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Research and application of a hybrid wavelet neural network model with the improved cuckoo search algorithm for electrical power system forecasting

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HIGHLIGHTS

- Propose a hybrid model that can be used to forecast the complex electrical power system.
- Enhance the speed of local convergence and the accuracy of finding the optimal solution of CS.
- Use more accurate metrics to assess the forecasting performance of the proposed model.

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ABSTRACT

Electricity forecasting plays an important role in the operation of electrical power systems. Many models have been developed to obtain accurate forecasting results, but most of them focus more on a single forecasting indicator, such as short-term load forecasting (STLF), short-term wind speed forecasting (STWSF) or short-term electricity price forecasting (STEPF). In this paper a new hybrid model based on the singular spectrum analysis (SSA) and modified wavelet neural network (WNN) is proposed for all the short-term load forecasting, short-term wind speed forecasting and short-term electricity price forecasting. In this model, a new improved cuckoo search (CS) algorithm is proposed to optimize the initial weights and the parameters of dilation and translation in WNN. Case studies of half-hourly electrical load data, 10-min-ahead wind speed data and half-hourly electricity price data are applied as illustrative examples to evaluate the proposed hybrid model, respectively. Experiments show that the hybrid model resulted in 46.4235%, 31.6268% and 25.8776% reduction in the mean absolute percentage error compared to the comparison models in short-term load forecasting, short-term wind speed forecasting and short-term electricity price forecasting, respectively.

1. Introduction

In energy systems, short-term load forecasting (STLF), short-term wind speed forecasting (STWSF) or short-term electricity price forecasting (STEPF) plays an important role in electrical power system operation [1]. Accurate forecasting of them seems to be a difficult task due to many unavoidable factors (e.g., activities, climate, weather and season).

Up to now most of the forecasting models focus more on the forecasting of a single indicator, STLF, STWSF or STEPF. Actually, STLF yields the basic information for scientific operations of an electrical power system, STWSF directly influences the electricity generation from wind power [2], and STEPF provides price reference for market participants [3].

In recent decades, many studies on STLF, STWSF and STEPF have been presented, and the forecasting methods can be divided into three categories [4]: (a) statistical models; (b) artificial neural networks (ANNs); and (c) hybrid forecasting models.

Statistical models are built based on statistical equations to get the potential change rule from history data sampling [4–10]. However, these models cannot address special and nonlinear events effectively because of their own weaknesses [11,12], and certain hypotheses must be developed based on the characteristics of the load data prior to forecasting. Overestimation of the future load pattern can cause the start-up of additional or unnecessary generating units, resulting in increased costs for reserves and operation. Underestimation of the future load pattern will result in an inability to provide the required operating reserves and to maintain the

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Nomenclature

α	step size of CS
a_j	scaling factor of the wavelet basis function
A_n	forecasting accuracy of the *n*th datum
b_j	translation factor of the wavelet basis function
C	input of WNN
δ	convergence tolerance of BFGS
d_t	search direction of BFGS
DM	statistic value
$\boldsymbol{D}_t$	symmetric matrix at $\boldsymbol{x}^t$
ε_n	forecasting error of the *n*th datum
F_i	fitness function of nest *i*
g	current iteration number of CS
Gen_{Max}	maximum number of iterations
h_j	wavelet basis function
$h(j)$	output of the *j*th hidden layer node
H	continuous function
$Iter_{max}$	maximum number of iterations of BFGS
K	number of lagged vectors
K^*	maximum between *L* and *K*
L	windows length
L^*	minimum between *L* and *K*
m^k	*kth*-order forecasting effectiveness unit
M	number of repetitions of each trial
λ_t	step length of BFGS
n	number of host nests
N	length of a time series
p_a	parameters of the cuckoo search algorithm
t	current iteration number of BFGS
w_{ij}	connection weights between the input layer and hidden layer
x_i^t	cuckoo *i* at iteration *t*
$\boldsymbol{x}_i$	nest *i*
X	trajectory matrix
y	expectation of the observed values
y_n	observed value of the *n*th datum
$\hat{y}_n$	predicted value of the *n*th datum
Y	predicted output of WNN
$z_{\alpha/2}$	upper (or positive) *z*-value
$-z_{\alpha/2}$	under (or negative) *z*-value

Abbreviation

AA	adaboost algorithm
ANN	artificial neural network
BPNN	back propagation neural network
BFGS	Broyden-Fletcher-Goldfarb-Shanno
CPSO	chaotic particle swarm optimization
CS	cuckoo search
CS-WNN	cuckoo search-optimized wavelet neural network
DM	Diebold-Mariano
EA	evolutionary algorithm
EEMD	ensemble empirical mode decomposition
EMD	empirical mode decomposition
FEEMD	fast ensemble empirical mode decomposition
FVD	forecasting validity degree
GA	genetic algorithm
GABPNN	genetic-algorithm-optimized back propagation neural network
MAE	mean absolute error
MAPE	mean absolute percentage error
MSE	mean square error
PSO	particle swarm optimization
RBFNN	radical basis function neural network
SA	simulated annealing
STEPF	short-term electricity price forecasting
STLF	short-term load forecasting
STWSF	short-term wind speed forecasting
WNN	wavelet neural network

stability of the system, likely triggering a breakdown of the power system network [13]. Recently, ANNs with high adaptability to nonlinear series have attracted the interest of researchers in the areas of STLF, STWSF and STEPF [14–19].

Meanwhile, to decrease the negative influences that are intrinsic to individual models, many hybrid approaches that combine the advantages of individual ones have been proposed [20–24].

To achieve higher forecasting accuracy, some data-processing algorithms, such as empirical mode decomposition (EMD) [25], the ensemble empirical mode decomposition (EEMD) algorithm [26] and the fast ensemble empirical mode decomposition (FEEMD) algorithm [27], have been employed in ANNs to build hybrid models. The data decomposition, which could reduce the non-stationary feature of the original data, promotes the forecasting performance indirectly.

Moreover, intelligent optimization algorithms including the chaotic particle swarm optimization (CPSO) [28], the genetic algorithm (GA) [29], the particle swarm optimization (PSO) [30], the evolutionary algorithm (EA) [31] and the adaboost algorithm (AA) [32], have been utilized to determine the initial weights and thresholds of ANNs. In 2009, Yang proposed a meta-heuristic cuckoo search (CS) algorithm that integrates the *Lévy* flight observed in certain species of birds with cuckoo breeding behavior [33]. In various fields [34–40], CS has been demonstrated to successfully solve optimization problems. Simultaneously, the superior availability of CS over other optimization algorithms such as PSO and GA has been proven with benchmark functions [41,42]. Yang and Deb analyzed the causes of the efficiency of CS in [33]. Based on the outstanding features of CS (including broad applicability, quick convergence, robustness to dynamic changes, ease of implementation, conceptual simplicity, ease of hybridization with other methods, and the ability to solve problems with no definite solutions), a combined forecasting model with weight coefficients determined by CS provides more accurate results than other individual models [43].

For a whole electrical power system, different forecasting models to obtain corresponding indicators possibly result in inconveniency and inefficiency for planning and management of grids. Thus, it is required to build a widely applicable model to achieve accurate results for STLF, STWSF and STEPF. Among various ANN models, the wavelet neural network (WNN) is a good choice to achieve high convergence rates and accurate results [44]. In this paper, a modified WNN model with the singular spectrum analysis (SSA), which is used to decompose the original data, is proposed for all of STLF, STWSF and STEPF. In the modified WNN model, an improved CS algorithm, which is on the basis of Broyden–Fletcher–Goldfarb–Shanno (BFGS) quasi-Newton method to speed up the local convergence in the late period of optimization, is introduced to optimize the initial weights and the parameters of dilation and translation.

To evaluate the proposed model, the half-hourly electric load and electricity price data from New South Wales, the State of Queensland and the State of Victoria in Australia and the wind data from four wind power stations in Penglai, China for multi-step forecasting are used as test data, respectively. The main contributions in this paper are demonstrated as follows.