Improved Electric Load Prediction with Transfer Learning and Temperature Data

Rania Farah[1,*], Brahim Farou[1], Zineddine Kouahla[1] and Hamid Seridi[1]

[1]University 8 Mai 1945, Guelma
Department of Computer Science, LabStic Laboratory, 24000, Guelma , ALgeria

Abstract

Accurate prediction of electrical load is crucial for optimising energy management, especially in areas where temperature fluctuations directly influence energy demand. This study proposes an innovative approach by applying transfer learning to improve the accuracy of electrical load predictions by integrating a temperature database. A pre-trained base model is fitted to local temperature data to take advantage of the relationship between climatic conditions and load variations. Results show that this method offers significant performance gains by reducing prediction errors while optimising training time resources. The proposed approach opens up interesting prospects for resource-constrained environments and use cases requiring fast, reliable predictions.

Keywords

Prediction, Optimizing Energy, Temperature, Transfer Learning.

1. Introduction

Electricity load forecasts play a central role in the management and planning of energy resources, particularly in regions where consumption is strongly influenced by climatic variations [1]. Studies show that rising temperatures often lead to higher electricity demand [2], due to increased use of air conditioning in summer and, in some areas, heating in winter. This correlation highlights the importance of integrating temperature data into predictive models to improve forecast accuracy, ensuring more reliable and efficient energy planning.

Accurate electricity load prediction is often hindered by several challenges. One primary issue is the dynamic relationship between climatic variations and consumption patterns, which can differ across regions and seasons. Moreover, traditional predictive approaches often require extensive computational resources and training time, especially when starting from scratch with new datasets. These limitations can delay the deployment of forecasting models and reduce their scalability for localised applications.

Transfer learning, which involves adjusting a pre-trained model to suit the particularities of a specific dataset, presents itself as an effective solution in this context. This technique exploits the knowledge of an existing model, trained on similar data, to adapt it to local specificities, such as temperature fluctuations and consumption patterns. By reducing training time and computational demands, transfer learning can significantly streamline the model development process.

Several studies have explored the use of transfer learning in electricity load forecasting, demonstrating its potential to enhance prediction accuracy while reducing resource usage. For example, models pre-trained on national-level consumption data have been adapted to predict load at regional or urban scales, achieving promising results. However, limitations remain: many approaches struggle to generalise well across datasets with starkly different features, such as unique temperature-consumption relationships

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*Corresponding author.
†These authors contributed equally.
farah.rania@univ-guelma.dz (R. Farah); farou.brahim@univ-guelma.dz (B. Farou); kouahla.zineddine@univ-guelma.dz (Z. Kouahla); seridi.hamid@univ-guelma.dz (H. Seridi)
0000-0002-8794-8691 (R. Farah); 0000-0002-1609-6006 (B. Farou); 0000-0001-8105-9810 (Z. Kouahla); 0000-0002-0236-8541 (H. Seridi)

or seasonal variations. Additionally, some methods require significant fine-tuning, which can offset the computational benefits of transfer learning.

This study aims to address these gaps by leveraging transfer learning to adapt predictive models to local temperature and consumption data. By focusing on these specific variables, the approach ensures better alignment with regional dynamics, enhancing forecast accuracy while maintaining computational efficiency. The insights gained from this work can aid energy planners in making more informed decisions, optimising resource allocation, and improving the sustainability of energy systems.

The remainder of this paper is organised as follows: Section 2 details the data analysis and describes the datasets used. Section 3 presents methodology and the application of transfer learning. Section 4 offers the results of the forecasting models, comparing performance metrics and discussing the impact of transfer learning and a critical discussion, highlighting the implications of the findings in the context of energy management. Finally, Section 5 concludes the paper by summarising the key insights and proposing future research directions.

2. Data Analysis

2.1. Data Description

The datasets used in this study comprise two primary components: temperature data and electricity consumption data. The temperature dataset includes daily minimum, maximum, and average values, offering a comprehensive view of climatic conditions over approximately eight years. This data is crucial, as temperature variations directly influence electricity demand, particularly during extreme weather conditions.

The electricity consumption dataset contains daily profiles with 24 columns, each representing hourly consumption from 1h to 24h. The rows correspond to individual days, providing detailed temporal patterns of electricity use. This structure captures not only the daily peaks but also intraday fluctuations that reflect user behaviour and external factors like weather.

Both datasets underwent preprocessing to ensure consistency. Missing values were interpolated where necessary, and anomalies were removed to enhance data quality. The strong correlation between these datasets, highlighted by exploratory analysis, provides an excellent foundation for transfer learning approaches, as the relationship between temperature and electricity consumption is a key driver of energy demand.

2.2. Data Analysis

In this context, it is essential to perform an exploratory analysis of the data to understand the impact of temperature variations on electricity consumption. Calculating the linear correlation coefficient, we confirmed that temperature is strongly correlated with electricity demand, revealing a direct and significant relationship between these two variables, as shown in Figure 1. This correlation is mathematically expressed by Equation 1:

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{1}$$

When analysing consumption profiles, we observed peaks in summer, particularly in August, as shown in Figure 2. These peaks are driven by high temperatures [3], which increase demand for air conditioning and other cooling systems [2]. These observations underline the importance of modelling these seasonal variations in forecasts to more accurately anticipate energy needs and meet demand requirements.

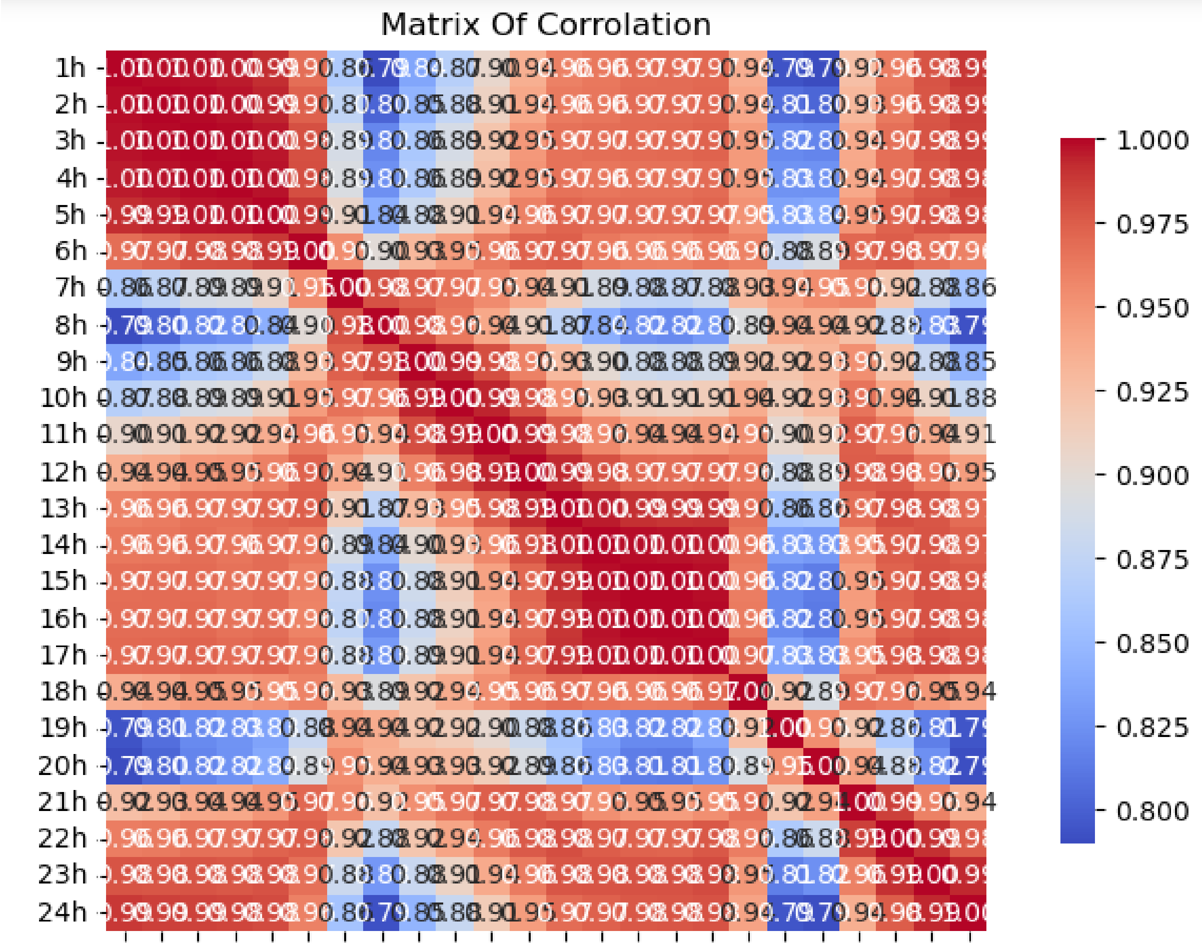

Figure 1: Matrix correlation

3. Approach-Based Transfer Learning

Transfer learning is a technique that involves reusing a model pre-trained on one task and adapting it for another related task. By transferring the learnt knowledge, such as feature representations, this approach accelerates the learning process and enhances predictive performance, particularly when data or computational resources are limited [4].

3.1. Base Model and Pre-training Data

In this study, the base model used is a feedforward artificial neural network (ANN). This model was first trained on historical temperature data to predict daily maximum temperatures. The pre-training dataset included key meteorological variables such as minimum, maximum, and average temperatures over several years, providing a rich source of patterns for the model to learn. During this stage, the ANN learnt the intricate relationships between daily temperatures and their influencing factors, producing accurate maximum temperature predictions.

3.2. Adapting to Electricity Consumption

Once the temperature prediction model was trained, its weights—representing the features and relationships it learnt—were transferred to a second ANN model designed for electricity load forecasting. This adaptation required minimal adjustments, as both tasks are closely related due to the significant influence of temperature on electricity consumption.

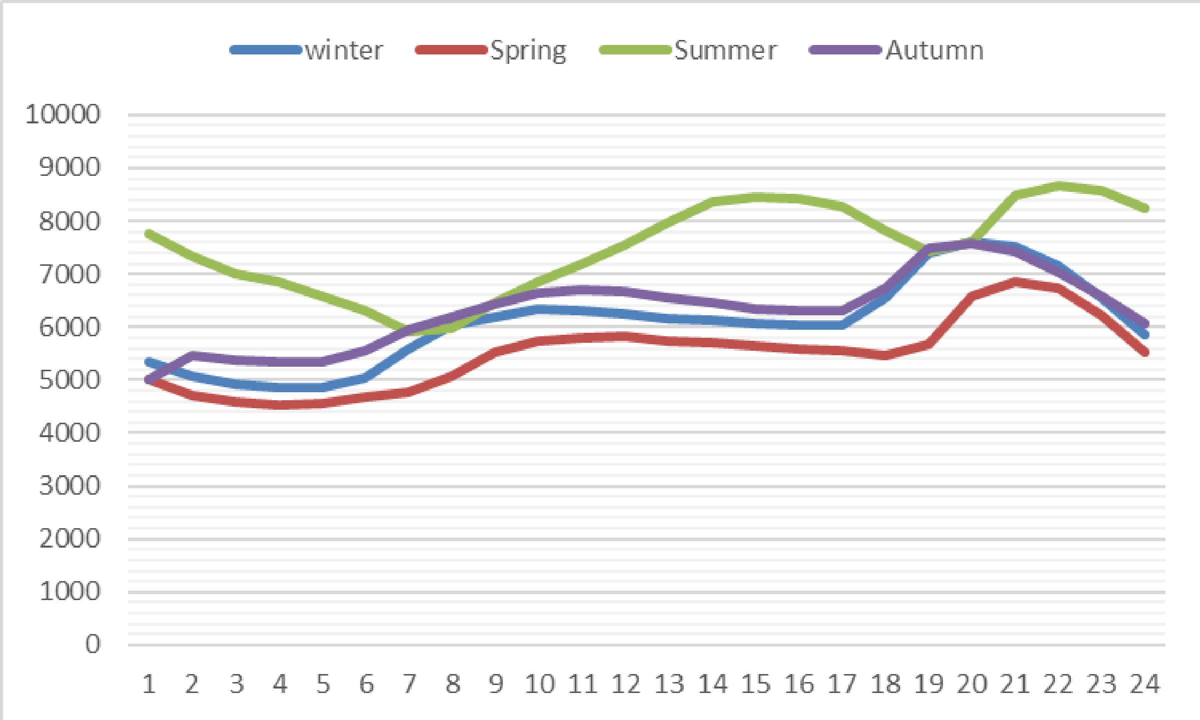

Figure 2: Seasonality

The adaptation process involved fine-tuning the transferred weights using a dataset of electricity consumption. This dataset consisted of daily maximum consumption values and hourly consumption profiles, combined with corresponding temperature data. The model was further optimised to capture the specific characteristics of the local energy demand, such as peak usage during hot weather.

3.3. Projection of 24-Hour Demand

After predicting the daily maximum electricity consumption, the model projected this value onto a predetermined consumption profile to estimate hourly electricity demand over 24 hours. This projection ensured that the forecast aligned with observed daily patterns, effectively capturing both peak and off-peak periods.

3.4. Key Features of the Approach

Consistency Across Years: Electricity consumption data revealed stable demand profiles over time, despite seasonal variations (Figure 3 3). This consistency made the application of transfer learning particularly effective, as the learnt relationships between temperature and consumption generalised well across different periods.

Resource Optimisation: By leveraging pre-trained models, this methodology minimised the need for extensive training on large datasets, significantly reducing computational costs and storage requirements.

Accuracy and Efficiency: Transfer learning improved the model's ability to predict electricity consumption accurately, achieving results with far fewer training epochs compared to training a model from scratch.

This methodology provides a robust framework for energy demand forecasting, enabling efficient resource management while maintaining high prediction accuracy.

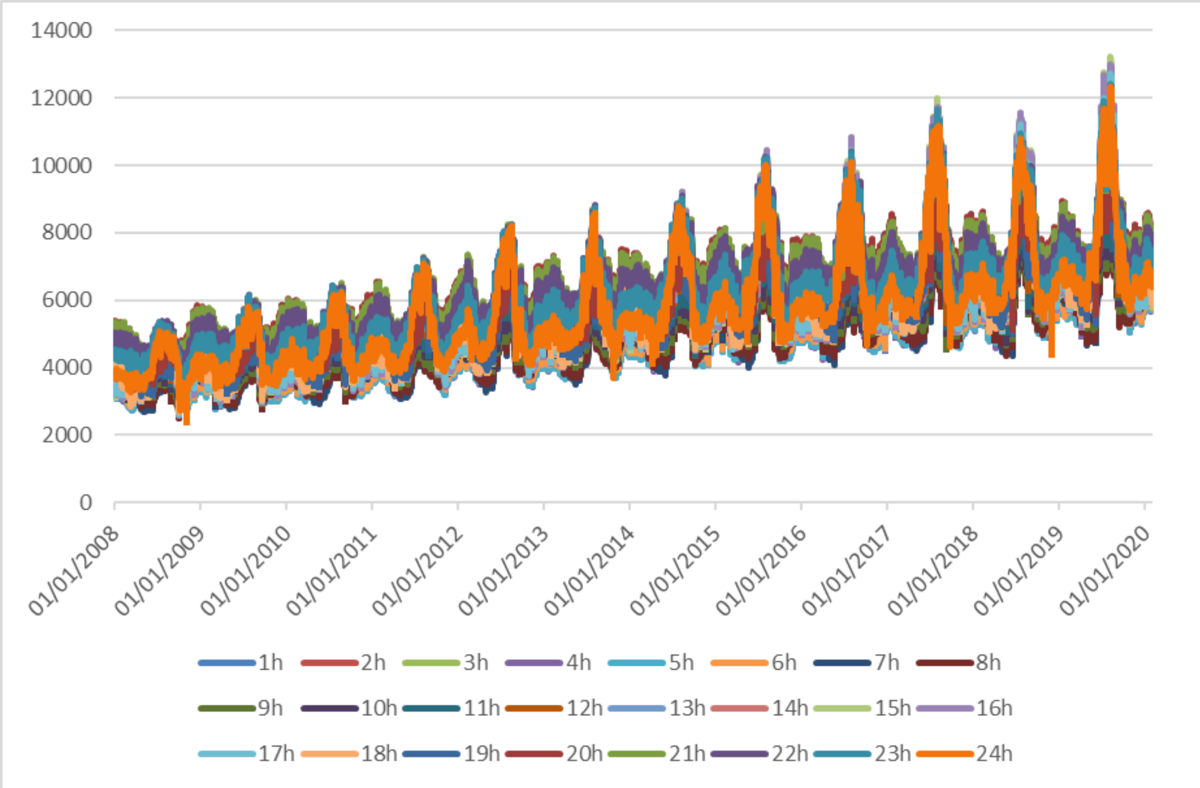

Figure 3: Trend cycle for each Year

Table 1
The Obtained Results.

Models	Accuracy (%)	RMSE	MAE
ANN	99	65	76.3
Transfer Learning	100	53.47	45.3

4. Results

Transfer learning demonstrates significant advantages in the domain of electric load prediction, as validated by this study. By leveraging pre-trained artificial neural networks (ANNs), the approach effectively reduces the computational burden and time required for training, which is especially critical when working with data that is resource-intensive to collect. This efficiency is evident in our experiments, where transfer learning required only 20 epochs to achieve optimal performance, compared to 200 epochs for models trained from scratch.

The methodology also enhances predictive accuracy by transferring generalisable features learnt during the temperature prediction task to the electricity consumption task. In this study, the ANN was initially trained to predict daily maximum temperatures, capturing fundamental patterns in the data. To evaluate the performance of the forecasting models, three key metrics were used: root mean squared error (RMSE), mean absolute error (MAE), and accuracy (calculated as 100 − mean absolute percentage error (MAPE)). Each metric provides a distinct perspective on the model's prediction quality:

RMSE measures the standard deviation of prediction errors, giving greater weight to large errors, which makes it useful for identifying significant deviations. A lower RMSE indicates a model with better overall accuracy.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

MAE quantifies the average magnitude of prediction errors without considering their direction. It is straightforward and easy to interpret, offering insight into the typical error magnitude.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{3}$$

Accuracy, derived from 100 − MAPE, reflects the proportion of correct predictions relative to the actual values. It is a valuable metric for assessing the model's practical utility, as it indicates the percentage of accurate forecasts.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{4}$$

$$\mathrm{Accuracy} = 100 - \mathrm{MAPE} \tag{5}$$

Together, these metrics provide a comprehensive evaluation of the model's predictive performance, balancing sensitivity to outliers (RMSE), average error magnitude (MAE), and overall prediction reliability (accuracy).

The model's pre-trained weights were then adapted to forecast daily maximum electricity consumption, utilising the strong correlation between temperature and energy demand. As shown in Table 1, this transfer approach successfully identified consumption variations linked to temperature fluctuations, achieving high reliability and precision.

Another key benefit of transfer learning is its adaptability to local data. By fine-tuning the pre-trained model, it effectively captured regional patterns, such as increased electricity usage during hot weather, which are critical for accurate demand forecasting. Additionally, the approach reduced data requirements, making it possible to generate reliable predictions even with limited training data by leveraging the foundational knowledge embedded in the initial model.

Overall, the results highlight the value of transfer learning in improving forecasting accuracy, reducing computational overhead, and addressing data limitations, making it a powerful tool for energy management and planning.

5. Conclusion

This study demonstrates the effectiveness of transfer learning in improving the accuracy of electrical load predictions by leveraging the strong correlation between temperature variations and electricity demand. By adapting pre-trained models to local data, we successfully reduced training time and computational requirements while enhancing prediction reliability. The results highlighted notable seasonal patterns, such as summer peaks in electricity consumption, particularly in August, driven by high temperatures. Moreover, the transfer learning approach significantly reduced the need for extensive data storage, making it a practical and resource-efficient solution for energy management.

In the future, this methodology could be extended by integrating additional weather variables, such as humidity and wind speed, to refine model accuracy and capture complex interactions influencing electricity consumption. Applying the transfer learning approach to datasets from diverse regions with varying climatic conditions would further validate its adaptability and generalizability. Additionally, developing real-time prediction systems based on this approach could enable energy providers to anticipate short-term fluctuations, optimize grid operations, and better integrate renewable energy sources.

This study not only provides a robust framework for forecasting but also highlights promising directions for advancing predictive modeling in the energy sector.

Declaration on Generative AI

During the preparation of this work, the author used Chat-GPT-3 order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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