Research on an Enhanced Exponential Smoothing Method in Campus Electricity Demand Forecasting

Yanzhe Wang
Shenghua Zizhu Academy, Shanghai, 201100, China;

Abstract. Campus electricity consumption exhibits distinct periodicity, high volatility, and susceptibility to external disturbances. Therefore, accurate forecasting is crucial for optimizing power allocation and reducing operational costs. However, traditional exponential smoothing methods often fail to effectively capture the differences in electricity consumption between weekdays and weekends, resulting in limited prediction accuracy. To address this issue, this study improves the traditional exponential smoothing method by introducing a binary seasonal factor. This approach successfully distinguishes between weekday and weekend electricity consumption patterns without increasing model complexity. Validation using simulated campus hourly electricity consumption data demonstrates that the improved model significantly outperforms the traditional model. Experiments reveal substantial reductions in mean squared error, root mean squared error, and mean absolute percentage error for the new method. These findings demonstrate that this low-cost, interpretable, and efficient tool will support campus logistics in electricity procurement and peak-valley shifting strategies, contributing to low-carbon campus development. Future work will explore adaptive seasonal factors and their integration with machine learning models.

Keywords: Smoothing Method; Electricity Consumption; Seasonal Factors; Performance Enhancing; Short-term Prediction.

1. Introduction

Campuses, as major energy consumers worldwide, exhibit distinct cyclical and unpredictable patterns in electricity usage. This is due to the unique features of campus environments. A school typically comprises facilities for teaching, research, training, and daily life. Consequently, campus electricity usage involves diverse scenarios, including lighting systems for classrooms, offices, and laboratories, as well as teaching aids and experimental equipment [2]. Furthermore, campus electricity consumption exhibits distinct patterns [1-3]. For instance, faculty and students use electrical appliances more frequently during weekday daytime hours, while consumption declines on weekends due to reduced campus occupancy. Particularly, during winter and summer vacations, campus electricity consumption reaches its annual low. Although the consumption follows these patterns most of the time, unexpected events, such as major events or exam weeks, may cause sustained peak consumption periods that last several days. Summarizing data analysis from relevant literature [1,4], campus electricity consumption exhibits characteristics including strong periodicity, high volatility, susceptibility to external disturbances, and frequent occurrence of outliers. Therefore, forecasting both short-term and long-term electricity demand is crucial for optimizing power resource allocation, achieving energy conservation and emission reduction, and planning operational costs. For school logistics departments and regional power authorities, this enables the development of more precise power procurement plans, implementation of peak-shifting strategies, and assurance of uninterrupted campus operations.

Past research has commonly applied four distinct model types for campus electricity forecasting and analysis. We first discuss time series models, which are based on exponential smoothing and ARIMA models [5-7]. These models demand high data quality and require multiple conditions to be met. When data exhibits stationarity, time series models can achieve efficient electricity consumption forecasting. Their advantages lie in straightforward computation and transparent analysis processes. When employing ARIMA models, non-stationary sequences require differencing [5,9]. For short-term forecasting, time series experiments in the literature demonstrate high accuracy, contingent upon data characteristics and the number of model parameters [5,7]. In general, time series models offer significant efficiency and accuracy advantages over traditional management systems [8].

The second type of model is a forecasting model based on grey theory [10,11]. Compared to linear models, including time series models, its distinctive property belongs to effectively handling nonlinear relationships within data, making it suitable for settings with small sample sizes or missing data [11]. When campus electricity measurement devices failed, relevant data might be missing. Similarly, when the data involved numerous influencing factors, the relationships between variables became complicated. In this case, time series models are difficult to capture the nonlinear relationships in the data, while grey prediction models are more suitable.

Additionally, machine learning and deep learning models are also commonly used approaches in campus electricity consumption scenarios [12,13]. As previously mentioned, random events such as conferences and academic activities may occur during holidays with low electricity usage, leading to outliers in the data. In such cases, fuzzy neural networks can more stably handle the uncertainties in campus electricity consumption [15]. Furthermore, when applying more data analysis to campus electricity consumption, the Informer model efficiently processes large-scale data samples [14], enabling effective cross-period predictions [13]. It is worth noting that the aforementioned models demand extremely high computational resources. Although these models perform better in scenarios requiring high accuracy, their computational costs shall not be overlooked.

Finally, we introduce a hybrid model. As the name suggests, hybrid models leverage the strengths of different models to address distinct data characteristics, thereby achieving superior predictive performance compared to single models. For example, the EMD-ARIMA-SVR hybrid forecasting model [16] combines Empirical Mode Decomposition, Autoregressive Integrated Moving Average, and Support Vector Regression techniques. Within this model, the EMD model functions as a signal decomposer. It decomposes the originally chaotic, non-stationary electricity time series data into a series of sub-sequences with different frequencies and relative stationarity. These sub-sequences are termed the Eigenmode Functions (EMFs) and the Residual Terms. The previously mentioned ARIMA model serves as the second stage of this model, used to forecast the EMFs with pronounced linear characteristics and the Residual Terms. The ARIMA model captures linear autocorrelation relationships and future trends within the data [5,9]. Support Vector Regression (SVR) is commonly used to predict nonlinear, highly volatile transient magnetic field components [17]. By leveraging traditional statistical theory, SVR models effectively capture correlations within samples. Through data decomposition, SVR reduces data complexity, thereby enhancing prediction accuracy. This approach aligns exceptionally well with campus power supply data, which simultaneously exhibits linear, nonlinear, periodic, and random fluctuation characteristics.

From the above introduction, we can see that most popular models possess unique strengths, yet they also come with corresponding limitations. Time series models call for high-quality data, but due to technical and cost constraints, most schools' electricity equipment introduces much noise into the data. As a result, electricity consumption data often exhibits fluctuations, anomalies, and missing values, posing challenges for the application of time series models. Furthermore, while novel methods like machine learning achieve high accuracy in power forecasting, they depend on training with large-scale datasets. This not only costs substantial computational resources but also makes parameterization a difficult step in achieving predictions. More importantly, the black-box nature of machine learning methods leads to low interpretability. This limitation restricts the effectiveness of new models in practical applications.

To address the aforementioned challenges, this study aims to propose a novel composite model based on exponential smoothing to enhance the accuracy of campus electricity consumption forecasting. Exponential smoothing has been widely adopted in prior research. While the classic exponential smoothing method is straightforward and easy to use, its ability to capture complex relationships falls somewhat short when handling data with pronounced periodicity and instability, such as campus electricity consumption. Nevertheless, in practice, this method remains more attractive and applicable than black-box models like machine learning. This paper attempts to incorporate a binary seasonal factor into the exponential smoothing method, primarily to distinguish between the markedly different electricity consumption patterns of weekdays and weekends. This approach does not significantly increase model complexity but holds promise for substantially improving campus electricity forecasting capabilities. Beyond improving prediction accuracy, this research offers a low-cost, high-benefit, practical, and easily scalable solution for campus energy management. Ultimately, its significance lies not only in demonstrating optimized time-series applications for specific scenarios but also in providing reliable analytical models for campus power departments. This supports national energy conservation policies and advances low-carbon campus development.

Outline. In Section 2 of this paper, we first describe traditional exponential smoothing and the improved one-period exponential smoothing incorporating binary seasonal factors, as detailed in Sections 2.1 and 2.2. We then analyze the advantages and disadvantages of each forecasting model. Section 3 presents the forecasting results for the sample data using both methods. It is evident that the exponential smoothing method incorporating binary seasonal factors yields more accurate predictions compared to the traditional exponential smoothing method. Moreover, computational time and cost do not increase significantly, supporting our earlier model analysis findings. Section 4 discusses the data prediction results from Section 3. It primarily analyzes the advantages of introducing binary seasonal factors into the model and the parameter selection methods. A comparative analysis with previous research findings is also conducted.

2. Method Development

2.1 Traditional Exponential Smoothing Method

Exponential smoothing is a data forecasting method based on the concept of weighted averaging [18-20]. Simple exponential smoothing serves as its foundational form [21], and the model analysis in this paper will commence from this point. The model comprises two core formulas: the core recursive equation and the forecasting formula

$$S_t = \alpha \cdot Y_t + (1 - \alpha) \cdot S_{t-1}, \tag{1}$$

$$F_{t+m} = S_t \,. \tag{2}$$

In the above equations (1) – (2), S_t represents the smoothed value at the time point t, i.e., the level estimate after noise extraction. S_{t-1} denotes the smoothed value at time point $t-1$. Y_t represents the actual observed value at time t, while F_{t+m} denotes the forecast value for the m-th time step following t, where m is the forecast horizon. α is the smoothing coefficient, typically ranging from $0 < \alpha < 1$. Its magnitude directly determines how quickly the smoothing model responds to recent changes. When α approaches 1, the model assigns greater weight to recent data, enabling a rapid response to changes. However, it becomes more susceptible to random fluctuations, leading to unstable predictions. When α approaches 0, the model assigns greater weight to distant data, resulting in stronger smoothing effects. While this enhances resistance to random fluctuations, it also causes the model to respond relatively slowly to actual data changes.

The advantage of this model lies in its simplicity and computational efficiency, making it suitable for short-term forecasting. Its calculation involves storing the previous smoothed value and the parameter α to generate predictions. However, it lacks sufficient capability for handling trends and seasonality. On a coordinate axis, simple exponential smoothing appears as a horizontal straight line. If the data exhibits a pronounced upward or downward trend, its forecast values will systematically lag behind actual values, leading to persistent forecasting bias. Additionally, first-order exponential smoothing lacks mechanisms to identify and model cyclical patterns. Overall, when forecasting campus electricity consumption, predictions may be inflated on weekdays while inevitably falling short of actual values during weekends or winter/summer breaks.

2.2 Exponential Smoothing with Binary Seasonal Factors

This improvement primarily addresses the fundamental flaw in seasonal handling within traditional models. By introducing a binary seasonal factor β_t, it achieves a significant enhancement in forecasting accuracy without increasing model complexity.

We introduce the improved recursive equation as

$$S_t = \alpha \cdot (\beta_t \cdot Y_t) + (1-\alpha) \cdot S_{t-1}. \tag{3}$$

In this case, the forecasting formula is as shown in (4):

$$F_{t+m} = S_t. \tag{4}$$

The smoothing coefficient α in (3) is determined using optimization methods such as genetic algorithms or particle swarm optimization, consistent with traditional approaches. The seasonal factor β can be determined by the average ratio of weekend electricity consumption to weekday consumption in historical data.

The primary objective of this improvement is to address the periodicity in electricity consumption between weekdays and holidays. The introduced parameter β_t adds minimal complexity and computational load to the model while significantly enhancing prediction accuracy. Its physical meaning is clear, preserving model interpretability, and its magnitude directly reflects the actual difference in electricity consumption between weekdays and holidays.

3. Experimental Results

3.1 Traditional Exponential Smoothing Method

For the two models mentioned in the previous section—traditional exponential smoothing and first-order exponential smoothing incorporating binary seasonal factors—numerical experiments were conducted using simulated campus electricity consumption data to validate the effectiveness of the improved model. First, an analysis of the electricity forecast results for the traditional model is presented.

Figure 1 displays the simulated time-series characteristics of campus electricity consumption, calculated on an hourly basis. The blue line represents the electricity consumption curve. The blank areas indicate weekdays, while the gray shaded areas denote weekend periods. Significant differences exist in the consumption patterns between the two. In detail, the local spikes in the blue curve represent peak consumption periods within a day. For instance, during teaching hours, the high density of faculty and student activities triggers consumption peaks. Similarly, during lunch and dinner periods, high personnel flow in the cafeteria causes spikes. Conversely, the troughs in the curve correspond to leisure periods or minor random fluctuations, indicating breaks between classes or the cessation of teaching activities. Overall, the simulated data exhibits periodic patterns detectable by the model while incorporating real-world random noise. Campus electricity consumption shows pronounced cyclical fluctuations, reflecting the regular variations tied to faculty and student daily routines. This demonstrates the temporal correlation of electricity usage behavior.

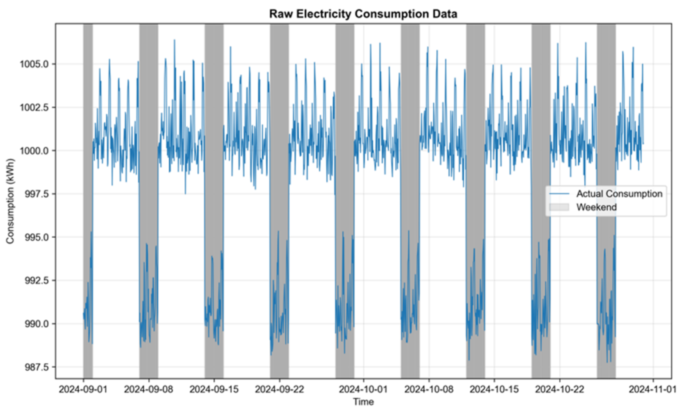

Figure 1. Campus electricity consumption.

Figure 2 illustrates the fitting performance of the traditional exponential smoothing model on the training set. The blue curve represents the actual electricity consumption of the training set, while the orange curve shows the model's predicted values. The black dashed line marks the boundary where the training set ends. The overall fluctuation trend of the orange curve closely aligns with that of the blue curve. This indicates the model successfully captures the periodic peaks and troughs in electricity consumption within the training set. This capability stems from the traditional exponential smoothing model's weighted averaging mechanism applied to historical data, enabling it to effectively learn linear relationships within the training data. However, the model relies on a single smoothing factor, limiting its ability to distinguish structural seasonal variations such as weekends versus weekdays, as subsequent experiments will demonstrate.

Figure 2. Traditional exponential smoothing model for the training set.

Figure 3 illustrates the predictive performance of the traditional exponential smoothing model on the test set. The blue curve represents the actual test set data. The green straight line shows the model's predicted values for the test set. The light green area indicates the error range predicted by the model. The prediction results reveal that the green prediction curve reflects the long-term average level of actual electricity consumption. That is, the traditional exponential smoothing model can capture the baseline of campus electricity usage. However, it is evident that the model struggles to track short-term fluctuations effectively. The actual electricity consumption curve exhibits distinct cyclical variations, whereas the prediction curve remains linear, failing to capture these short-term fluctuations—a characteristic inherent to linear fitting. This indicates that the traditional exponential smoothing model tends to emphasize stable long-term averages. This limitation underscores the significance of proposing an improved model.

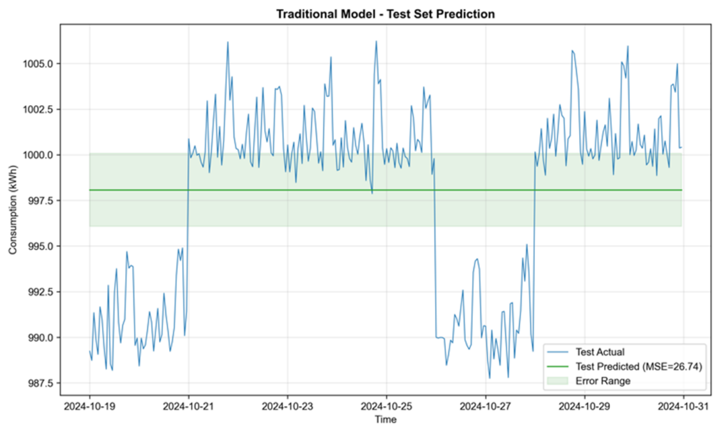

Figure 3. Traditional exponential smoothing model for the testing set.

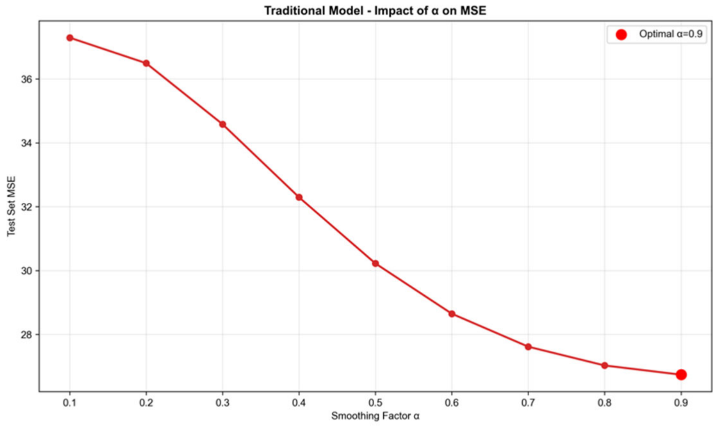

Figure 4. Impact of the smoothing factor.

Figure 4 and Table 1 illustrate the impact of the smoothing factor on the mean squared error (MSE) of the test set in the traditional exponential smoothing model. In the figure, the horizontal axis represents the smoothing factor's range from 0.1 to 0.9, while the vertical axis shows the MSE of the test set. The red curve depicts the relationship between these two variables. The smoothing factor acts as a forgetting coefficient within the model. That is, a larger smoothing factor assigns greater weight to recent data. The figure demonstrates that as the smoothing factor gradually increases, the mean squared error of the test set continuously decreases. This trend confirms that in scenarios with periodic fluctuations and strong patterns in electricity consumption, the smoothing index model's emphasis on the latest data effectively enhances prediction accuracy.

Table 1. Traditional smoothing factors comparison.

Smoothing Factor (α)	Test Set MSE	Optimal
0.1	37.29	
0.2	36.49	
0.3	34.58	
0.4	32.30	
0.5	30.22	
0.6	28.65	
0.7	27.61	
0.8	27.03	
0.9	26.74	✓

3.2 Exponential Smoothing with Binary Seasonal Factors

For the simulated dataset under the same campus electricity consumption scenario, as shown in Figure 1, this paper applied a modified exponential smoothing method incorporating a binary seasonal factor for refitting and forecasting. The results obtained are as follows:

Figure 5. Incorporating a binary seasonal factor on the training set.

Figure 5 illustrates the fitting performance of an exponential smoothing model incorporating a binary seasonal factor on the same training data. The blue curve represents the training set, i.e., actual electricity consumption. The orange curve shows the seasonal model's predictions for the training set. The black dashed line, with the same meaning as in Figure 2, indicates the boundary where training ends. Intuitively, the prediction curve of the traditional model may appear to align more closely with the actual electricity consumption curve. However, it fails to adequately capture the differences in electricity usage between weekends and weekdays. The seasonal model, incorporating a binary seasonal factor, specifically adjusts electricity levels for different periods. While this nuanced differentiation in fitting may not be as visually apparent as broad overlap, it substantially improves the mean squared error of the predictions. A more detailed example follows.

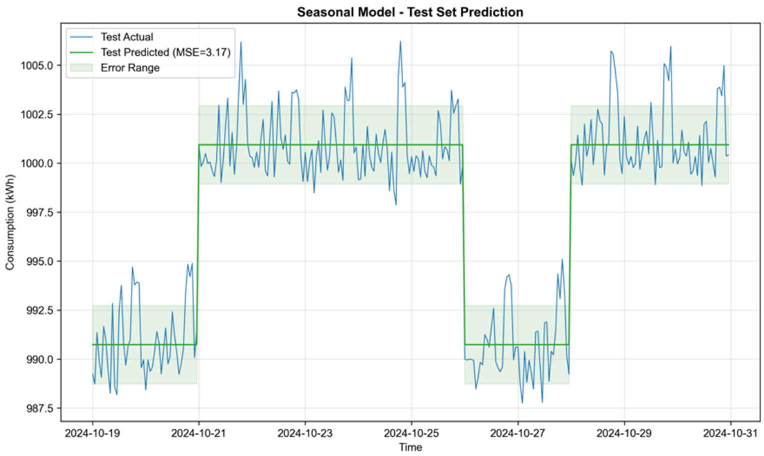

Figure 6. Incorporating a binary seasonal factor on the testing set.

Figure 6 shows the prediction performance of the exponential smoothing model incorporating a binary seasonal factor on the test set. The blue curve represents the actual electricity consumption of the test set. The green curve indicates the electricity consumption forecast from the improved model. The light green area denotes the range of prediction errors. Compared to Figure 3, it is evident that the green curve can follow the fluctuations of the blue actual curve in distinct regions, accurately capturing the differences in electricity consumption between weekends and weekdays within the test set. This demonstrates the seasonal factor's precise capture of structural consumption patterns. Furthermore, compared to Figure 3, the light green error range more comprehensively covers the fluctuation range of the actual curve. This indicates the improved model's relatively accurate estimation of uncertainty in predictions. This phenomenon reflects the stability of the binary seasonal factor improvement in controlling the error range. In other words, it provides reliable boundaries for the model's predictions.

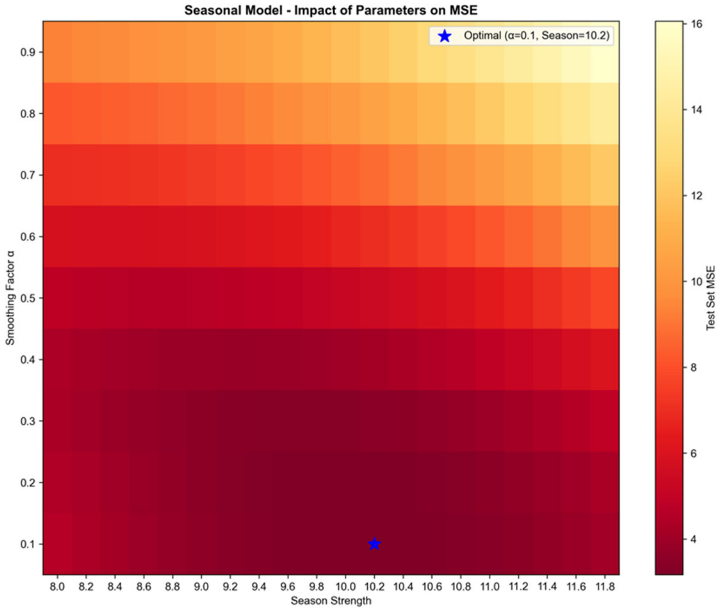

Figure 7. Heatmap of the impact of two parameters.

Figure 7 is a heatmap illustrating the impact of two parameters—smoothing factor and seasonal strength—on the mean squared error (MSE, can be found in the following equation (5)) of the test set. The horizontal axis represents seasonal factor strength, while the vertical axis denotes the magnitude of the smoothing factor. Darker colors indicate lower MSE, whereas lighter colors correspond to higher MSE. By analyzing color intensity, the optimal parameter combination can be selected to achieve the most accurate model predictions. The blue star visible in the figure indicates the parameter combination point with the smallest mean squared error. This image illustrates the model complexity resulting from incorporating the binary seasonal factor. It also demonstrates the existence of an optimal parameter combination through the low MSE region.

Table 2. Binary seasonal factors comparison.

Smoothing Factor (α)	Season Strength	Test MSE
0.1	8.0	4.66
0.1	11.8	4.12
0.2	11.8	4.29
0.3	11.8	4.90
0.4	11.8	6.05
0.5	11.8	7.77
0.6	11.8	9.89
0.7	11.8	12.15
0.8	11.8	14.27
0.9	11.8	16.06

Table 2 presents a table illustrating parameter selection and the mean squared error on the test set. We observe that as the smoothing factor increases, the MSE value continues to rise—a result contrary to traditional smoothing models. Delving deeper into the cause reveals that the improved model captures long-term structural patterns in the data through the seasonal strength parameter. If the smoothing factor is too large at this point, it will place excessive emphasis on the short-term volatility of new data. This, in turn, may disrupt stable cyclical patterns, leading to increased forecasting errors. This also reflects that the new model does not need to rely on a large smoothing factor to capture new changes, but instead achieves more accurate predictions through structural patterns and smoothing historical data.

4. Discussion

Table 3 compares the performance of the traditional exponential smoothing model with the improved model incorporating binary seasonal factors. First, we define the three metrics. MAE denotes the Mean Absolute Error, which is the average of the absolute differences between the forecast values and the actual values. It reflects the magnitude of the average error. MAPE stands for Mean Absolute Percentage Error, calculated as the average of the absolute error divided by the actual value. It reflects the relative proportion of the error.

Table 3. Error comparison between two models.

Metric	Traditional Model (Test)	Seasonal Model (Test)	Improvement
MSE	26.74	3.17	88.1%
MAE	4.42	1.40	68.3%
MAPE (%)	0.44	0.14	68.4%

Comparing the mean squared errors, the improved model demonstrates superior performance. This is because the calculation of mean squared error often amplifies the accumulation of small errors and is more sensitive to systematic bias. The definition of MSE is

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

Even if the error in a single sample is small, squaring it significantly increases the total error. Therefore, while models incorporating binary seasonal factors may appear less effective than traditional exponential smoothing methods when visually assessing the fitted image, the corrected model substantially reduces the mean squared error of predictions by correcting minor errors across a large number of samples. Additionally, the seasonal strength parameter warrants mention here. Its function is to correct structural biases such as those between weekdays and weekends. For instance, traditional models tend to overestimate weekend electricity consumption. Models incorporating seasonal factors, however, make targeted upward adjustments. These small systematic corrections result in a visually discernible curve shift. Yet they reduce the sum of squared errors across numerous samples, thereby driving down the MSE. Similarly, MAE and MAPE improved by over 68% compared to the traditional model, fully validating the enhancement of seasonal factors to forecasting performance.

5. Conclusion

This paper addresses the short-term forecasting challenge for campus electricity consumption by enhancing the traditional exponential smoothing method. The core improvement focuses on the periodic characteristics of weekdays versus holidays in campus scenarios. We incorporate a binary seasonal factor into the original model, thereby constructing a novel forecasting model capable of distinguishing different cycles. Subsequent experimental validation using simulated data demonstrates that the proposed model achieves significantly improved forecasting accuracy. This improvement primarily stems from enhanced cyclical forecasting performance. Parameter optimization experiments reveal that incorporating the seasonal factor alters the model's dynamics, thereby increasing its robustness. Finally, the findings provide campus logistics departments with a computationally efficient, low-cost, and user-friendly tool for short-term electricity forecasting. This facilitates optimized campus power procurement planning and holds significant practical value for allocating electrical equipment resources and reducing campus operational costs.

Despite the achievements outlined above, this study has certain limitations. For instance, the selection of seasonal factors. Future research could explore adaptive seasonal factors, specifically designing adaptive algorithms that enable the model to automatically learn and update based on recent data to better accommodate shifts in electricity consumption patterns and unexpected events.

Additionally, future studies could investigate integrating this improved model with other more complex models to construct novel hybrid models. For instance, this model could capture fundamental electricity consumption cycle while leveraging LSTM residual networks from machine learning to learn nonlinear fluctuations within the data. However, computational resource constraints and computational costs must be carefully considered.

References

[1] Getu, B. N., & Attia, H. A. (2016). Electricity audit and reduction of consumption: Campus case study. IJAER, 11(6), 4423-4427.

[2] Jafary, M., Wright, M., Shephard, L., Gomez, J., & Nair, R. U. (2016, April). Understanding campus energy consumption - people, buildings and technology. In 2016 IEEE Green Technologies Conference (GreenTech) (pp. 68-72). IEEE.

[3] Hafer, M. (2017). Quantity and electricity consumption of plug load equipment on a university campus. Energy Efficiency, 10(4), 1013-1039.

[4] Ding, Y., Wang, Q., Wang, Z., Han, S., & Zhu, N. (2019). An occupancy-based model for building electricity consumption prediction: A case study of three campus buildings in Tianjin. Energy and Buildings, 202, 109412.

[5] Mansor, R., Zaini, B. J., & Yee, C. S. (2019). Forecasting of electricity consumption and supply for campus university using time series models. Int. J. Supply Chain Manag, 8(5), 467-472.

[6] Baek, M., & Seo, Y. (2025). Hybrid forecasting of university electricity demand using time series and deep learning. Energy and Buildings, 116400.

[7] Pradeep, B., Kulkarni, P., Ullah, F., & Lakas, A. (2024). Energy use and demand prediction using time-series deep learning forecasting techniques: Application for a university campus. IEEE Open Journal of the Computer Society.

[8] Reyes, J. L. R., Sosa, G. U., Funes, F. J. G., Ángeles, B. R., Baez, I. F., & Baez, M. F. (2022). Statistical Analysis and SARIMA Forecasting Model Applied to Electrical Energy Consumption in University Facilities. Científica, 26(2), 1-22.

[9] Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014, March). Stock price prediction using the ARIMA model. In 2014 UKSim-AMSS 16th international conference on computer modelling and simulation (pp. 106-112). IEEE.

[10] Chen, H. Y., & Lee, C. H. (2019). Electricity consumption prediction for buildings using multiple adaptive network-based fuzzy inference system models and gray relational analysis. Energy Reports, 5, 1509-1524.

[11] Choi, K., & Joe, J. (2022). Grey-box Model Develop and MPC Simulation of campus office zone based on actual measurement. Journal of The Korean Solar Energy Society, 42(3), 103-115.

[12] Adedeji, P. A., Akinlabi, S., Madushele, N., & Olatunji, O. O. (2022). Hybrid adaptive neuro-fuzzy inference system (ANFIS) for a multi-campus university energy consumption forecast. International Journal of Ambient Energy, 43(1), 1685-1694.

[13] Oladipo, S., Sun, Y., & Adeleke, O. (2023). An improved particle swarm optimization and adaptive neuro-fuzzy inference system for predicting the energy consumption of university residence. International Transactions on Electrical Energy Systems, 2023(1), 8508800.

[14] Zhou, H., Zhang, S., Peng, J., Zhang, S., Li, J., Xiong, H., & Zhang, W. (2021, May). Informer: Beyond efficient transformer for long sequence time-series forecasting. In Proceedings of the AAAI conference on artificial intelligence (Vol. 35, No. 12, pp. 11106-11115).

[15] Zhang, Y., Yang, J., & Shao, R. (2024, October). Long-term prediction of building energy consumption based on improved LSTM and informer models. In Proceeding of the 2024 5th International Conference on Computer Science and Management Technology (pp. 1181-1186).

[16] Yang, H. L., & Lin, H. C. (2016). An integrated model combined ARIMA, EMD with SVR for stock indices forecasting. International Journal on Artificial Intelligence Tools, 25(02), 1650005.

[17] Sun, Y., Ding, S., Zhang, Z., & Jia, W. (2021). An improved grid search algorithm to optimize SVR for prediction. Soft Computing-A Fusion of Foundations, Methodologies & Applications, 25(7).

[18] Gardner Jr, E. S. (1985). Exponential smoothing: The state of the art. Journal of forecasting, 4(1), 1-28.

[19] Chatfield, C., Koehler, A. B., Ord, J. K., & Snyder, R. D. (2001). A new look at models for exponential smoothing. Journal of the Royal Statistical Society: Series D (The Statistician), 50(2), 147-159.

[20] Brown, R. G., & Meyer, R. F. (1961). The fundamental theorem of exponential smoothing. Operations Research, 9(5), 673-685.

[21] Ostertagová, E., & Ostertag, O. (2011, September). The simple exponential smoothing model. In The 4th International Conference on modelling of mechanical and mechatronic systems, Technical University of Košice, Slovak Republic, Proceedings of Conference (pp. 380-384).