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Multi-step wind speed and power forecasts based on a WRF simulation and an optimized association method

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HIGHLIGHTS

- A novel design: divide multi-step forecast into waves base on synoptic background.
- Improve NWP output combining fuzzy cluster, association rule and optimization.
- The proposed method is quite effective in real operational forecast of wind farms.

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ABSTRACT

At present, operational power forecasts are primarily based on the predicted wind speed of a single-valued deterministic Numerical Weather Prediction (NWP) simulation. However, due to the unavoidable uncertainties from model initialization and/or model imperfections, recent numerical techniques cannot directly meet the actual needs of grid dispatch in many cases, which means that achieving accurate forecasts of wind speed and power is still a critical issue. On this topic, our paper contributes to the development of a new multi-step forecasting method termed CSFC-Apriori-WRF, providing a one-day ahead wind speed and power forecast consisting of 96 steps. This method is based on a Weather Research and Forecasting (WRF) simulation, a Cuckoo search (CS) optimized fuzzy clustering, and an Apriori association process. First, a wind speed forecast is generated by running a configured WRF model. Next, the wind speed forecasting series is divided into segments that meet certain conditions and are defined as "waves" in this paper. Next, combining the CS-optimized fuzzy clustering and Apriori algorithm, the proposed method extracts the association rules between the shape characteristics and the forecasting error of the divided waves. Applying the association rules in the final optimization process, the proposed method significantly reduces the uncertainties of the WRF simulation and performs best among other models to which it is compared.

1. Introduction

As the most active sustainable energy supply alternative, wind power shows its clear benefits and good prospects [1], while its power output is quite difficult to accurately forecast mainly due to the complex fluctuations of wind speed. In 2011, the National Energy Bureau (NEB) drafted a regulation for power reports and checks, which requires a day-ahead power forecast of 96 steps. Wind farms will be fined for exceeding the error threshold of their power forecast. This regulation prompts the related wind forecast to become one of the most important techniques of the modern wind industry.

1.1. Existing wind forecasting methods and operational forecasts for wind farms

In the literature, two categories of wind forecasting methods were studied—statistical and physical models. At present, statistical methods are the most active research area on this topic, such as the Box-Jenkins method [2–4], neural networks [5–7], Kalman filtering [8,9], and hybrid statistical models [3,9–13], forecasts of

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Nomenclature

Abbreviations

BH	Binhai
CS	Cuckoo search
CS-FC	CS-optimized fuzzy C -means clustering
CSFC-Apriori-WRF	Cuckoo search optimized fuzzy Cluster-Apriori-WRF
GFS	Global Forecast System Model
LHS	left-hand-side
MRE	mean relative error
NEB	National Energy Bureau
NWP	numerical weather prediction
RH	relative height
RL	relative length
RHS	right-hand-side
RMSE	root mean square error
SC-Apriori-WRF	simple cluster Apriori WRF
SJD	Sujiadian
WRF	Weather Research and Forecasting

Variables, functions and parameters

v_t, $\hat{v}_t$	observed and forecasted wind speed at time t [m/s]
p_t, $\hat{p}_t$	observed and forecasted wind power at time t [MW]
Cap	wind power capacity of a specific wind farm [MW]
Ep	wind power forecasting error [%]
Δ	cutoff length
$G(\cdot)$	convolution kernel function
$\theta(\cdot)$	step function
$\widehat{V}_i$, V_i	forecasted wind speed series of WRF simulation and the corresponding observation
$\widehat{W}_i^{(p)}$, $W_i^{(p)}$	waves divided from $\widehat{V}_i$, and the corresponding observation
k_i	number of waves divided from $\widehat{V}_i$
$X = (x_j)$	a sample set of shape characteristics
X_i	a group of shape characteristics
$U = (\mu_{i,j})$	membership matrix
m	fuzzification level
$d_{i,j}$	Euclidean distance between x_j and V_i
C	given number of categories
$J_m(U, V)$	objective function of the fuzzy C -means cluster
$J_{UV}(U, V, C)$	validity standard function of the fuzzy C -means cluster
$\widehat{C}_L$, $\widehat{C}_H$	clustering number of RL and RH
V_L, V_H	central vector of RL and RH
$pSize$	number of nests in CS
$iter_{max}$	maximum iteration step
V_i^t	nest position in CS
$f_i(\cdot)$	fitness function of CS-FC
V_i^t	nest position of t -th iteration
V_{best}^t	the best nest position of t -th iteration
ρ_{best}	the global best nest position
$H(\cdot)$	indicator function
D	transaction set
$Sup(X, D)$	the rate of X contained in D
$Conf(X \Rightarrow Y)$	the confidence level of given association rule $X \Rightarrow Y$
$MinSup$	minimum support coefficient
$MinConf$	minimum confidence coefficient
ω	optimization coefficient in CSFC-Apriori-WRF

which are constructed based on analyzing and modeling the inner relationships among historical observations. Pure statistical forecasts could show excellent performance under specific local conditions but are usually unavailable beyond 6 h [14]. For the wind forecasts up to 48–72 h ahead, numerical weather prediction (NWP) simulations, utilizing fundamental principles of physics [15,16], are generally used, which is more skilled than pure statistical methods over longer periods [17,18]. Current wind farms generally adopt the deterministic forecasts from a single-valued NWP model; however, even with the recent advances in numerical simulations it is still difficult to directly meet the operational demands of both wind farms and the grid system [19]. This causes the wind power generation system to assume financial risks exacerbated by the unavoidable uncertainties in forecasting [20].

Generally, the uncertainties of numerical simulation come from two aspects: model initialization and/or model imperfections [20]. Model initialization is essential for numerical simulations. However, limited by technical skills, precision of observation instruments, impacts from the objective environment and more, observational errors are unavoidable. In another aspect, uncertainties of numerical simulation may also be produced by the inaccurate representation of physical and dynamical processes. Even the high-resolution model cannot precisely reflect the sub-grid-scale process and the microphysical process of real atmospheric motions. This causes model uncertainties stemming from simplifications and parameterizations in the physical representation [21,22]. Apart from these, another non-ignorable reason is the computational error including primarily, discretization, truncation and round-off errors. All these factors bring great challenge to numerical wind forecast. In the situation of operational wind forecasting, reducing model uncertainties is of great importance in improving the performance of an NWP simulation [23], primarily due to the unstable movements of the atmosphere and the chaotic characteristics of wind.

At present, many works have been done on the reduction of NWP uncertainties from several aspects. On the one hand, efforts were put forth on the improvement of numerical model itself. Some studies researched on target observation [24] and data assimilation [25] to reduce the numerical uncertainties from initial errors. Some studies focused on the optimization of parameterization scheme of numerical model's physical processes [26–28]. On the other hand, some recent research used the NWP–based process as the first step of an auxiliary input for other statistical models [29,30] such as Kalman filtering [18,31] and neural networks [14,32,33]. Some other literature studies on ensemble methods [34–36], in which individual simulations were conducted by setting different initial conditions after which the deterministic NWP model was run [37]. However, applications to actual wind farms are rarely mentioned and this is still an exploratory research area. This paper focuses on the improvement of single-valued NWP simulations in operational wind forecasting, which will benefit the NWP–based ensemble methods and other applications, as well.

1.2. Data mining in operational wind forecast

According to the wind power generation industry, a great deal of atmospheric observations and analysis/reanalysis data have been accumulated, while the influence of these on wind forecasting is not clear to date. At present, data mining, widely used in many other areas, has become a new but crucial tool to improve forecasting performance by promoting a more efficient usage of existing data sets. In general, data mining is expressed as a process