[Green AI for Energy: An Energy-Efficient Model for Regional Load Forecasting]

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Overview

Accurate load forecasting is critical for unit commitment and scheduling in electrical systems. However, traditional forecasting models often entail high energy consumption due to their computationally intensive nature. Conventional approaches, typically based on deep learning (DL) models such as long short-term memory (LSTM), rely on nonlinear activation functions and backpropagation mechanisms, which contribute to significant energy requirements. This study presents a green learning (GL) framework aimed at reducing the energy consumption of load forecasting models. The GL framework substitutes traditional activation functions with a hybrid feature extraction method that integrates categorical and numerical inputs, including seasonal climate data and multi-autoregressive terms. Furthermore, it replaces backpropagation with an innovative optimization technique that leverages seasonal centroids and the quantile autoregression forest algorithm for classification and regression tasks. Case studies demonstrate that the GL model achieves substantial energy savings without compromising forecasting accuracy, with energy reductions equivalent to the annual electricity consumption of 211–565 households. This research underscores the potential of energy-efficient models to reduce industrial carbon emissions and explores policy implications for the adoption of GL frameworks.

The paper is organized as follows: The first section is an introduction to our work and its approach. The second section provides a brief overview of the GL model, including its description and methodology. The third section outlines the data sources and processing methods. The fourth section presents the analysis results on the energy savings and accuracy of the GL model. Finally, the conclusion and its policy implications are discussed in the last section.

Methods

The paper develops a hybrid model for regional electrical load forecasting based on the GL framework and compares the proposed GL model with LSTM models in terms of accuracy and energy consumption in a case study.

Results

This study addresses the challenges of high computational complexity, energy consumption, and limited interpretability in neural networks for electrical load forecasting. Motivated by the GL framework's success in image recognition, we developed a GL-based model for regional electrical load forecasting. The model integrates a hybrid feature extraction method that combines climate clustering with auto-regression (AR) terms, replacing activation functions and LSTM mechanisms in traditional DL models. Using quantile auto-regression forest (QARF), the GL model eliminates backpropagation, reducing training time and energy consumption. The framework was validated against DL models in a Taiwanese case study, providing important insights for energy-efficient predictive modeling.

The proposed GL model demonstrated significant energy savings while maintaining accuracy comparable to DL models. The addition of AR terms enhanced the accuracy of LSTM models without significantly increasing energy consumption (EC). However, the GL model's EC (0.01697 kWh per computation) was substantially lower than that of LSTM (0.0094~0.0480 kWh). Annual energy savings (AES) from the GL model adoption are estimated to reach 2,300 MWh at a high penetration rate, equivalent to the electricity consumption of 565 households in Taiwan. At a low penetration rate, the AES corresponds to the annual electricity consumption of 211 households, further highlighting the GL model's energy efficiency advantages over DL models.

Conclusions

The development of forecasting models within the GL framework was shown to reduce model complexity, computation time, and energy consumption, while enhancing interpretability and preserving accuracy at a level comparable to that of DL methods. We developed a hybrid feature extraction scheme, which uses categorical and numerical features to extract regional seasonal climate features and AR terms of regional electrical load, as an alternative to the automated feature extraction mechanisms (nonlinear activation functions and backpropagation optimization) used in DL models.

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