Enhancing Energy Consumption Forecast Using Climate-Informed Neural Networks

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Abstract

Accurately predicting energy consumption is critical for efficient analysis of energy distribution and consumption planning. This project hypothesizes that integrating climate patterns into energy consumption prediction models can enhance forecasting accuracy. Furthermore, transfer learning techniques may prove beneficial in scenarios where climatic data is available but energy consumption records are limited. We present an approach that combines historical energy consumption data with climate patterns, leveraging transfer learning to improve performance and reduce the mean absolute error (MAE) compared to traditional models.

1. Introduction

Accurately predicting energy consumption is crucial for optimizing energy distribution and supporting sustainable energy planning. Numerous models have been developed based on historical energy utilization data. Traditional approaches primarily rely on past consumption patterns and often fail to account for external factors such as climatic conditions, which significantly impact energy demand.

Energy consumption is highly sensitive to climatic variations such as temperature fluctuations, humidity levels, and seasonal changes. This project proposes an enhanced predictive approach that integrates climate patterns into energy consumption forecasting models, aiming to improve prediction accuracy. Additionally, we explore the effectiveness of transfer learning, particularly in cases where historical energy data is limited but climatic data is available.

2. Problem Statement

This project hypothesizes that integrating time-series climate data into predictive models can enhance forecasting accuracy, leading to more informed decision-making in energy management. Additionally, the application of transfer learning techniques could prove particularly beneficial in scenarios where climatic data is available for a region, but energy consumption records are limited.

3. Related Works

Recent advances in energy consumption forecasting have increasingly highlighted the importance of incorporating climate information to enhance model accuracy. In particular, several studies have demonstrated that climatic conditions play a crucial role in predicting energy demand.

Weiss (2021) presents a climate-informed framework for predicting installation total energy consumption. By integrating historical energy usage data with CMIP5 temperature projections, the thesis achieves improved forecasting performance—especially during periods of extreme energy demand such as the summers. This work highlights that external climate variability is a key contributor to energy consumption patterns which thereby motivates the inclusion of climate factors in predictive models.

Similar to the above study, Yan et al (2022) introduced a climate-informed monthly runoff prediction model that employs machine learning techniques combined with feature importance analysis. Although their work targets runoff prediction, the methodology - particularly the selection of salient predictors from a broad array of climate variables using mutual information and random forest-based importance ranking - demonstrates the efficacy of integrating climate data with advanced learning algorithms. This approach provides valuable insights that can be useful for the objectives we are trying to achieve.

Furthermore, Li (2024) explores deep learning architectures for household electricity consumption forecasting. The work leverages time-series data, which include energy consumption profiles and meteorological information, to compare various models such as recurrent neural networks and temporal convolutional networks. The empirical findings reveal that the inclusion of weather data significantly enhances prediction accuracy, emphasizing the potential of deep neural networks to capture the complex, nonlinear interactions between climate variables and energy demand.

Building upon these studies, our project aims to develop climate-informed neural networks for energy consumption forecasting. By incorporating diverse climate inputs via transfer learning techniques, we seek to improve prediction accuracy—particularly in scenarios where historical energy data is sparse. This synthesis of methodologies, drawn from Weiss, Yan et al (2022), and Li (2024), forms the foundation for our work and highlights the promising role of climate-informed models in advancing energy forecasting.

4. Approach

The project will be carried out in the following stages:

- **Data Collection and Preprocessing:** Gathering historical energy consumption and climate data, followed by exploratory data analysis (EDA).
- **Baseline Model Development:** Constructing and training initial models using energy consumption data alone to establish a performance benchmark.
- **Transfer Learning Implementation:** Applying transfer learning techniques by incorporating climate data to refine the model and improve forecasting accuracy.
- **Evaluation and Validation:** Conducting rigorous performance assessments to compare model effectiveness.

Previous studies have explored machine learning and deep learning techniques for energy forecasting, but they typically lack climate integration or require extensive tuning. Our approach explicitly integrates climate data within a neural network model, capturing the direct correlation between climatic factors and energy demand.

5. Timeline

- **Weeks 1–2 (March 10 – March 24):** Data collection, preprocessing, and exploratory analysis.
- **Weeks 2–4 (March 24 – April 7):** Development and training of baseline models using only energy consumption data, followed by initial evaluations.
- **Weeks 4–6 (April 7 – April 21):** Implementation of transfer learning, incorporating climate data, and fine-tuning model parameters.
- **Weeks 6–8 (April 21 – May 5):** Comprehensive hypothesis testing, model comparisons, and performance evaluations.
- **Week 9 (May 5 – May 12):** Iterative refinements to improve model accuracy and validation.

6. Contributions

- **Data Collection and Preprocessing:** Led by Kartikay, supported by Varun and Garvita.
- **Baseline Model Development:** Led by Varun, supported by Kartikay and Garvita.
- **Transfer Learning Implementation:** Led by Garvita, supported by Varun and Kartikay.
- **Evaluation:** Conducted collaboratively by all group members.
- **Final Report Preparation:** Conducted collaboratively by all group members.

7. Expected Outcome

This project aims to improve energy consumption forecasting accuracy by integrating climate data into predictive models. The anticipated outcome is a measurable reduction in mean absolute error (MAE) compared to models trained solely on historical energy consumption data.

8. Worst-Case Outcome

If the integration of climate data does not produce significant improvements, the project will still result in a well-structured baseline model for the prediction of energy consumption, providing a solid foundation for future research.

References

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