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A Study on Regional Power Load Forecasting Using an ARIMA-CNN-LSTM Residual Correction Model

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Abstract: This paper presents a hybrid ARIMA-CNN-LSTM model for accurate regional power load forecasting. The model leverages the ARIMA model's ability to capture linear trends and the CNN-LSTM network's strength in modeling nonlinear dependencies and temporal patterns. Experimental results demonstrate that the hybrid model outperforms the standalone ARIMA model, achieving significant improvements in forecasting accuracy. With an RMSE of 3504.08, an MAE of 1466.66, and an R-squared value of 0.9902, the hybrid model proves to be an effective tool for energy management and grid planning. Its balance between accuracy and computational efficiency makes it suitable for real-time forecasting applications.

Keywords: Power Load Forecasting,ARIMA-CNN-LSTM,Hybrid Model,Time Series Analysis,Energy Managementt

1. Introduction

Accurate forecasting of regional power load is a critical component in the operation and planning of modern power systems. With the rapid development of renewable energy and the increasing complexity of load patterns, traditional forecasting methods are often inadequate in capturing the intricate dynamics of power load variations. As a result, there is a growing need for more sophisticated models that can effectively predict power load with higher precision.

Time series forecasting models such as ARIMA (AutoRegressive Integrated Moving Average) have been widely used in power load prediction due to their statistical reliability and simplicity. However, these models often struggle with non-linear patterns and fail to capture complex temporal dependencies inherent in power load data. To address these limitations, deep learning models, particularly those based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have been introduced. CNNs excel in feature extraction by capturing local patterns in the data, while LSTM networks are well-suited for modeling long-term dependencies, making them ideal for time series prediction.

Despite the success of CNN and LSTM models in various applications, their direct application to power load forecasting may still result in suboptimal performance due to model residuals — errors that persist after the primary model has made its prediction. These residuals can be attributed to the models' inability to fully capture the underlying stochastic properties of the load data. Therefore, a hybrid approach that combines the strengths of traditional statistical methods and advanced deep learning techniques presents a promising solution.

This study proposes a novel hybrid model that integrates ARIMA, CNN, and LSTM with a residual correction mechanism. The proposed model first applies the ARIMA model to capture linear trends in the power load data. The residuals generated by the ARIMA model are then passed through a CNN-LSTM network to capture non-linear patterns and long-term dependencies. Finally, the model corrects the residuals, thereby enhancing the overall prediction accuracy.

The primary objective of this research is to develop a robust forecasting model that not only improves prediction accuracy but also addresses the shortcomings of existing approaches. By leveraging the complementary strengths of

ARIMA and CNN-LSTM models, this study aims to provide a more reliable tool for power load forecasting, which is essential for ensuring the stability and efficiency of power systems.

2. Related Work

In recent years, power load forecasting has become a prominent topic in power system research. With the development of data-driven technologies, more scholars have explored hybrid models and deep learning methods to improve forecasting accuracy. Existing studies indicate that traditional time series models like ARIMA exhibit certain limitations when applied to power load forecasting, while the integration of deep learning methods can effectively capture nonlinear features in the data, thus enhancing prediction performance.

Yang et al. (2024) combined decomposition strategies with attention-based long short-term memory networks for multi-step ultra-short-term agricultural power load forecasting, showing the superiority of such hybrid models in handling complex time series tasks[1]. Similarly, Fan et al. adopted a hybrid model that integrates deep learning with feature extraction statistical techniques for short-term power load forecasting, further enhancing the model's prediction accuracy[2].

Research combining various technological approaches is also extensive. Zou et al. (2023) utilized an integrated approach of variational mode decomposition and TCN-BiGRU for short-term power load forecasting, showing the potential of multi-model integration[3]. Liu and Chen (2023) conducted a study on power load forecasting based on an improved Harris Hawk optimization algorithm, further proving the role of optimization algorithms in enhancing model performance[4].

In ultra-short-term power load forecasting, Pang et al. (2023) adopted a stochastic configuration network and empirical mode decomposition-based method, demonstrating its effectiveness in handling extremely short time frame forecasts[5]. Wan et al. (2023) combined CNN-LSTM with an attention mechanism for short-term power load forecasting in combined heat and power systems, achieving significant predictive results[6].

Moreover, significant progress has been made in machine learning model ensembles for mixed power load forecasting across multiple time horizons. Giamarelos et al. (2023) proposed an ensemble method for power load forecasting across different time granularities, showcasing its predictive capabilities[7]. Cheng et al. (2023) introduced a hybrid feature pyramid CNN-LSTM model with seasonal inflection month correction, effectively improving medium- and long-term power load forecasting accuracy[8].

Overall, current research indicates that combining various models and techniques significantly enhances the accuracy of power load forecasting. These findings provide a solid theoretical foundation for the stable operation and optimization of power systems, while also pointing the way forward for future developments.

3. Methodology

3.1. Research Design

The primary goal of this study is to develop a robust forecasting model for regional power load, leveraging both statistical and deep learning techniques to improve prediction accuracy. To achieve this, we design a hybrid approach that integrates the strengths of ARIMA (AutoRegressive Integrated Moving Average) and deep learning models, specifically Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, complemented by a residual correction mechanism.

2.2. Data Source

The dataset utilized in this study provides a comprehensive record of power consumption for a specific region, recorded at 15-minute intervals. This dataset consists of two primary columns: 'Time' and 'Power Load'. The 'Time' column records each data point with precise timestamps in the format 'YYYY-MM-DD HH:MM', while the 'Power Load' column quantifies the electricity consumption at each corresponding time point in kilowatts (kW). The data spans from January 1, 2020, to August 31, 2023, covering a total of 128,155 entries.

This dataset exhibits clear fluctuations in power consumption, typically associated with daily human activities and seasonal variations, such as the differences between weekdays and weekends, or daytime and nighttime usage. Notably, the dataset is free from missing values, ensuring the continuity and accuracy necessary for reliable analysis. The data is sourced from Alibaba's Tianchi Laboratory, a renowned platform for data science competitions and research. This extensive and detailed dataset serves as a solid foundation for various applications, including power load forecasting, grid planning optimization, and enhancing energy management efficiency.

2.3. Model Construction

The model construction in this study involves developing a hybrid approach that integrates the ARIMA (AutoRegressive Integrated Moving Average) model with a CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory) network. The hybrid model is designed to leverage the strengths of both traditional statistical methods and modern deep learning techniques to improve the accuracy of regional power load forecasting.

2.3.1.ARIMA Model for Initial Prediction

The ARIMA model is employed to capture the linear patterns and trends within the time series data. ARIMA is well-suited for modeling time series data where linear relationships dominate and can provide a strong baseline for prediction.

The ARIMA model is configured by selecting optimal parameters for autoregression (p), differencing (d), and moving average (q). These parameters are determined using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to ensure the model's effectiveness. The ARIMA model is then trained on the historical power load data, and predictions are generated for the entire dataset. The residuals, which are the differences between the actual power load values and the ARIMA model's predictions, are calculated and used as input for further modeling.

2.3.2. Residual Correction with CNN-LSTM

While ARIMA captures linear trends, it may not fully account for the nonlinearities and complex temporal dependencies present in the data. To address this, the residuals from the ARIMA model are passed through a CNN-LSTM network. This deep learning model is designed to correct the residuals, thereby enhancing the overall accuracy of the predictions.

CNN Layer: The CNN layer is utilized to extract local features from the residuals. This layer applies convolutional filters to detect patterns within short sequences of residual data, effectively capturing local dependencies.

LSTM Layer: Following the CNN layer, the LSTM layer is employed to capture long-term dependencies in the time series data. LSTM networks are particularly effective at retaining information over extended sequences, making them ideal for time series forecasting tasks.

Output Layer: After processing through the CNN and LSTM layers, the network generates corrected predictions, which are then combined with the initial ARIMA predictions to produce the final forecast.

2.3.3. Training and Optimization

The CNN-LSTM model is trained on the residuals using the backpropagation algorithm, with the aim of minimizing the mean squared error (MSE) between the predicted and actual residuals. The model's hyperparameters, such as the number of convolutional filters, LSTM units, and learning rate, are fine-tuned to optimize performance.

The performance of the hybrid ARIMA-CNN-LSTM model is evaluated against the baseline ARIMA model and other conventional methods. Metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) are used to assess the accuracy of the forecasts.

This hybrid approach effectively combines the strengths of ARIMA in capturing linear trends and CNN-LSTM in modeling nonlinearities and temporal dependencies, resulting in a robust model capable of accurate regional power load forecasting.

2.4. Residual Correction Mechanism

The residual correction mechanism in the hybrid ARIMA-CNN-LSTM model is designed to enhance forecasting accuracy by addressing the limitations of the ARIMA model in capturing nonlinear patterns and long-term dependencies. After generating initial predictions with ARIMA, the residuals (errors) are calculated as the difference between actual and predicted values. These residuals are then fed into a CNN-LSTM network:

CNN Layer: The CNN layer extracts local features from the residuals, identifying patterns that ARIMA missed.

LSTM Layer: The LSTM layer captures long-term dependencies in the residuals, modeling how these errors evolve over time.

Final Correction: The corrected residuals produced by the CNN-LSTM network are added to the ARIMA predictions, resulting in a more accurate final forecast.

This mechanism effectively refines the initial ARIMA predictions by incorporating complex patterns, significantly improving the overall model performance.

4. Experimental results and analysis

The experimental results and analysis section aims to evaluate the performance of the hybrid ARIMA-CNN-LSTM model in forecasting regional power load data. This section presents a detailed examination of the model's ability to capture both linear and nonlinear patterns within the time series, assesses the effectiveness of residual correction, and compares the hybrid model's performance with that of baseline ARIMA models. Key metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the R-squared coefficient, are employed to quantify the accuracy of the forecasts. The analysis will further explore the computational efficiency of the proposed model, with a particular focus on its execution time and practical applicability in real-world scenarios. By systematically analyzing these aspects, we aim to demonstrate the superiority of the hybrid ARIMA-CNN-LSTM model in achieving higher prediction accuracy and its potential for improving decision-making in power grid management and energy planning. The following sections will present the results obtained from both the ARIMA and CNN-LSTM components, leading to a comprehensive evaluation of the integrated model's performance on the test dataset.

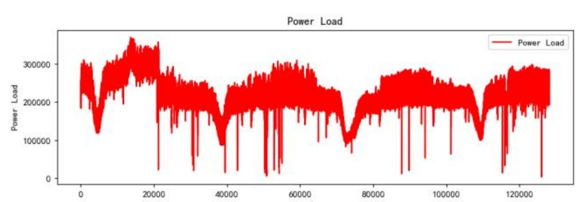

***Figure 1.** Power Load Time Series Plot.*

4.1. ARIMA Model Preliminary Analysis

The ARIMA (AutoRegressive Integrated Moving Average) model was employed as the initial step in the hybrid forecasting approach to capture the linear dependencies within the regional power load time series data. To determine the optimal parameters for the ARIMA model, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were utilized. The model with p=3, d=2, and q=1 was identified as the best fit, minimizing both AIC and BIC values, and thus selected for further analysis.

Upon fitting the ARIMA model to the training data, predictions were generated and compared against the actual power load values. The initial results demonstrated that while the ARIMA model successfully captured the overall trend and linear patterns within the data, it left significant residuals, indicating the presence of nonlinear dependencies and other complexities not accounted for by the model. These residuals were calculated as the difference between the actual values and the ARIMA predictions and were subsequently used as inputs for the CNN-LSTM model to address the shortcomings of the ARIMA approach.

4.2. Residual Correction with CNN-LSTM Model

After generating initial predictions using the ARIMA model, the residuals—defined as the difference between the actual power load values and the ARIMA model's predictions — were used as input for a CNN-LSTM network. This approach aimed to address the nonlinear dependencies and temporal complexities that the ARIMA model failed to capture. The CNN-LSTM model was specifically designed to correct these residuals, thereby enhancing the overall accuracy of the power load forecasts.

Table 1. *Parameter Settings*

Layer Type	Parameters
Conv1D	Filters: 16, Kernel Size: 2, Activation: ReLU
MaxPooling1D	Pool Size: 1
Conv1D	Filters: 16, Kernel Size: 2, Activation: ReLU
MaxPooling1D	Pool Size: 1
Flatten	-
LSTM	Units: 50, Activation: Tanh, Return Sequences: True
LSTM	Units: 100, Activation: Tanh, Return Sequences: True
LSTM	Units: 250, Activation: Tanh, Return Sequences: False
Dropout	Rate: 20%
Dense	Units: 1

The model was trained on the residual data using the Adam optimizer, which was chosen for its efficiency and adaptive learning rate capabilities. The Mean Squared Error (MSE) was used as the loss function, reflecting the average of the squared differences between the predicted and actual residuals.

The training process spanned 100 epochs, with a batch size of 64. The loss function's evolution over these epochs was closely monitored, with the loss gradually decreasing, indicating that the model was effectively learning to correct the residuals. The final model achieved a significant reduction in loss, underscoring its capability to refine the ARIMA predictions and enhance overall forecasting accuracy.

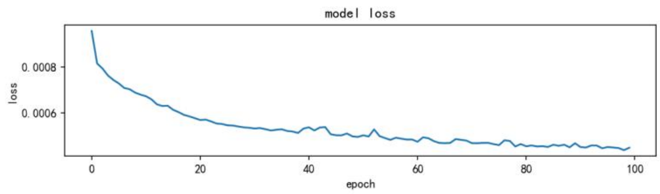

Figure 2. *Loss Curve during CNN-LSTM Training.*

The corrected residuals generated by the CNN-LSTM model were added to the initial ARIMA predictions to produce the final power load forecasts. These forecasts were compared against the actual power load values, with the results demonstrating a marked improvement in accuracy over the ARIMA model alone. The CNN-LSTM network effectively captured the complex, nonlinear patterns in the residuals, leading to more precise and reliable forecasts. This highlights the model's strength in addressing the limitations of traditional linear models like ARIMA, particularly in handling the intricacies of real-world time series data such as regional power load.

4.3. Final Performance of the Hybrid ARIMA-CNN-LSTM Model

The final performance of the hybrid ARIMA-CNN-LSTM model was evaluated using the test dataset to assess its accuracy in forecasting regional power load. The hybrid model combined the strengths of both ARIMA and CNN-LSTM components: ARIMA effectively captured linear patterns, while the CNN-LSTM model corrected the residuals left by ARIMA, addressing the nonlinear dependencies and complex temporal dynamics that the ARIMA model alone could not capture.

To quantitatively evaluate the model's forecasting accuracy, three key performance metrics were used:

Root Mean Squared Error (RMSE): This metric provides a measure of the average magnitude of the forecasting error. For the hybrid model, the RMSE on the test dataset was 3504.08, indicating the average deviation between the predicted and actual power load values.

Mean Absolute Error (MAE): The MAE measures the average absolute differences between the predicted and actual values, providing a straightforward interpretation of the model's accuracy. The hybrid model achieved an MAE of 1466.66, highlighting its ability to produce forecasts that are consistently close to the actual values.

R-squared : The R-squared value represents the proportion of variance in the dependent variable that is predictable from the independent variables. An R-squared value of 0.9902 for the hybrid model indicates that it explains over 99% of the variability in the power load data, demonstrating a high level of accuracy and fit to the actual data.

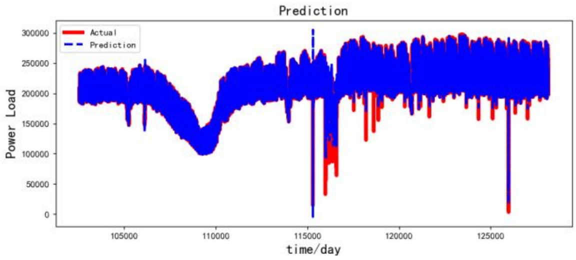

Figure 3. *Hybrid Model Test Set Prediction.*

The plot comparing the test set predictions with the actual power load values showed that the hybrid model closely followed the trends and fluctuations in the actual data. This indicates that the model effectively captured both the short-term and long-term patterns in the power load data.

4.4. Comparison with Baseline Models

When compared to the baseline ARIMA model, the hybrid ARIMA-CNN-LSTM model showed a marked improvement across all evaluation metrics:

The RMSE and MAE were significantly lower for the hybrid model, indicating that it made more accurate predictions with fewer large errors.

The R-squared value was notably higher for the hybrid model, underscoring its superior ability to explain the variability in the power load data.

This comparison highlights the advantages of integrating a deep learning model like CNN-LSTM with a traditional statistical model like ARIMA. The CNN-LSTM component effectively addressed the non-linearities and temporal dependencies that the ARIMA model could not, resulting in a comprehensive and highly accurate forecasting model.

5. Conclusions

This study introduced a hybrid ARIMA-CNN-LSTM model to enhance the accuracy of regional power load forecasting. By integrating the ARIMA model, which captures linear trends, with the CNN-LSTM network, which models nonlinear patterns and temporal dependencies, the hybrid approach significantly improved forecasting performance. The model achieved an RMSE of 3504.08, an MAE of 1466.66, and an R-squared value of 0.9902, outperforming the standalone ARIMA model. The visual and quantitative analyses demonstrated that the hybrid model closely follows actual power load trends, particularly during fluctuations, making it a reliable tool for energy management and grid planning. The model's balance between accuracy and computational efficiency suggests it is well-suited for real-time forecasting applications. Future work may explore extending this approach to other time series data and incorporating additional external factors to further enhance forecasting accuracy.

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