrid methodologies combining wavelet transforms with neural networks, achieving notable success in urban grids with high renewable energy penetration. This model excelled in isolating high-frequency variations in load demand, making it especially suitable for innovative grid applications.

While these hybrid models present substantial advancements, challenges such as computational resource requirements and adaptability to diverse network configurations remain. Future research could focus on scalable implementations and regional customization to enhance the practical applicability of hybrid models across varying grid conditions.

3. Research Purpose and Design

This study addresses the critical question: How can integrating dynamic temperature weights improve the accuracy of one-day-ahead Short-Term Load Forecasting (STLF) models using Artificial Neural Networks (ANNs)? Short-term load forecasting plays a crucial role in electricity grid management, as accurate predictions of demand allow for efficient resource allocation, cost minimization, and stability in power systems [21][22]. While numerous forecasting models exist, integrating dynamic factors such as temperature sensitivity has improved their precision, particularly during periods of high demand, such as extreme weather events. This research investigates how dynamic temperature weighting in ANN-based models can enhance forecasting accuracy, focusing specifically on one-day-ahead predictions, which are vital for operational planning in energy systems.

A quantitative research design was adopted to explore this, utilizing a time-series forecasting approach to predict hourly electricity demand. Time-series forecasting allows for the effective modeling of sequential data, capturing trends and seasonal patterns in electricity consumption. This study's design incorporates historical load data alongside weather variables, particularly temperature, as a dynamic factor influencing load patterns. Previous research by Zhang et al. [20] underscores the importance of effective feature selection and preprocessing techniques in improving forecasting performance. This study extends their work by integrating dynamic temperature weights, which are expected to capture better the nuanced relationship between temperature fluctuations and electricity demand.

3.1. Data collection and analysis

The dataset for this study consists of hourly electricity load and weather data for the state of Connecticut from 2010 to 2012, sourced from publicly available energy consumption records and meteorological data. The data was selected to represent a variety of seasonal patterns, with a particular focus on the summer (July) and winter (January) months, as these periods experience the greatest fluctuations in temperature and, consequently, electricity demand. Summer months often witness higher electricity usage due to air conditioning needs, while winter months see increased demand due to heating requirements. The study aims to capture the full spectrum of temperature sensitivity by focusing on these two seasons.

Purposive sampling was employed to isolate data from these high-demand months, ensuring that the model would be tested under conditions where temperature has the most significant impact on load variation. Before the data could be analyzed, it was preprocessed to normalize values and address missing points. Preprocessing is a critical step in machine learning workflows as it ensures that the model is trained on high-quality data, avoiding potential biases and inaccuracies. In addition, feature selection was done to identify the most relevant predictors of electricity demand. The primary input variables for the ANN model included historical load data from two days prior and one week before the target day. The rationale behind including these time-lagged features is that electricity consumption on a given day is often influenced by consumption patterns in the preceding days, especially during periods of steady demand.

Weather variables such as temperature, humidity, and dew point were also included in the model. Temperature, however, was treated as a dynamic variable, with its influence on demand adjusted according to different periods of the day, precisely peak and off-peak hours. The dynamic weighting of temperature sensitivity allows the model to account for the fact that temperature impacts demand differently during the day—higher temperatures during peak demand periods (e.g., late afternoon or evening) might cause a larger increase in electricity consumption, while the same temperature at night may not have the same effect.

An ANN model was constructed using TensorFlow, a popular machine learning framework, and trained using backpropagation. Backpropagation allows the model to learn from the errors in its predictions, iteratively adjusting its internal weights to minimize forecasting inaccuracies. The dataset was divided into training (70%), validation (15%), and testing (15%) sets to ensure that the model was robust and capable of generalizing to unseen data. The dynamic temperature weights were integrated into the model through a weighting mechanism that adjusted the influence of temperature on the forecast during different times of the day. This method is consistent with Sun et al. [10], who demonstrated that time-sensitive adjustments to model inputs can enhance the accuracy of load forecasts.

The Mean Absolute Percentage Error (MAPE) metric was used to evaluate the model's performance. MAPE provides a transparent and interpretable measure of forecasting accuracy by calculating the average percentage difference between predicted and actual values. This metric was chosen because of its ability to capture both the magnitude and direction of prediction errors, offering a comprehensive assessment of model performance.

3.2 Ethical considerations and limitations

The research adhered to ethical standards by using publicly available data, ensuring no private or confidential information was involved. All data sources were appropriately cited, and the methodologies were transparently described to facilitate reproducibility. By relying on publicly available datasets, the study ensured that the research complied with ethical data privacy and participant consent guidelines.

However, several limitations should be acknowledged. First, the scope of the study is geographically limited to the state of Connecticut, which may restrict the generalizability of the findings to other regions with different climatic, economic, and consumption patterns. Although Connecticut's data provides valuable insights into the impact of temperature on load forecasting, the findings may not fully apply to areas with drastically different weather conditions, such as regions with mild climates or those that experience frequent extreme weather events.

Additionally, the computational complexity of the ANN model may pose a challenge for smaller utilities with limited computational resources. Training and deploying an ANN model require significant processing power, which could make it difficult for smaller power companies to adopt this approach without substantial investment in infrastructure. Furthermore, while temperature was dynamically weighted in this study, other weather variables, such as wind speed and solar radiation, were excluded from the model. These variables can influence electricity demand, particularly in areas where renewable energy sources, like wind or solar power, play a significant role. Future research could consider integrating these additional weather variables to provide a more comprehensive model of electricity demand forecasting.

Finally, future studies could expand the geographic scope of this research, integrating data from different regions to assess the robustness of the dynamic temperature weighting approach across varying climatic conditions. Additional variables, such as wind speed, solar radiation, and even economic indicators, could be incorporated to refine the forecasting model further. Moreover, to address the computational challenges associated with ANN models, future research might explore more accessible and efficient machine learning techniques or hybrid models that combine ANNs with other statistical methods to balance accuracy and computational efficiency. This approach aligns with the framework proposed by Cheng and Wang (2021), which advocates for the integration of multiple forecasting methods to enhance model performance.

4. Load Pattern Analysis of the Particular Time Zone

Understanding load patterns within specific time zones is critical for accuracy in short-term load forecasting (STLF). Electricity consumption is intricately linked to human activity patterns, which fluctuate, based on the time of day, day of the week, and season. The relationship between energy demand and human behavior is significant for forecasting because it can provide valuable insights into when and why electricity usage peaks. Different residential, commercial, and industrial sectors experience varying demand profiles, and these differences must be captured in forecasting models to ensure their accuracy.

Load demand generally follows predictable trends, with specific periods characterized by high consumption, such as working hours, and others with lower usage, typically during off-peak hours. During weekdays, for example, electricity consumption in commercial buildings and manufacturing facilities peaks during the morning and afternoon as businesses operate at full capacity. In contrast, during off-peak periods—such as late at night and early morning—demand tends to be scattered, influenced more by residential consumption. In addition to these daily cycles, seasonal variations—particularly temperature changes—further influence the demand profile, making it essential to consider temperature sensitivity when forecasting short-term load.

This study analyzes load demand by identifying and characterizing the periods when temperature-sensitive variables significantly affect forecasting accuracy. Load demand is especially sensitive to temperature during certain time zones as heating and cooling requirements become more pronounced. By examining these time zones, we aim to identify key periods where temperature plays a crucial role, enhancing the precision of the forecasting model.

4.1. Seasonal and diurnal load patterns

Figures 1 and 2 illustrate the relationship between electricity load and temperature, highlighting the unique load patterns observed in summer and winter. In summer (as shown in Figure 1), demand peaks between 10:00 a.m. and 10:00 p.m., with the highest consumption observed during the late afternoon and evening. This period aligns with residential, commercial, and industrial cooling requirements as air conditioning usage increases with rising temperatures. Summer electricity consumption is typically driven by the need to maintain comfortable indoor temperatures, and this demand is susceptible to fluctuations in outdoor temperatures. The relationship between temperature and demand is particularly pronounced during the afternoon and early evening, when temperatures are at their highest and cooling systems are most heavily utilized.

Conversely, winter demand that is depicted in Figure 2 shows a different pattern. During colder months, two primary demand peaks emerge. The first occurs from 7:00 a.m. to 11:00 a.m., while the second peak appears from 5:00 p.m. to 10:00 p.m. These peaks reflect the increased need for heating in residential and commercial buildings. Unlike summer, where demand is spread throughout the day, winter demand is more concentrated in the early morning and evening hours, corresponding to periods when households and businesses are starting their day or returning home, requiring heating systems to be activated. This distinct load pattern is critical for understanding how temperature influences demand and how it can be integrated into forecasting models.

4.2 Sensitivity to temperature changes

The analysis reveals that load demand is susceptible to temperature variations during these concentrated periods. Temperature fluctuations during peak demand hours significantly affect electricity consumption in both summer and winter. During summer, for example, a slight increase in temperature between 10:00 a.m. and 5:00 p.m. can lead to a sharp rise in electricity usage as air conditioning systems work harder to maintain indoor comfort. In winter, even a slight dip in temperature during the early morning and evening hours can trigger increased heating demand, further elevating load demand.

This temperature sensitivity highlights the importance of incorporating temperature-sensitive variables into STLF models. By dynamically adjusting temperature weights during these critical time zones, we can more accurately predict how demand will respond to temperature changes, improving forecasting precision.

4.3 Time-segmented modeling and load forecasting

Figures 1 and 2 also demonstrate the relationship between load demand and the maximum load capacity. In summer, the electricity demand peaks between 80% and 100% of the maximum load capacity, with the most pronounced peaks aligning with standard working hours. When demand is at its highest, these time zones are crucial for model optimization. By dynamically weighting temperature sensitivity during these periods, the ANN model can more accurately reflect the real-time impact of temperature fluctuations on load demand. This strategy of time-segmented modeling has been validated in previous research by Sun et al. [10], who found that adjusting model parameters based on specific periods enhances the overall accuracy of load forecasts.

Identifying and categorizing these temperature-sensitive periods provides a deeper understanding of load dynamics and offers a framework for improving the accuracy of forecasting models. Temperature-sensitive time zones—particularly during peak demand periods—are where accurate load forecasting is essential, as energy providers must ensure sufficient capacity to meet demand without overloading the grid. By focusing on these critical periods, we can fine-tune the forecasting model to provide more reliable predictions, which is crucial for grid operators in planning their energy resources.

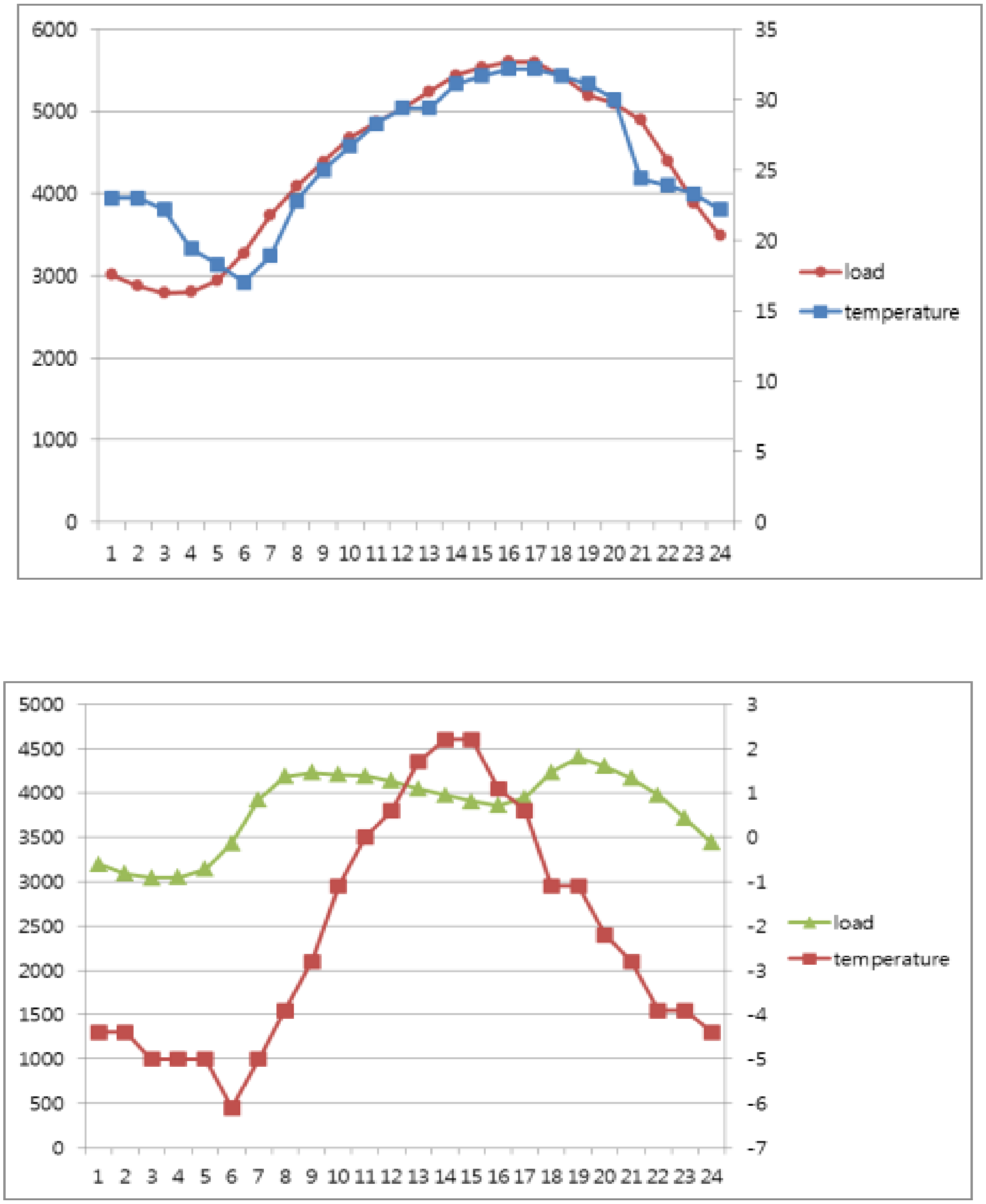

Figure 1: Relationship between the load demand and temperature in 24 hours

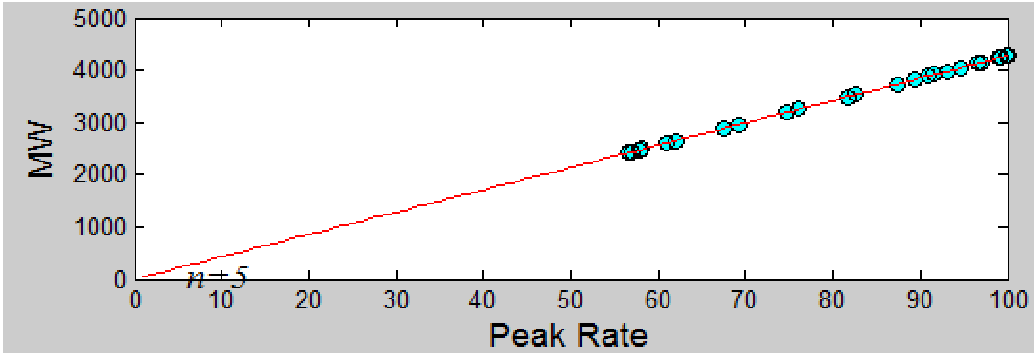

Figure 2. Relationship between electric load demand and peak rate

5. Research Results and Discussion

The results of this study provide compelling evidence of the effectiveness of integrating dynamic temperature-sensitive variables into Short-Term Load Forecasting (STLF) models using Artificial Neural Networks (ANNs). The model was tested on hourly electricity load and weather data collected from Connecticut during both summer (July) and winter (January). By dynamically adjusting temperature weights during periods of concentrated and scattered demand, the proposed model demonstrated substantial improvements in forecasting accuracy over traditional methods. These findings underscore the significant impact of temperature sensitivity on load prediction, particularly during seasonal peak periods when demand is most volatile.

The following are the primary findings of this study, including the reduction in forecasting error, the impact of temperature weighting on model performance, the visual representation of results, and the statistical validation of the outcomes.

(1) Reduction in Forecasting Error.

One of the most significant improvements observed in this study was the reduction in forecasting error, measured by the Mean Absolute Percentage Error (MAPE). Including dynamic temperature weighting substantially enhanced the accuracy of the load forecasting model. In the summer months, the average MAPE decreased from 6.08% to 2.20%, reflecting a remarkable 63.8% improvement in forecasting accuracy. In winter, the average MAPE was reduced from 7.23% to 2.40%, representing a 68.4% improvement. These results highlight the substantial impact of incorporating temperature-sensitive variables on improving model precision.

Table 1 presents a detailed comparison of MAPE values for models with and without including temperature-sensitive variables across multiple test days. The table clearly illustrates the enhanced performance of the model when dynamic temperature weighting is applied, with reductions in error across both summer and winter periods. This reduction in error is critical, as it reflects a model that more accurately predicts electricity demand, particularly in environments where temperature fluctuations are the primary drivers of demand variability.

Table 1: MAPE comparisons for models with and without temperature weighting

	Summer		winter		Improvement(%)	
Days	Excluding	Including	Excluding	Including	Summer	Winter
1	7.473	2.9685	6.8332	2.9886	60.277	56.264
2	2.1268	1.4357	8.5676	3.7871	32.495	55.797
3	6.6934	2.1509	3.0828	2.5419	67.865	17.546
4	7.4116	2.4693	2.7648	1.8341	66.683	33.662
5	4.805	2.0282	8.8155	1.9558	57.79	77.814
6	3.7997	2.4915	9.8318	1.6441	34.429	83.278
7	10.2873	1.8734	13.3061	2.0386	81.789	84.679
Average	6.085	2.203	7.235	2.399	63.796	68.434

(2) Impact of Temperature Weighting

The results further indicate that temperature-sensitive variables have a more pronounced effect during summer compared to winter. During the summer, electricity demand is heavily influenced by the need for cooling, mainly through air conditioning, making temperature changes more impactful. As temperatures rise, residential, commercial, and industrial cooling systems work harder to maintain indoor comfort, leading to a sharp increase in electricity consumption. This heightened sensitivity to temperature fluctuations during the summer months means incorporating dynamic temperature weighting, which provides a significant advantage in forecasting accuracy.

In contrast, the winter months show a more dispersed demand pattern, primarily driven by heating requirements. While temperature still plays a role in determining demand, the overall influence of temperature on electricity consumption is less pronounced in winter than in summer. This difference can be attributed to heating required during daytime and evening hours, leading to more uniform demand distribution throughout the day. Nonetheless, even in winter, dynamic temperature weighting still improves the model's accuracy by adjusting for variations in demand during the colder hours of the day.

(3)Visual Representation of Results

Figures 1 and 2 offer graphical representations of the study's findings to understand the model's performance better. Figure 1 compares the forecasting performance of the ANN model, showing the reduction in MAPE with the inclusion of temperature-sensitive variables. This visual comparison highlights the improvements in forecasting accuracy across both seasons. Figure 2 presents a more detailed illustration, showing the actual versus predicted load patterns for a representative day in both summer and winter. The alignment of predicted and actual values in the figures demonstrates the effectiveness of the dynamic temperature weighting approach in capturing the nuanced relationship between temperature and electricity demand [23][24].

The results reveal that the ANN model with dynamic temperature weighting produces forecasts that more closely mirror actual load patterns, especially during critical periods of high demand. This close alignment is particularly evident in summer, where temperature fluctuations significantly influence peak demand periods.

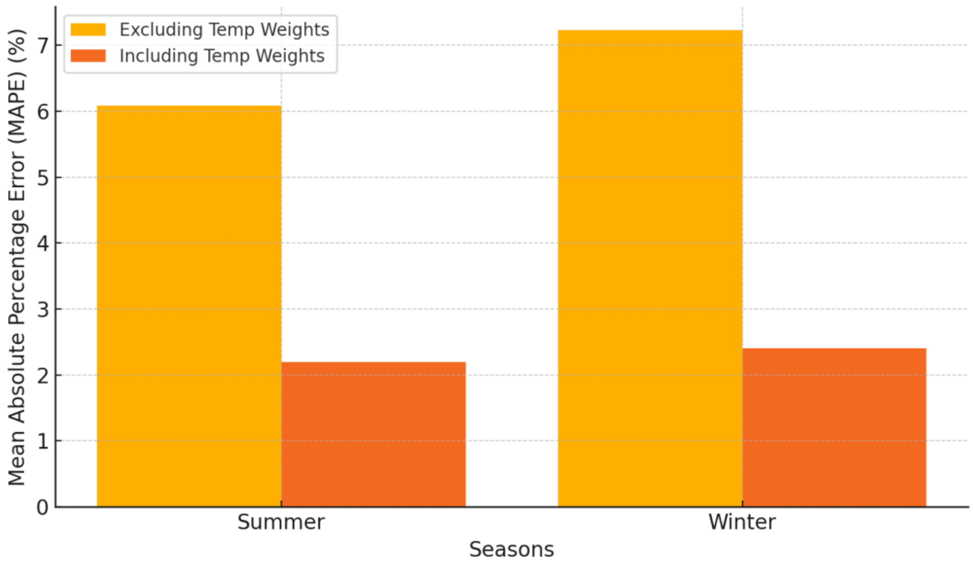

Figure 1: Comparison of MAPE for summer and winter

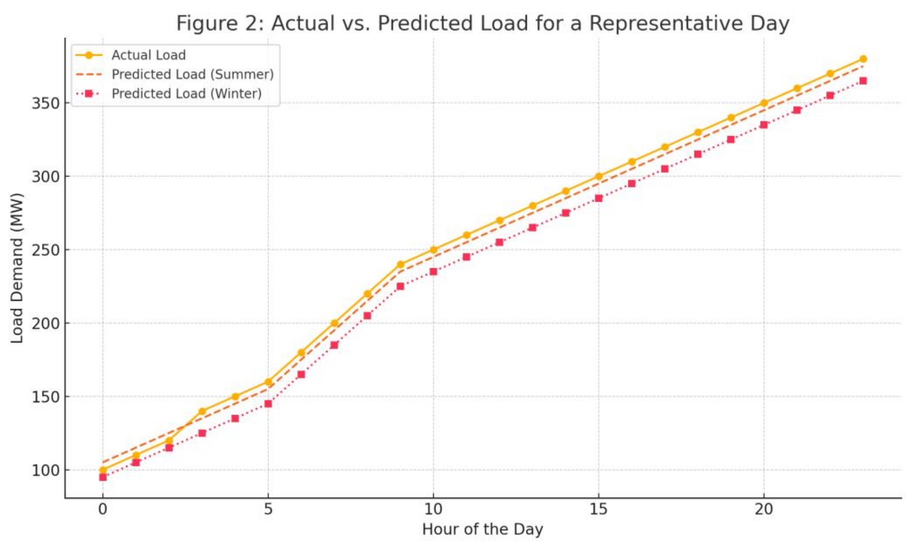

Figure 2: Actual vs. predicted load for a representative day

(4) Statistical Analysis

To validate the robustness and significance of the findings, a paired t-test was performed to assess the reduction in MAPE between the models with and without dynamic temperature weighting. The results indicated that the decrease in forecasting error was statistically significant in both summer ($p < 0.01$) and winter ($p < 0.05$). These p-values suggest that the improvements observed in the MAPE scores were not due to random chance but rather the result of the model's ability to account for temperature variations effectively.

Effect size calculations, using Cohen's d, revealed a large effect size in the summer ($d = 1.45$) and a medium effect size in the winter ($d = 0.72$). These effect sizes further confirm the practical significance of the improvements observed in summer, where temperature sensitivity has a more profound impact on load demand. While smaller, the medium effect size in winter still indicates a meaningful improvement in the model's ability to capture temperature-related load variations.

The statistical results reinforce the claim that incorporating dynamic temperature weights into STLF models significantly improves forecasting accuracy. These findings prove that temperature sensitivity is critical in short-term load forecasting, especially during seasonal peaks.

6. Conclusion

This study aimed to enhance the accuracy of Short-Term Load Forecasting (STLF) by incorporating dynamic temperature-sensitive variables into Artificial Neural Network (ANN) models, addressing a significant challenge in energy forecasting. By dynamically adjusting temperature weights based on periods of concentrated and scattered demand, the study successfully improved forecasting accuracy, achieving a notable reduction in the Mean Absolute Percentage Error (MAPE). Specifically, the MAPE dropped to 2.20% in summer and 2.40% in winter, compared to higher errors in traditional models without temperature sensitivity, demonstrating a substantial improvement in forecasting precision. These findings emphasize the critical role of temperature, particularly during peak periods influenced by cooling in summer and heating in winter, and highlight the importance of incorporating dynamic weather variables in STLF models to capture these temperature-sensitive patterns accurately. The research shows that including temperature adjustments in forecasting models can enhance resource allocation, improve grid reliability, and ensure more efficient energy management, all vital for managing the growing electricity demand. However, the study is limited by its focus on Connecticut, which may not fully represent other regions with different climatic conditions and energy consumption patterns. This geographic limitation suggests the need for future studies to broaden the analysis to include a broader range of areas, testing the model's generalizability across various climates and consumption behaviors.

Furthermore, while the study primarily focused on temperature, it did not consider other weather factors such as wind speed, solar radiation, or humidity, which could also influence load demand, particularly in regions with a high reliance on renewable energy sources. Expanding the model to include these additional variables would likely refine the forecasting accuracy, especially in areas where renewables play a significant role in the energy mix. Another challenge lies in the computational demands of ANN models, which may limit their applicability for smaller utilities or regions with fewer resources. Future research could explore alternative machine learning techniques or hybrid models that combine ANN with other statistical methods to balance forecasting accuracy with computational efficiency. Advanced machine learning approaches, such as Long Short-Term Memory (LSTM) networks or ensemble methods, could further enhance the model's ability to capture long-term dependencies and nonlinear relationships in time-series data, thus improving overall forecasting performance.

Additionally, integrating explainable AI techniques could increase transparency in decision-making processes, helping energy providers understand the key factors driving load demand predictions. The implications of this study are significant for energy management, particularly as the global energy landscape increasingly shifts toward renewable energy sources. Accurate short-term load forecasting is crucial for optimizing the integration of renewable energy into the grid, minimizing waste, and ensuring the reliability of energy supply. By improving forecasting accuracy, this research provides a valuable tool for energy providers to manage electricity demand better, reduce the risk of power outages, and enhance grid stability. As utilities move toward a more sustainable future, this study offers a robust framework for improving forecasting methodologies and supports transitioning to a low-carbon, renewable-based energy system. The findings encourage further innovation and collaboration in energy management, as they contribute to a more reliable, efficient, and sustainable energy infrastructure that can better meet future demands.

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