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Ensemble Empirical Mode Decomposition Based Deep Learning Model for Short-Term Wind Power Forecasting

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Abstract. In the last few years, wind power forecasting has established itself as an essential tool in the energy industry due to the increase of wind power penetration in the electric grid. This paper presents a wind power forecasting method based on ensemble empirical mode decomposition (EEMD) and deep learning. EEMD is employed to decompose wind power time series data into several intrinsic mode functions and a residual component. Afterwards, every intrinsic mode function is trained by means of a CNN-LSTM architecture. Finally, wind power forecast is obtained by adding the prediction of every component. Compared to the benchmark model, the proposed approach provides more accurate predictions for several time horizons. Furthermore, prediction intervals are modelled using quantile regression.

Introduction

Wind energy provides an alternative source of electricity generation. Compared to traditional sources of energy, wind is a highly intermittent and volatile resource. Therefore, accurate wind power forecasts are fundamental for the proper operation of the grid [1], as well as maximizing results in the electricity market [2].

Many forecasting techniques have been proposed to forecast wind power generation [3]. They can be broadly divided into physical and statistical methods. The first approach makes use of meteorological information and the specific site conditions of the wind farm. Statistical models are usually built using historical data. Conventional statistical methods use time series modelling to predict future values of wind power output. For instance, [4] proposed a method based on wavelets and the improved time series method (ITSM) to forecast wind speed and wind power. An alternative statistical approach is to employ deep learning techniques as artificial neural networks (ANNs) [5, 6].

In addition, several models have been introduced to build prediction intervals (PIs). Quantile regression (QR) is a well-known technique characterized by its distribution-free approach [7]. Other non-parametric forecasting models are based on kernel density estimation [8, 9]. [10] employs the lower upper bound estimation (LUBE) method, based on a neural network with two outputs to build the endpoints of the PI.

Section II introduces the proposed approach to compute deterministic wind power forecasts and PIs. Section III presents a case study with data from Ireland. Section IV draws conclusions from this paper.

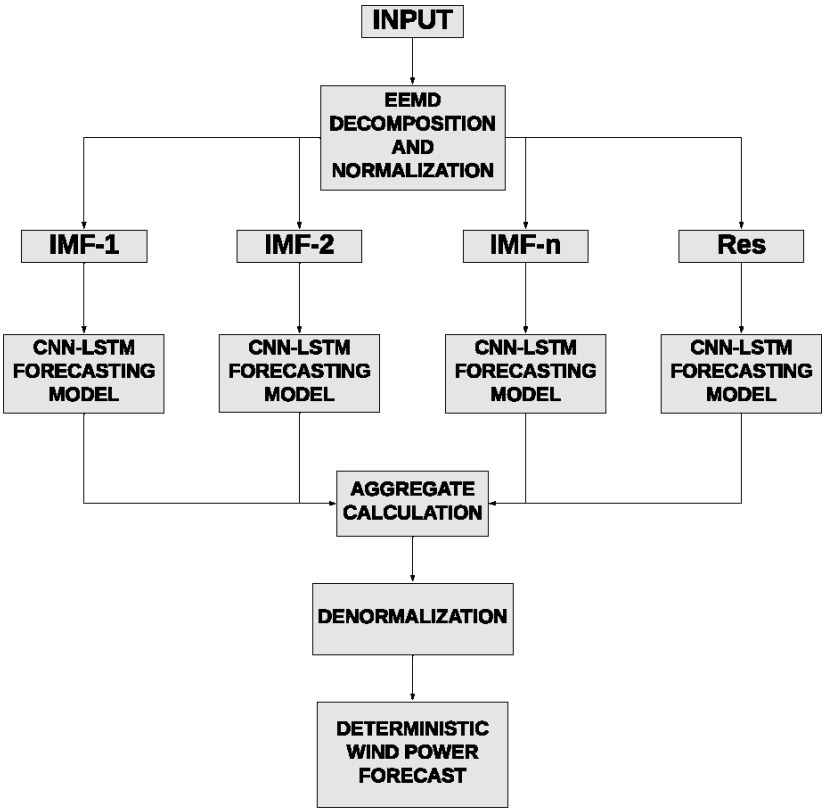

Fig. 1. Flowchart of the proposed model.

Methodology.

Deterministic forecasts. Empirical mode decomposition (EMD) [11] is a technique suitable for processing non-linear and non-stationary time series by dividing a series into modes known as intrinsic mode functions (IMFs). Nonetheless, EMD is susceptible to mode mixing. This issue can be overcome using EEMD [12], an enhanced version of EMD that adds different Gaussian white noise series of finite amplitude to the original signal. The various noise-added copies of the original signal are decomposed, and the mean value of the IMFs is taken as the result. This process helps to mitigate mode mixing.

Once the signal has been decomposed and normalized for every IMF, each one is trained separately by means of a CNN-LSTM architecture (Convolutional neural network and Long short-term memory). This neural network architecture allows to first extract features on input data with the CNN layer, while the LSTM layer [13] is a special recurrent neural network (RNN) structure that behaves as a memory cell and overcomes exploding and vanishing gradient problems that can occur with regular RNNs.

After each IMF has been trained, the original signal is denormalized and reconstructed to provide deterministic forecasts (Fig. 1).

In order to measure the performance of the proposed approach, the resulting point predictions are evaluated with the following metrics [14]: the normalized mean absolute error (NMAE), and the normalized root-mean-square error (NRMSE).

$$\mathrm{NMAE} = \frac{1}{P_{inst} \cdot N} \sum_{i=1}^{N} |p_i - r_i|. \quad (1)$$

$$\mathrm{NMRSE} = \frac{1}{P_{inst}} \sqrt{\frac{1}{N} \sum_{i=1}^{N} |p_i - r_i|}. \quad (2)$$

where N is the number of samples, p_i is the forecast wind power, r_i the actual wind power and P_{inst} is the total power capacity installed.

A CNN-LSTM architecture where wind power is not decomposed by EEDM is used as a benchmark to verify the accuracy of the model.

Prediction intervals. Deterministic forecasts cannot estimate the uncertainty of a given prediction. Therefore, the use of probabilistic forecasts is essential to obtain better economic results in the day-ahead electricity market [15].

PIs can be modelled by QR. The main advantage of this approach is that assumptions of any specific distribution are not needed. This methodology has been discussed in [16-18]. To obtain the forecast quantiles, simple ANN structures (CNN-LSTM, CNN and LSTM respectively) will be trained using the quantile regression loss function.

The reliability of the PI will be verified with an index termed as average coverage function (ACE) [19]:

$$\mathrm{ACE} = \mathrm{PICP} - \mathrm{PINC}. \quad (3)$$

where PINC is the PI nominal coverage and PICP is the PI coverage probability, which is defined by:

$$\mathrm{PICP} = \frac{1}{N} \sum_{i=1}^{N} c_i. \quad (4)$$

where N is the number of samples and c_i is a variable that indicates whether the measured value falls within the interval or not:

$$c_i = \begin{cases} 1, \text{if } r_i \in L_\alpha \\ 0, \text{if } r_i \notin L_\alpha \end{cases} \quad (5)$$

where L_α is the prediction interval. The PI will be more reliable the closest the ACE is to zero.

Case study

Data. The proposed approach has been tested and benchmarked with data from Ireland, obtained from EirGrid [20]. The wind power generation data ranges from 30-03-2019 to 03-07- 2019. As only historical wind power generation data were available, wind power is the only variable used as a predictor to train the model.

The dataset was divided into training, validation and testing sets to perform the study of the forecast model (Fig. 2). 80% percent of the data were employed to train the model. Considering the amount of data available, it is a reasonable proportion to train the model. The last five days of the dataset were used as a benchmark to compare the predictions with the actual values of wind power output.

Results. Errors for deterministic predictions for 1-h, 6-h and 24-h ahead forecasts for the proposed approach and the benchmark model are shown in Table 1. It can be seen that both NMAE and NRMSE are similar for the 1-h ahead forecasts. However, the EEDM-CNN-LSTM model clearly outperforms the benchmark model for longer forecast horizons. The increase of performance is notably high for the 24-h ahead forecast: the proposed approach obtains NMAE and NRMSE of 7.034% and 9.161%, whereas the CNN-LSTM model produces NMAE and NRMSE of 16.78% and 19.547% respectively.

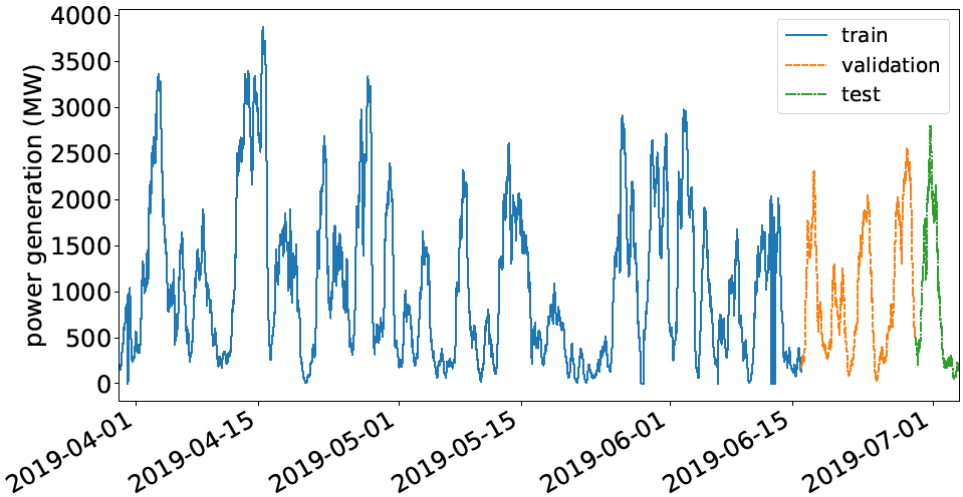

Fig. 2. Wind power time series.

Fig. 3 shows the prediction results for each horizon using both models. It is observed that the effect of decomposing the wind power into different sub-series using EEMD, and training each one separately, as it allows for the capture of the dynamics of the wind power output, such as spikes or sudden drops, in a more accurate way. On the other hand, the benchmark model can predict wind power fairly well 1-h ahead, but the accuracy of its forecasts decreases dramatically as the forecast horizon is increased.

The forecast quantiles were built by training three different models: a combined CNN-LSTM model, a simple CNN architecture, and a LSTM model. 95% and 80% PIs were computed 1-h and 6-h ahead. Table 2 shows the results of the different methods. Specifically, PICP and ACE have been used to evaluate the PIs. In terms of reliability, the CNN-LSTM model outperforms the other models in most of the scenarios. For instance, the 95% PIs constructed with the CNN- LSTM architecture for 1-h ahead forecasts produce a PICP of 91.25% in comparison to the PIs built by the CNN model (89.17%) and the LSTM model (83.75%). In this same scenario, the CNN-LSTM architecture has obtained a better ACE (-3.75%) than the ACE obtained by the other models (-5.83% and -11.25% for the CNN and LSTM models respectively).

The 95% and 80% PIs for every model are shown in Fig. 4. It can be observed that satisfactory PIs can be constructed by QR for short-term horizons.

Both proposed approaches to obtain deterministic predictions and PIs provide fairly reasonable results. These results could be improved by including more predictors, such as wind speed or numerical weather prediction data, and by training the model with a larger quantity of data, as limited amount of data has a negative impact on the performance of ANN models.

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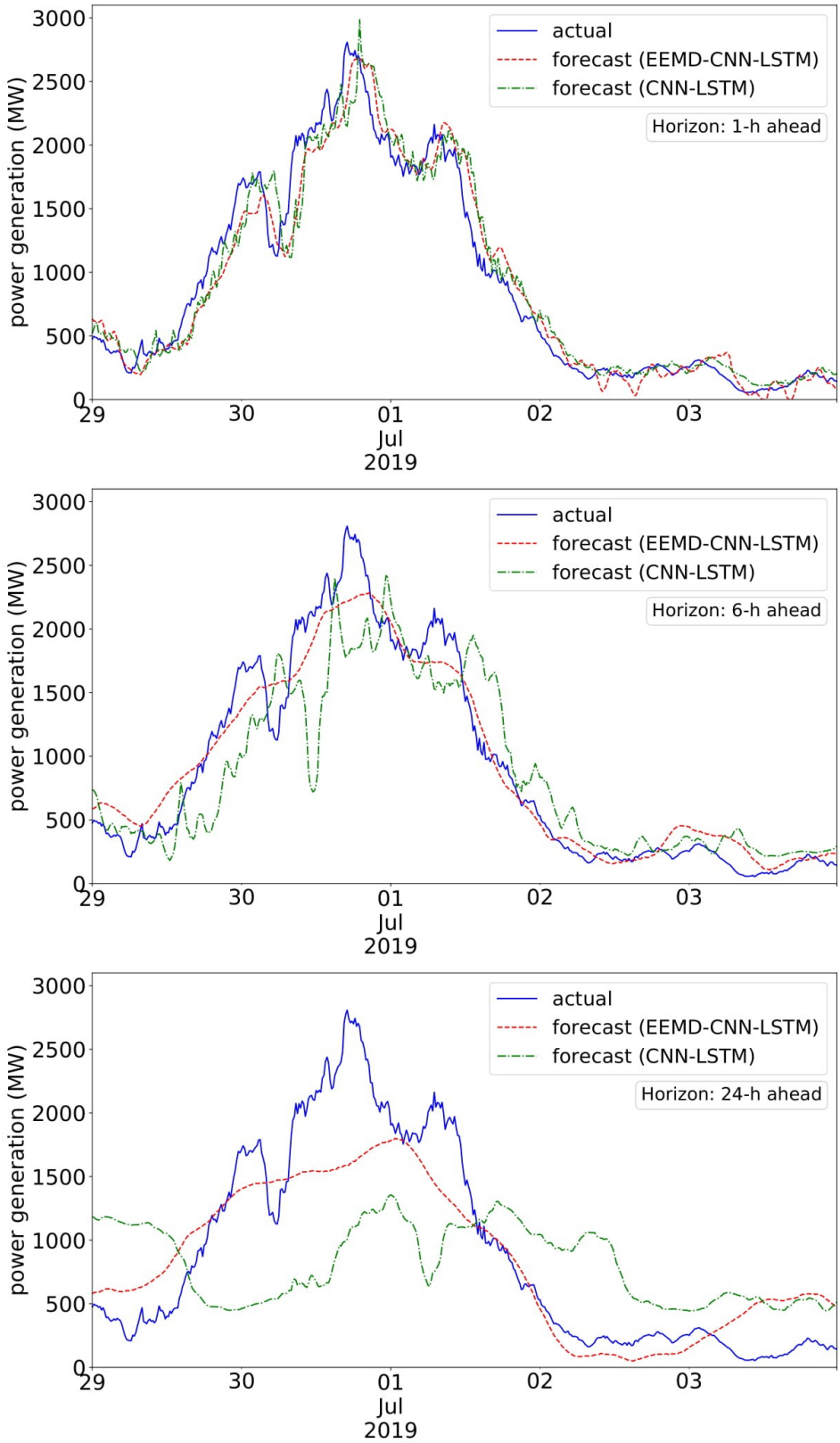

Fig. 3. Comparison of actual wind power and deterministic forecasts (1-h, 6-h, and 24-h ahead).

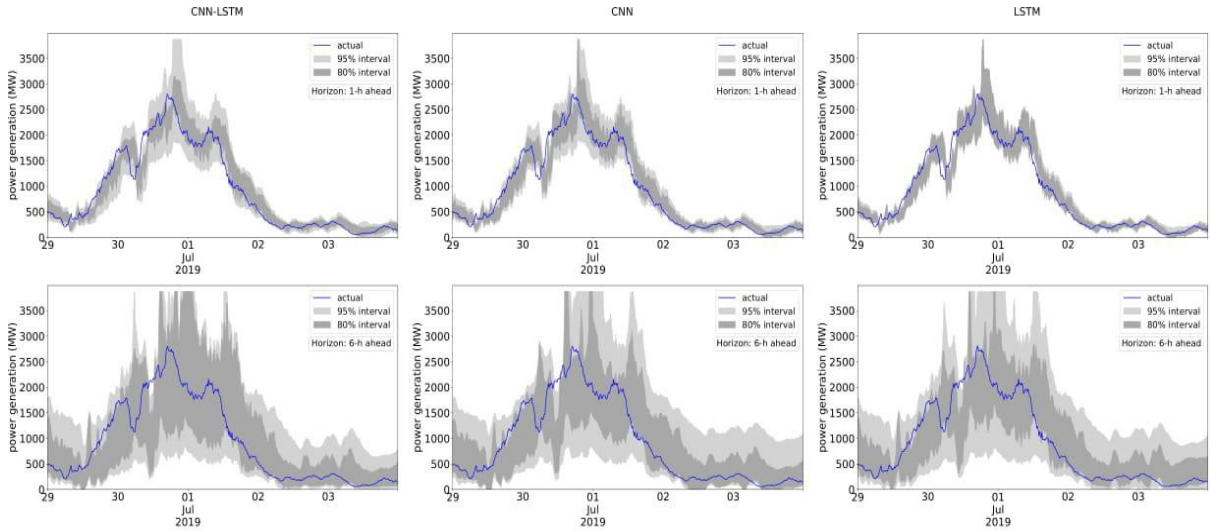

Fig. 4. Prediction intervals for 1-h and 6-ahead forecasts.

Table 1. Errors for deterministic forecasts.

Horizon	Error	CNN-LSTM	EEDM-CNN-LSTM
1-h	NMAE (%)	3.542	3.311
	NRMSE (%)	5.047	4.389
6-h	NMAE (%)	6.903	3.564
	NRMSE (%)	9.563	4.527
24-h	NMAE (%)	16.780	7.034
	NRMSE (%)	19.547	9.161

Table 2. Errors for prediction intervals.

95 (%)	CNN-LSTM		CNN		LSTM	
	PICP (%)	ACE (%)	PICP (%)	ACE (%)	PICP (%)	ACE (%)
1-h	91.25	-3.75	89.17	-5.83	83.75	-11.25
6-h	98.12	3.12	96.46	1.46	98.75	3.75
80 (%)	**CNN-LSTM**		**CNN**		**LSTM**	
	PICP (%)	ACE (%)	PICP (%)	ACE (%)	PICP (%)	ACE (%)
1-h	59.17	-20.83	64.17	-15.83	66.25	-13.75
6-h	88.33	8.33	83.75	3.75	78.75	-1.25

Conclusions

This paper presents an algorithm that combines EEDM and deep learning to provide short-term wind power forecasts, and the construction of PIs by QR. A case study using wind power generation data from Ireland has demonstrated that the proposed approach outperforms the benchmark model, especially for longer forecast horizons.

The model can improve in several ways. First, deep learning model benefits from having a larger quantity of data, and the data available in this case study were scarce. Therefore, increasing

their amount will result in better predictions. Secondly, only historical wind power data have been used as predictor. Multivariate models that include other variables such as wind speed or wind direction as predictors improve the final forecast as well. Finally, the whole installed power capacity was considered as a single wind farm, since data were not available on a wind farm level.

Afterwards, PIs were constructed by using QR. Three different models were used to obtain the forecast quantiles: a combined CNN-LSTM architecture, a CNN model, and a LSTM model. The reliability of the PIs was evaluated by using two indices: PICP and ACE. In most scenarios, the CNN-LSTM model provides the most reliable PIs. Further evaluation of the PIs can be done by assessing other parameters of the PI such as its sharpness [21]. As discussed for the deterministic model, forecast quantiles would benefit from larger amount of data and using other variables as predictors.

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