ABSTRACT

Accurate electricity load forecasting is crucial for efficient energy management, enabling utility companies to optimize resource allocation, reduce operational costs, and ensure a reliable power supply. Various factors, including weather conditions, economic activities, and demographic changes, significantly influence electricity load. Existing methods, such as the BiLSTM model without signal decomposition, have been applied to capture temporal dependencies in load forecasting. However, this approach demonstrates lower accuracy, with a Correlation Coefficient (CC) of 0.925, a Root Mean Square Error (RMSE) of 432.825, a Mean Absolute Percentage Error (MAPE) of 3.510%, and an R-squared (R^2) value of 0.851, as indicated by our baseline model. To address these limitations and mitigate the risks of energy wastage and grid instability, we developed a machine learning model for electricity load forecasting, leveraging weather data as the primary feature and signal decomposition as an additional feature. This study employs Principal Component Analysis (PCA) and the Correlation Coefficient (CC) to select the most relevant weather parameters as inputs for the model. Additionally, spatial correlation is introduced to identify optimal weather stations. For feature extraction, we propose the Ensemble Empirical Mode Decomposition (EEMD) technique to decompose the load signal into Intrinsic Mode Functions (IMFs). These are subsequently used as supplementary features in the prediction model. A case study was conducted in the Jakarta-Banten region of Indonesia, known for its high consumer and industrial activity. The results demonstrate that the combination of the BiLSTM model and EEMD achieves high prediction accuracy, with a CC of 0.956, an RMSE of 330.219, a MAPE of 2.824%, and an R^2 value of 0.913. Compared to the baseline model, the inclusion of EEMD resulted in a 3.35% improvement in CC, a 23.70% reduction in RMSE, a 19.56% decrease in MAPE, and a 7.29% increase in R^2..

Keywords: electricity load forecasting, BiLSTM, EEMD, spatial correlation