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An improved multi-step forecasting model based on WRF ensembles and creative fuzzy systems for wind speed

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HIGHLIGHTS

- The creative Fuzzy System is used to obtain the feature of WRFs' outputs.
- This system can reduce the NWP uncertainties and improve the forecasting accuracy.
- The evolutionary algorithm, CS, can correct WRF's forecasting values.
- This novelty model outperforms other approaches in different wind farms.
- The method is used for operational wind forecast within acceptable computations.

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ABSTRACT

Accurate wind speed forecasting, which strongly influences the safe usage of wind resources, is still a critical issue and a huge challenge. At present, the single-valued deterministic NWP forecast is primarily adopted by wind farms; however, recent techniques cannot meet the actual needs of grid dispatch in many cases. This paper contributes to a new multi-step forecasting method for operational wind forecast, 96-steps of the next day, termed the CS-FS-WRF-E model, which is based on a Weather Research and Forecasting (WRF) ensemble forecast, a novel Fuzzy System, and a Cuckoo Search (CS) algorithm. First, the WRF ensemble, which considers three horizontal resolutions and four initial fields, using a 0.5° horizontal grid-spacing Global Forecast System (GFS) model output, is constructed as the basic forecasting results. Then, a novel fuzzy system, which can extract the features of these ensembles, is built under the concept of membership degrees. With the help of CS optimization, the final model is constructed using this evolutionary algorithm to adjust and correct the results obtained based on physical laws, yielding the best forecasting performance and outperforming individual ensemble members and all of the other models for comparison.

1. Introduction

As the most active renewable energy resource, wind power exhibits strong benefits and positive prospects [1,2], but unlike other energy sources, its power output is difficult to accurately forecast [3] and always results in a gird imbalance between supply and demand; the error prediction costs can be as much as 10% of a wind farm's annual total income from selling energy [4].

The modern wind farms are required to report the forecasted power output one day in advance, the accuracy of which greatly depends on the performance of wind speed forecast. Due to the

Abbreviations: Avg., Average; CS, Cuckoo search; CS-FS-WRF-E, Cuckoo Search-Fuzzy System-WRF ensemble; CS-M-WRF-E, Cuckoo search-Mean-WRF ensemble; CST, China Standard Time; FS-WRF-E, Fuzzy System-WRF ensemble; GFS, Global Forecast System Model; MAE, Mean Absolute Error; Med., Median; MSE, Mean Square Error; M-WRF-E, Mean-WRF Ensemble; NWP, Numerical Weather Prediction; UTC, Coordinated Universal Time; Var., Variance; WRF, Weather Research and Forecasting.

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complex fluctuations of wind speed, it is quite difficult to generate an accurate forecast, and two categories of methods were generally reported—statistical and physical approaches. Statistical methods make forecasts by modeling the inner relationship among the historical observations, such as Kalman filtering [5,6], auto-regressive [7,8], neural networks [9–11] and hybrid statistical models [6,8,12]. Pure statistical forecasts could show excellent performance under specific local conditions but are usually unavailable beyond about 6 h [13]. In the operational wind forecasts up to 48–72 h ahead, numerical weather prediction (NWP) models outperform pure statistical forecasts [14,15] and are widely used, by providing more skilled forecasts over longer periods to supply the operational demand of both wind farms and the power grid. NWP models consist of discretized conservation equations of mass, momentum, energy and other fundamental principles of physics [16]. Recent research claimed that an accurate operational wind prediction method must include the NWP-based process [17], and it was sometimes the first step as an auxiliary input for other statistical models like Kalman filtering [15,18], neural networks [13,19,20], etc., in the literature.

1.1. Uncertainties of NWP forecasts

Current wind farms widely adopt the deterministic forecasts from single-valued NWP models, mainly due to their great advantages; however, at the same time, wind farm operations also involve financial risks that are exacerbated by uncertainties in two aspects: model initialization and/or model imperfections [21].

Considering model initialization, which is an approximation of the true atmospheric state primarily a result of objective factors [21], is essential for NWP simulation. In particular, observational errors are unavoidable; they are limited by technical skills, precision of observation instruments, impacts from the objective environment and more. Furthermore, the coverage of general observation stations is incomplete, especially in remote and ocean areas. This causes the distributions of various observational data to always be inconsistent with the NWP model configuration in both space and time. Although the target observation [22] and data assimilation [23] techniques are developed to reduce the initial errors, uncertainties created by all of these factors cannot be eliminated.

Table 1
Model configuration of WRF simulation.

	Physical options
Cumulus parameterization	Grell 3d ensemble cumulus scheme
Short-wave radiation	RRTM scheme
Long-wave radiation	Dudhia scheme
Surface layer physics	Eta similarity
Land surface processes	Noah Land Surface Model
Planetary Boundary layer	Mellor–Yamada–Janjic scheme

Uncertainties may also be produced by NWP models themselves, for several reasons [21]; importantly is the error caused by inaccurate representations of physical and dynamical processes. Although the high-resolution NWP models cannot precisely reflect atmospheric movements, the scales are smaller than the model grid, known as the sub-grid-scale process. Consequently, the sub-grid-scale turbulence and microphysical processes of real atmospheric motions are difficult to describe in a NWP model. This causes model uncertainties stemming from simplifications and parameterizations in the numerical model's physical representation of the system it simulates [24,25]. Apart from this, another non-ignorable reason is the computational error during the numerical simulation process, including, primarily, discretization, truncation and round-off errors.

1.2. Reducing the uncertainties of NWP forecasts: ensemble methods

Recently, the model resolution and calculation efficiency of NWP simulations have continuously improved, primarily as a result of the contributions of the more advanced atmospheric observation skills, the additional improvements in the parameter optimization of the physical process, and the application of a high-speed, large-capacity supercomputer with the relevant parallel techniques. However, even with the current development of the NWP model it is still difficult to meet the operational demand of both wind farms and the grid system [26].

Because atmospheric movements are instable, exhibiting chaotic characteristics, the deterministic prediction from a single-valued NWP simulation contains unavoidable errors. The most important for reducing the uncertainties of NWP simulations is the ensemble method, which conducts ensemble simulations by setting different initial conditions then running the deterministic NWP model [27]. The ensemble members differ from each other in the initial conditions and/or the numerical representation being used, generally consisting of three aspects: (i) different initializations, (ii) different model configurations, and (iii) multiple models [28,29]. As a consequence, a set of NWP-forecasted results can be obtained that describes the probable states of the future atmosphere.

Generally, the uncertainty problems can be divided into two categories: randomness, and fuzziness. The core of the randomness system is that the probable events are deterministic, but the occurrence of events is uncertain. It concerns the probability distribution of probable states in the future, and some studies researched on it [30–33]. This is important for weather prediction, especially for extreme weather prediction. However, few articles have covered the ensemble-based operational forecast for wind farms, in which forecasts up to 48–72 h are needed. Considering this problem, contribution of each ensemble member to the final forecast result is non-specific and is difficult to define using deterministic criteria, which shows the characteristics of fuzziness.

Table 2
Twelve members of WRF simulation constructed in this paper.

No.	Grid space	Initial field time	Initial boundary conditions	Grid points	Mark in this paper
MEM-1	27 km	0000 UTC	0.5° GFS	300 × 200	27km00
MEM-2	27 km	0600 UTC	0.5° GFS	300 × 200	27km06
MEM-3	27 km	1200 UTC	0.5° GFS	300 × 200	27km12
MEM-4	27 km	1800 UTC	0.5° GFS	300 × 200	27km18
MEM-5	3 km	0000 UTC	0.5° GFS	150 × 120	3km00
MEM-6	3 km	0600 UTC	0.5° GFS	150 × 120	3km06
MEM-7	3 km	1200 UTC	0.5° GFS	150 × 120	3km12
MEM-8	3 km	1800 UTC	0.5° GFS	150 × 120	3km18
MEM-9	9 km	0000 UTC	0.5° GFS	180 × 150	9km00
MEM-10	9 km	0600 UTC	0.5° GFS	180 × 150	9km06
MEM-11	9 km	1200 UTC	0.5° GFS	180 × 150	9km12
MEM-12	9 km	1800 UTC	0.5° GFS	180 × 150	9km18