

Power forecast of hydro–wind–photovoltaic hybrid system dual-driven by physics and data

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Abstract. Short-term power forecast is an important way to guide operation of renewable energy stations and hybrid energy system (HES). The current studies focus on power forecast of single renewable energy station. However, the universality and applicability of power forecast model for HES is not clear. This study proposes a physics and data dual-driven day-ahead power forecast model for hydro–wind–photovoltaic HES. The WRF model and Xinanjiang model are used to drive meteorological and hydrological forecasts respectively. The hybrid variational mode decomposition - principal component analysis method is applied to further extract the features hidden in the meteorology or hydrology factors. The long short-term memory network is used to drive power forecast. China's Guandi hydro–wind–PV HES is considered as a case study. Results show that the forecast root mean square error of dual-driven model decreases by 4.2% ~ 12.0% compared to single-driven model.

Keywords: hydro–wind–photovoltaic; hybrid energy system; power forecast; dual-driven

1. Introduction

Exploitation and utilization of renewable energy sources is an important way to meet sustainable development goal and reduce environment pollution[1]. However, the wind and photovoltaic (PV) power face the problem of grid consumption with the characteristics of randomness, intermittence, and volatility[2]. Joint operation of hydro–wind–PV hybrid energy system (HES) is an effective way to reduce wind and PV power curtailment[3]. Short-term power forecast is a vital and challenging task for renewable energy stations and hydro–wind–PV HES[4].

Data driven and physics driven models of power forecast have been developed in the literature[5]. Data driven models train the mapping relationship between power output and forecast factors by time-series methods, filtering methods, machine learning methods, deep learning methods and so on[6]. Single data driven model usually have a high forecast accuracy when the forecast horizon is less than 6 hours. However, the current renewable energy stations are generally required day-ahead power forecast for power generation scheduling, in which case single data driven model cannot meet the requirements of forecast horizon and forecast accuracy. Physics driven models consider meteorology process and physical laws to forecast wind and PV power by numerical weather prediction (NWP) based methods[7]. The meteorology-hydrology coupling models further consider hydrological process to forecast reservoir inflow and hydropower[8]. However, the physics driven models are difficult to guarantee forecast accuracy due to the uncertainties from model inputs, model structure and model parameter. The combination of different models is an effective way to improve power forecast accuracy[9]. However, these power forecast models are usually focus on single renewable energy station. The universality and applicability of power forecast model for HES is not clear.

This study proposes a physics and data dual-drive model to improve the day-ahead power forecast accuracy for hydro–wind–photovoltaic HES. The remainder of this paper is organized as follows. Section 2 describes the day-ahead power forecast model. Section 3 presents the case study of a hydro–wind–photovoltaic HES. Section 4 draws the conclusions.

2. Methodology

This study proposes a day-ahead power forecast model for the hydro–wind–PV HES dual-driven by physics and data. The proposed model comprises three parts: meteorological-hydrological elements forecast, forecast factors reconstruction, and power forecast. The steps are as follows:

- (1) The WRF-Xinjiang coupling model is used to forecast meteorological-hydrological elements including wind speed, solar radiation, precipitation and reservoir inflow (Section 2.1).
- (2) The forecast factors are reconstructed by the hybrid variational mode decomposition (VMD) - principal component analysis (PCA) method (Section 2.2).
- (3) The long short-term memory (LSTM) network is used to drive power forecast (Section 2.3).

2.1 Meteorological-hydrological elements forecast

The WRF-Xinjiang coupling model simulating regional meteorological process and hydrological process, is a physics driven forecast method to consider temporal and spatial correlation of meteorological-hydrological elements. The WRF-Xinjiang coupling model is used to drive meteorological-hydrological elements forecast of different power stations. The steps are as follows.

- (1) WRF model is used to forecast regional meteorological elements including wind speed, solar radiation, precipitation and so on. The precipitation data within the catchment area of reservoir is collected to calculate the average area precipitation.
- (2) Xinjiang model is used to forecast interval inflow of reservoir. The release evolution of upstream reservoir is considered to further forecast the inflow of downstream reservoir.
- (3) The forecast accuracy of wind speed, solar radiation and reservoir inflow is calculated.

2.2 Forecast factors reconstruction

The hybrid VMD-PCA method is applied to further extract the features hidden in the meteorology or hydrology factors[10]. The steps are as follows.

- (1) The VMD method is used to decompose the meteorological-hydrological elements series including wind speed, solar radiation and reservoir inflow obtained by WRF-Xinjiang model.
- (2) The PCA method is used to reconstruct the subseries of meteorological-hydrological elements.
- (3) The threshold of accumulative contribution rate is set to extract the principal component of the subseries.

2.3 Power forecast of HES

The LSTM network is used to construct power forecast model. The different power forecast schemes are as follows.

Dual-driven model: the forecast factors including forecast factors reconstructed by section 2.2 and historical power series.

$$N_{t+L} = f(w_{t+L-1}, \dots, w_{t+L-m}; N_{t-1}, \dots, N_{t-n}) \quad (1)$$

where N is the power output; L is the forecast step; m and n are the embedding dimension; $f(\cdot)$ is the fitting function; w is the meteorological-hydrological element.

Single-driven model: the forecast factors only including historical power series.

$$N_{t+L} = f(N_{t-1}, \dots, N_{t-n}) \quad (2)$$

The forecast accuracy of power output is evaluated as the root mean square error (RMSE).

$$RMSE = \frac{\sqrt{\sum_{i=1}^M (N_i - \hat{N}_i)^2}}{N_{Cap} \sqrt{M}} \quad (3)$$

where M is the number of sampling points; N_{Cap} is the installed capacity.

3. Case study

3.1 Study area and model initialization

The proposed model is applied to day-ahead power forecast Guandi hydro–wind–PV HES located in Yalong river basin, China. The Yalong river has a catchment area of approximately 136000 square kilometers. Guandi hydropower station, located in the lower reaches of Yalong river, has the daily regulation ability with regulation storage 0.1232 billion m³. The selected case hydro–wind–PV HES comprises Guandi hydropower station and surrounding wind and PV stations. The total installed capacities of hydropower station, wind farm and PV station are 2400 MW, 2411 MW, and 920 MW, respectively.

The dataset of hydro–wind–PV HES from September 2015 to August 2017 is collected to test the performance of the proposed model. The data from September 2015 to August 2016 is taken as the training dataset and the remaining data is taken as testing dataset. The observed wind speed dataset with 10-minute time step is collected from 70-meter-high meteorological towers. The photovoltaic dataset with 1-hour time step is collected from PVGIS. The hydropower dataset with 1-h time step is collected from Guandi station. All the datasets are tackled as 1-hour time step series and normalized for power forecast.

The day-ahead WRF forecast is run with 10-min time interval. The horizontal resolutions of WRF model are 10 km and 3.33 km. The WRF model uses lambert projection and the vertical is 32.

3.2 Forecast results of HES

Fig.1 to Fig.3 show the forecast results of physics and data dual-driven model. The forecast accuracy of various meteorological-hydrological elements and power output shows significant seasonal differences.

Due to seasonal differences in wind speed, the forecast performance of wind speed and wind power vary in different months. The wind speed in winter and spring is relatively high, resulting in high forecast errors; The summer and autumn seasons have lower wind speeds and lower forecast errors. There is a good positive correlation between wind speed forecast error and power forecast error, that is, when the wind speed forecast error is small, the power forecast accuracy is usually higher. The seasonal differences in wind power forecast errors are higher than those in wind speed forecast.

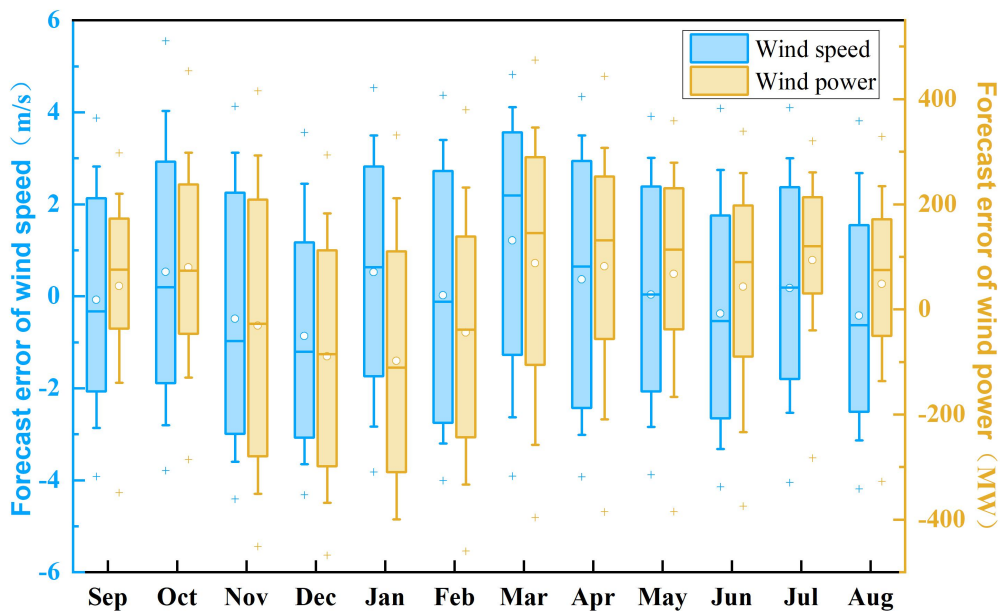


Fig. 1 Forecast error of wind speed and wind power

There are differences in the performance of the WRF model in forecasting solar radiation in different seasons. The summer solar radiation is high, and the forecast error is high, while the

forecast error for autumn, winter, and spring is low. The WRF model has high accuracy in forecasting solar radiation and is suitable for forecasting the photovoltaic.

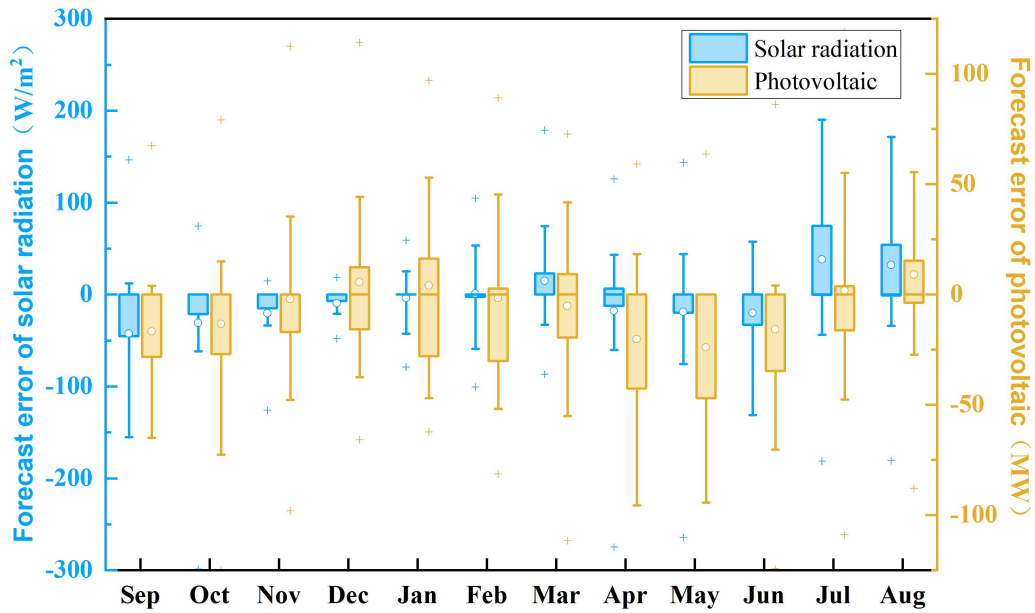


Fig. 2 Forecast error of solar radiation and photovoltaic

There are significant differences in the performance of the WRF-Xinjiang model in forecasting inflow in different seasons. The inflow during the flood season is relatively large, resulting in high forecast errors, while the non flood season forecast errors are relatively low.

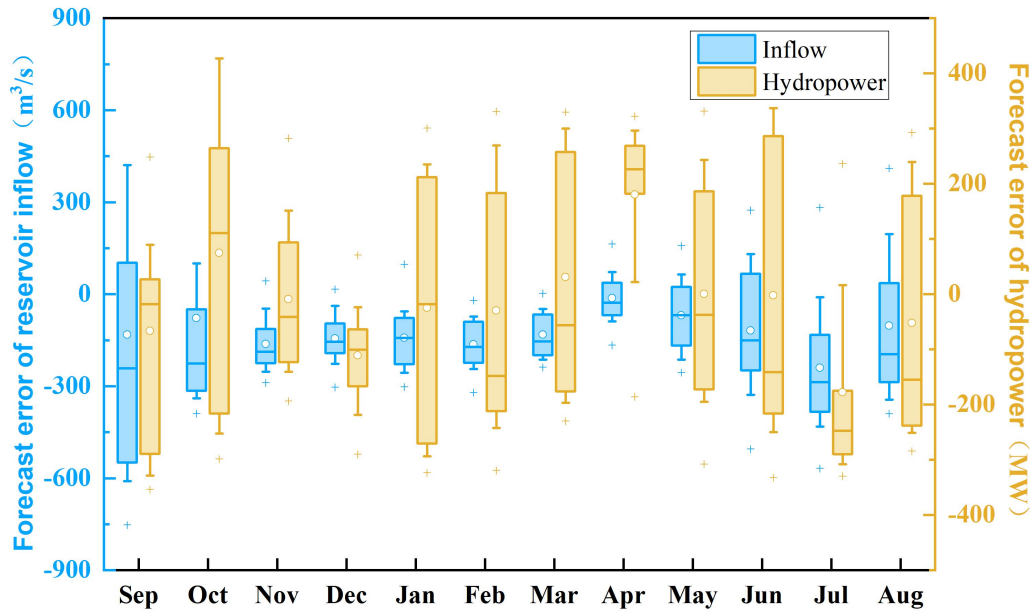


Fig. 3 Forecast error of reservoir inflow and hydropower

3.3 Discussion of various forecast schemes

The box plots and distribution of power forecast errors for various schemes are shown in Figure 4, and the root mean square error is shown in Table 1.

(1) For hydropower, wind power, and photovoltaic stations, the dual-driven model has lower annual forecast errors than the single-driven model. The root mean square error of power forecast has been reduced by 11.4%, 4.2%, and 12.0%, respectively.

(2) There is a seasonal difference in the forecast accuracy between the dual-driven model and the single-driven model. The power forecast accuracy of the dual-driven model is affected by the

forecast accuracy of meteorological and hydrological elements. For months with large forecast errors in meteorological and hydrological elements, the power forecast accuracy of the dual-driven model decreases accordingly.

(3) The power forecast errors of different driving models all approximate a normal distribution. Overall, the error distribution of the single-driven model is more dispersed, while the error distribution of the dual-driven model is more concentrated. Compared to the dual-driven model, the single-driven model is more prone to large forecast errors, which is not conducive to the power consumption of power stations in the grid.

(4) The wind power forecast error is the largest, followed by the hydropower power forecast error, and the photovoltaic power forecast error is the smallest. The accuracy of power forecast is influenced by the fluctuation of meteorological and hydrological elements, and is also related to the installed capacity of power stations.

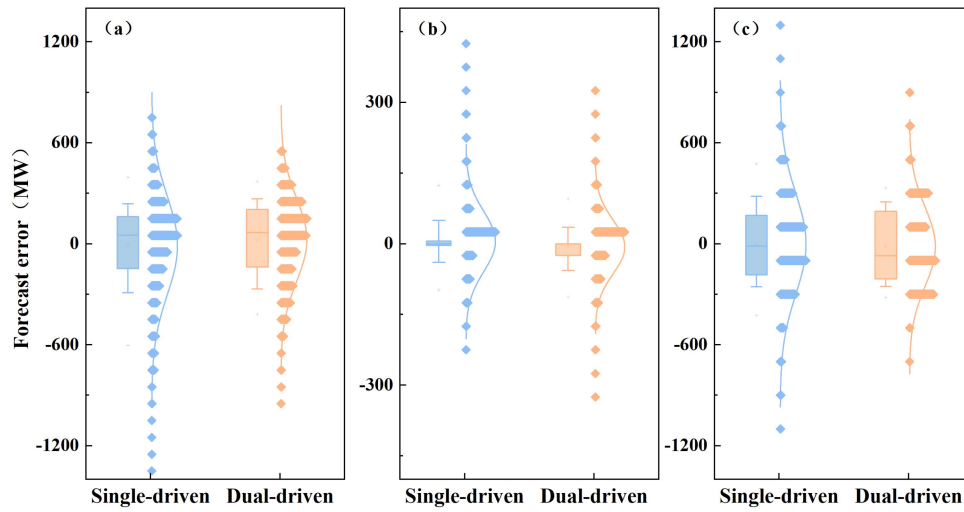


Fig. 4 Power forecast error of dual-driven model and single-driven model: (a) wind power; (b) photovoltaic; (c) hydropower

Table 1. Root mean square error of various forecast schemes

	Wind power		Photovoltaic		Hydropower	
	Single-driven	Dual-driven	Single-driven	Dual-driven	Single-driven	Dual-driven
January	0.1552	0.1152	0.0464	0.0502	0.1130	0.0984
April	0.1130	0.1061	0.0738	0.0652	0.0728	0.0949
July	0.0695	0.0815	0.0659	0.0642	0.0756	0.1021
October	0.0768	0.0848	0.0618	0.0602	0.1616	0.1241
Annual average	0.1094	0.0969	0.0616	0.0590	0.1016	0.0894

4. Conclusions

The present study proposed a short-term power forecast model for hydro–wind–PV HES. The power forecast errors approximate a normal distribution. For hydropower, wind power, and photovoltaic stations, the dual-driven model has lower annual forecast errors than the single-driven model. The root mean square error of power forecast has been reduced by 11.4%, 4.2%, and 12.0%, respectively.

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