A multimodal approach to chaotic renewable energy prediction using meteorological and historical information

ABSTRACT

Wind energy, which exhibits non-stationarity, randomness, and intermittency, is inextricably linked to meteorological data. The wind power series can be broken down into several subsequences using data decomposition techniques to make forecasting simpler and more accurate. Because of this, a single prediction model does not perform well in extracting hidden information from each subsequence. To predict different frequency series, this paper employed shallow and deep learning models and proposed an improved hybrid wind power prediction model based on secondary decomposition, extreme learning machines (ELM), convolutional neural networks (CNN), and bidirectional long shortterm memory (BiLSTM). To begin, secondary decomposition was employed to break down the wind power series into several components. The ELM was used to forecast the low-frequency components. Following that, CNN was utilized to reintegrate the input characteristics of the high-frequency components, followed by BiLSTM prediction. Finally, the forecasting values for each component were added to generate the final prediction results. For one-, two-, and three-step predictions, the model was applied to the La Haute Borne wind farm. Additionally, four comparative experiments were conducted to validate the model's usefulness. The suggested model's mean absolute error (MAE), mean absolute percentage error (MAPE), and R-squared (R2) values for one-step prediction of the March data were 14.87 kW, 22.24 kW, and 0.984, respectively, which indicate the proposed model's superiority to other prediction models.