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Impacts of Climate Change on Hourly Electricity Load in China#

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ABSTRACT

Accurate forecasting of electricity load is crucial for the stable operation of power systems and research related to energy systems. Electricity load is influenced not only by long-term socioeconomic factors but also by weather conditions. This study developed a high-resolution hourly electricity load forecasting model for China, utilizing machine learning techniques that integrate meteorological and socioeconomic data. The model demonstrates high accuracy in forecasting. National electricity demand and peak load are projected to rise steadily through 2030 and 2060. The peak-to-off-peak gap is expected to widen, and seasonal fluctuations are expected to intensify. Electricity load shows a positive correlation with extreme temperature, highlighting the impact of heatwaves on demand. These findings provide a solid foundation for further research on power system transformation under carbon neutrality pathways.

Keywords: Climate change, Electricity load forecasting, Machine learning

1. INTRODUCTION

China has committed to peaking CO_2 emissions by 2030 and achieving carbon neutrality by 2060. Achieving carbon neutrality requires a profound transformation of the energy system, with the power sector at its core [1]. This transition places unprecedented pressure on the stability of the power grid, where balancing fluctuating renewable supply with real-time load is paramount.

Electricity load is influenced by multiple factors, including economic development, climate conditions, regional location, and industrial structure [2]. Short-term fluctuations, particularly at the hourly scale, are driven mainly by weather-dependent heating and cooling demands [3]. Traditional forecasting methods, such as trend extrapolation, time series analysis, and regression, often struggle to capture the nonlinear, seasonal, and abrupt variations in electricity load [4]. With China undergoing rapid economic structural transformation, accurately predicting electricity demand has become increasingly challenging [5]. Modern approaches are increasingly leveraging machine learning and climate-responsive modeling frameworks to enhance forecast accuracy. Previous studies have applied machine learning to hourly load prediction, examined the effects of extreme weather on transmission planning, or combined long-term socio-economic trends with short-term climate fluctuations [6-7]. However, a gap remains in applying these approaches to model hourly electricity loads in China, integrating both socioeconomic development and climate variability.

To fill this research gap, we developed a load forecasting model. The model is then used to predict hourly provincial electricity load in 2030 and 2060 under future climate scenarios. These projections offer crucial insights for power system planning and the transition toward carbon neutrality, laying the groundwork for advancing research on climate impacts, system reliability, and sustainable energy transitions.

2. METHODOLOGY

2.1 The load forecasting model

We built the hourly electricity load forecasting model using machine learning techniques. To forecast loads, the model integrates a diverse set of features, including meteorological, socioeconomic, temporal, region code, and holiday flags. For the training process, we aggregated high-resolution time series data to an hourly scale. The implementation process of the algorithm is illustrated in Algorithm 1. SHAP was used to quantify the impact of each input variable on the electricity load. We then used the model to forecast hourly loads in 2030 and 2060 under future climate conditions, and conducted an analysis based on the forecast results.

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Algorithm 1: Load forecasting model

Require: Electricity load dataset D = {***X***, ***Y***}, neural network parameters ***ϑ***, hyperparameter configuration ***C***, number of epochs ***E*,** and stopping criterion ***S***.

1. **Input:** ***X***
2. **Output:** ***Y***
3. Split D into training set D_train and test set D_test
4. Apply scaling to D_train and D_test
5. Split D_train into K-fold
6. for each fold ***k*** in [1, K] do
7. Set fold ***k*** as the validation set, and the remaining folds as the training set
8. **Initialize** MLP neural network with parameters ***ϑ***
9. **Configure** network architecture: hidden layers (γ1, γ2), ReLU activation, dropout (0.2), L2 regularization (α=0.005)
10. **Define** an enhanced loss function
11. Initialize the Adam optimizer with a learning rate
12. Apply early stopping
13. for epoch ← 1 to ***E*** do
14. for each batch in training data do
15. Compute predictions: $\widehat{\boldsymbol{Y}} = f_\theta(\boldsymbol{X})$
16. Calculate total loss: total loss $\mathcal{L}$
17. Update parameters: $\theta \leftarrow \theta - \eta \nabla_\theta \mathcal{L}$
18. end for
19. if epoch > ***S*** then
20. break
21. end if
22. end for
23. Evaluate model on validation set using MAE, MSE, RMSE, R^2, etc.
24. Store fold k's model and evaluation metrics
25. end for
26. Calculate average performance metrics
27. Train the final model on the full D_train
28. Apply learning rate reduction
29. **Evaluate** test set performance
30. **Analyze** feature importance
31. **Save** the model

2.2 Scenario settings

We selected two Shared Socioeconomic Pathway (SSP) scenarios to capture the uncertainties associated with climate change. SSP126 represents a low-emission pathway that combines sustainable socioeconomic development with stringent climate policies, leading to rapid renewable energy deployment and relatively low global warming. SSP245 depicts a medium-emission pathway with moderate mitigation efforts and moderate socioeconomic development, resulting in emissions stabilization around mid-century and higher warming compared to SSP126 [8-9]. The following analysis uses SSP126 as an example.

3. RESULTS

3.1 Performance and SHAP analysis of the load forecasting model

The load forecasting model demonstrates high accuracy after being evaluated with multiple error metrics. Model validation, as shown in Table 1, indicates that the predicted loads align well with the actual values, exhibiting minimal bias and minor errors. SHAP analysis shows that population and GDP are the primary drivers of overall load, while regional codes capture provincial differences. Meteorological factors (e.g., temperature, humidity) explain short-term fluctuations, and temporal variables (e.g., hour, month) effectively capture daily and seasonal patterns.

Table 1 Evaluation metrics

Matric	Test Set
MAE	3.62
MSE	21.12
RMSE	4.57
R2	0.94
Mean underprediction	2.56
Mean overprediction	3.56
Training Time	38.24

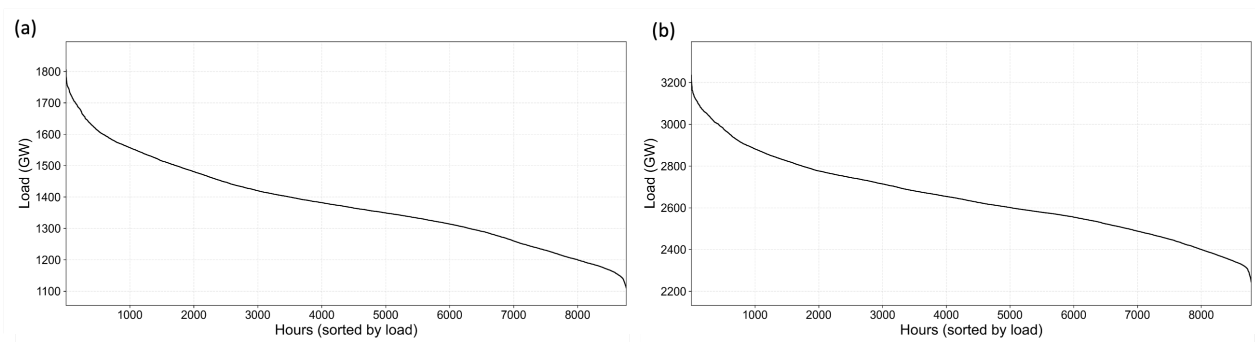

Fig. 1 LDC under SSP126. (a) LDC in 2030, (b) LDC in 2060.

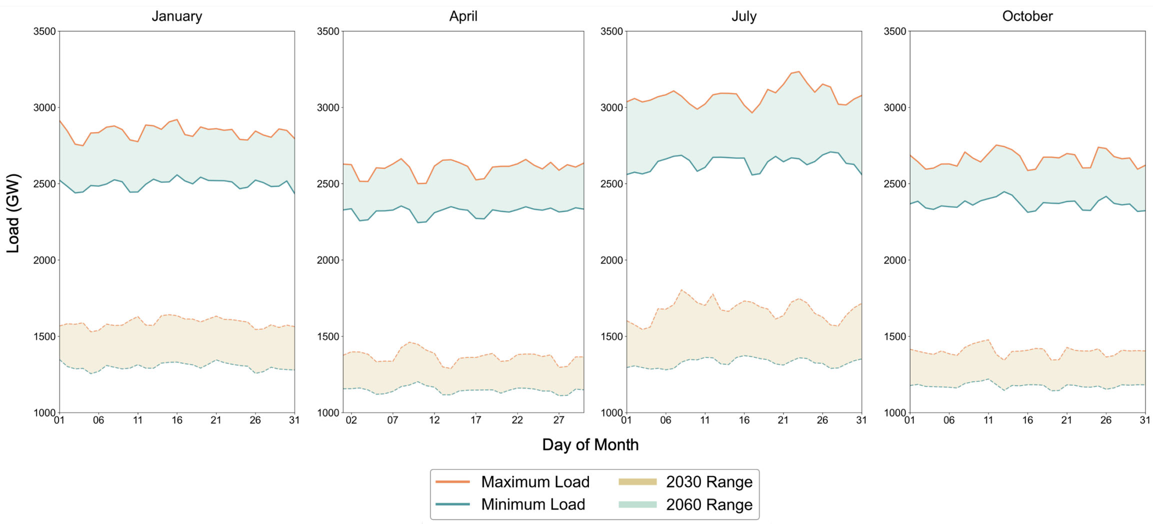

Fig. 2 China's load extremes in four months

3.2 Future electricity load patterns in China

We projected China's electricity demand in 2030 and 2060 based on provincial load forecasts. Using SSP126 as an example, national Load Duration Curves are plotted in Fig. 1. As the low-carbon transition advances and electrification rates increase, electricity demand is expected to continue rising. By 2030, national electricity demand is expected to reach over 12000 TWh. By 2060, national electricity demand is projected to nearly double compared to 2030. Fig. 2 illustrates the daily peak and off-peak load curves for China over four months. Model projections suggest that the national peak load will rise to over 1800 GW in July 2030 and further to more than 3000 GW by July 2060. Furthermore, analysis of daily peak and trough load curves indicates that the gap between peak and off-peak loads will widen from 2030 to 2060, with load fluctuations becoming increasingly pronounced.

3.3 Impact of extremely high temperatures on load

Based on the predicted electricity load, we analyzed the relationship between electricity load and extremely high temperatures across provinces. Days with daily maximum temperatures above the 90th percentile of the year were selected. Fig. 3a shows the linear coefficients and R^2 values. Twenty provinces achieved an R^2 value greater than 0.8, indicating strong linear relationships. As shown in Fig. 3b, a clear correlation exists between load and temperature in Hebei. Shanghai and Yunnan were lower, suggesting influence from other factors. All provinces had positive coefficients, confirming load rises with temperature. Shaanxi was highly sensitive, while high-latitude or high-altitude regions were less so. Overall, extremely high temperatures have an explicit impact on load, with regional variations reflecting differences in economic structure and climate.

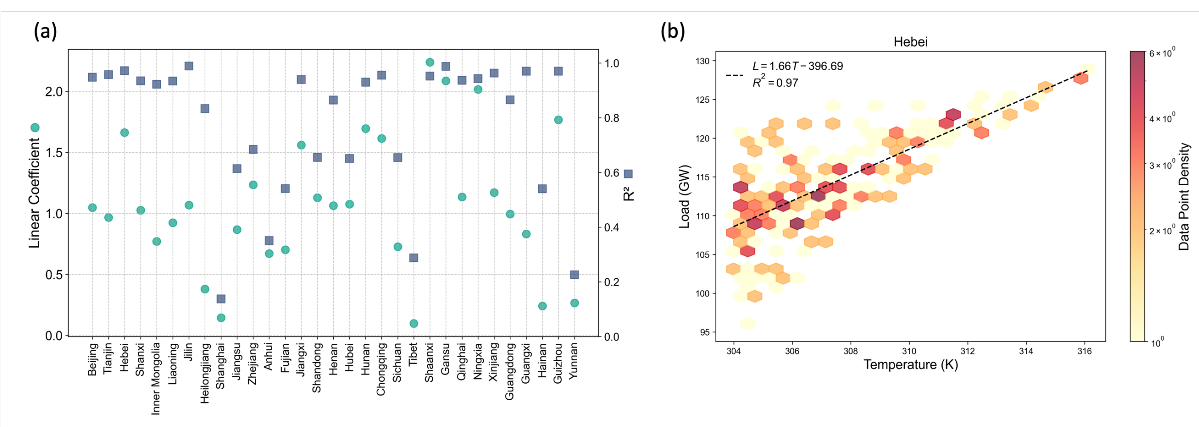

Fig. 3 Linear coefficient and R^2 for linearly fitted and an example in Hebei

4. CONCLUSION

Our study integrates the long-term effects of socioeconomic development with the short-term impacts of climatic extremes to project future electricity load. The results indicate that as electrification deepens, electricity demand will keep rising, and load patterns will become more sensitive to extreme temperatures. These shifts will intensify the pressure on system flexibility, regulation capacity, and balancing mechanisms.

In summary, the core contribution of this study lies not only in providing quantitative projections of future electricity loads using an innovative method but also in revealing the challenges and profound transformations encountered during the energy transition. Addressing sharp fluctuations and extreme peaks will be essential for achieving carbon neutrality goals. Building on this systematic characterization of future load, future research could explore transition pathways, evaluate system reliability under high renewable penetration, and assess the role of flexibility resources in mitigating risks.

5. DISCUSSION

From a national perspective, our findings underscore the need to shift power system planning away from a narrow focus on total demand growth toward an emphasis on flexibility and resilience. The sharper peaks and greater volatility observed demand enhanced balancing across timescales and regions, enabled by policies and markets that incentivize flexibility on both the supply and demand sides, and by digital and intelligent grid transformation that strengthens forecasting and coordination.

From a global perspective, the challenges of climate-driven load volatility during large-scale energy transition are universal. Extreme weather events and the variability of renewables are increasingly straining power systems worldwide. Developed economies must upgrade aging infrastructure to integrate renewables and electrify end-use sectors, while developing nations have the chance to leapfrog to more adaptive designs. Both will need market mechanisms, cross-border coordination, and investment that values flexibility and resilience.

The study we present is transferable, supporting localized forecasts and providing a common basis for international power system planning, thereby contributing to collective progress toward a secure and sustainable energy future under climate change.

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REFERENCE

[1] Zhang, S., Chen, W., 2022. Assessing the energy transition in China towards carbon neutrality with a probabilistic framework. Nat Commun 13, 87.

[2] Alipour, P., Mukherjee, S., & Nateghi, R., 2019. Assessing climate sensitivity of peak electricity load for resilient power systems planning and operation: A study applied to the Texas region. Energy.

[3] Staffell, I., Pfenninger, S., 2018. The increasing impact of weather on electricity supply and demand. Energy 145 65-78.

[4] Zhang, S., Liao, X., Cheng, Y., 2021. Short-term electricity demand forecasting method based on characteristic analysis and LSTM neural network. Electric Power Big Data 24(5), 9-17.

[5] Zhu, L., Li, B., Hu, X., Li, H., Tan, J., Han, J., 2018. Analysis and forecasting system for electricity demand under the new situation and its application. Electrical Times, (9): 23-24.

[6] Akdemir, K. Z., Mongird, K., Kern, J.D., Oikonomou, K., Voisin, N., Burleyson, C.D., Rice, J.S., Zhao, M., Bracken, C., Vernon, C., 2025. Investigating the effects of cooperative transmission expansion planning on grid performance during heat waves with varying spatial scales. Applied Energy 378, 124825.

[7] Tang, B., Wu, Y., Yu, B., Harmsen, R., Hu, J., Crijns-Graus, W., Wei, Y.-M., 2025. Integrating climate change impacts into power system planning for achieving carbon neutrality in China. Structural Change and Economic Dynamics 73, 248–261. https://doi.org/10.1016/j.strueco.2025.01.003

[8] O'Neill, B.C., Tebaldi, C., van Vuuren, D.P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., Meehl, G.A., Moss, R., Riahi, K., Sanderson, B.M., 2016. The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. Geosci. Model Dev. 9, 3461–3482. https://doi.org/10.5194/gmd-9-3461-2016.

[9] Luo, M., Zhao, X., Hao, D., Bond-Lamberty, B., Daigneault, A., Patel, P. L., Kou-Giesbrecht, S., Reyer, C. P. O., Dashti, H., Chen, M., 2025. Role of forest carbon change in shaping future land use and land cover change. Global Change Biology, 31, 70219. https://doi.org/10.1111/gcb.70219.