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An innovative integrated model using the singular spectrum analysis and nonlinear multi-layer perceptron network optimized by hybrid intelligent algorithm for short-term load forecasting

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ABSTRACT

Short-term power load forecasting is receiving increasing attention, especially because of intrinsic difficulties and practical applications. In this paper, the novel integrated approaches, combining longitudinal data selection (*LDS*), singular spectrum analysis (*SSA*) technique, adaptive particle swarm optimization based on gravitational search algorithm (*APSOGSA*) and the nonlinear multi-layer perceptron neural network (*NMLPNN*), were proposed for the short-term power load forecasting. Firstly, the *LDS*, which guarantees that the input and output data have the same properties to ensure abundant performance. Then, the *SSA* technique is used for identifying and extracting the trend and seasonality of power load time series. Finally, the *NMLPNN*, which is optimized by the *APSO, GSA*, and *APSOGSA*, is utilized to deal with the irregularity and volatility of the power load. These integrated methods are applied to forecast half-hour power load data from *New South Wales, Queensland* and *Singapore*. By comparison of the obtained experimental results, the proposed *SSA-APSOGSA-NMLPNN* integrated method indicates the superiority and promising performance and has a good robustness.

1. Introduction

Short-term power load forecasting (*STLF*) is a critical task for energy management of power grids because the accuracy of the forecasting affects power system operations. Modeling and prediction of short-term load time series have always been a challenge to the researchers and relevant authorities. So far, a lot of approaches have been presented for the *STLF* and these methods can be divided into three classifications: statistical approaches, meteorological numerical approaches and computational intelligence approaches. The statistical approaches such exponential smoothing [1–3], regression models [4], *ARIMA* [5], and seasonal *ARIMA* [1,6], Filtering methods [7–11], which are mainly solved by the linear problem. In spite of simple and easy to use, these methods are unfit for the *STLF* because the load series has the complex characters of non-stationarity, nonlinearity and high volatility. The meteorological numerical approach such as numerical weather prediction model [12], this method is often closely contact with meteorology. Just now, with the repaid development of the computing power for the computer, the computational

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intelligence approaches also known as machine learning are becoming more and more popular, such as, artificial neural network [13–17], support vector machine [1,17,18], support vector regression [19–21] and all kinds of heuristic optimization algorithm [1,8,10,18,22,23,24,25]. These computational intelligence prediction approaches have clearly shown good effectiveness for the time series of the chaos and the nonlinearity since these do not need to meet correlation between inputs and outputs or complex formulas.

The literature on load forecasting is vast, through the analysis of the literature over the past few years; the combination of different approaches has become a trend. For instance, Li et al. [22] proposed a hybrid load forecasting model, which combined the fruit fly algorithm and *GRNN*, and the performance of this combination model was proved to be effective; Liu et al. [8] presented a combination approach with parameter optimization, which including extended kalman filter, *EMD*, extreme learning machine and *PSO*. Meanwhile, four different cases are used to assess the accuracy and performance of this proposed prediction approach; However, Wang et al. [23] also presented a combination power load prediction method consists of *DE* and *SVR*, which the parameters of *SVR* are optimized by the *DE* algorithm. Simulation shows that the proposed hybrid method outperforms the *SVR, BPNN* and regression prediction models; Nevertheless, in order to solve the selection of an appropriate kernel function for kernel-based method, Che et al. [26] proposed a kernel-based *SVR* model by using individual model selection algorithm, which provides a novel way for the kernel function selection of *SVR* model. By the mean of the actual power load data evaluations, experiment results show that this hybrid approach improves power load prediction accuracy comparison with other model. Recently, Hernandez et al. [27] proposed a three-stage architecture approach, which starts with pattern recognition by a self-organizing mapping neural network, then a clustering of the previous partition via k-means algorithm, finally power load forecasting for each cluster with a multilayer perceptron, by comparison with other approaches, the empirical results indicate that this proposed model is effective.

Through the review of previous literatures, the processes of these papers mainly are data preprocessing, forecasting model and optimization method. For the preprocessing approaches primarily utilize the wavelet transform, empirical mode decomposition, and the popular forecasting models are support vector machine, extreme learning machine and artificial neural network. Nevertheless, it is very common to use single intelligent algorithm for parameters optimization. Hence, in this paper, our main contribution is to present a novel integrated approach, combining longitudinal data selection (*LDS*), Singular Spectrum Analysis technique (*SSA*), Adaptive Particle Swarm Optimization (*APSO*), Gravitational Search Algorithm (*GSA*), hybrid Adaptive Particle Swarm Optimization and Gravitational Search Algorithm (*APSOGSA*) and the Nonlinear Multi-layer Perceptron Neural Network (*NMLPNN*), for the *STLF*. In this study, by means of the *SSA* technique the high frequency components of the noisy power load time series were removed in order to enhance the forecasting performance of *NMLPNN* model, while the weights and biases of the *NMLPNN* were optimized by the *APSO, GSA, and parallel APSOGSA* to obtain the optimal forecasting performance. Meanwhile, the data structure of the *NMLPNN* was used the *LDS*, which guarantees that the input and output data have the same properties to ensure abundant performance. Finally, the half-hour power load time series from New South Wales, Queensland and Singapore were used as examples to evaluate the performance of this proposed approach. To avoid randomness due to the *APSO, GSA, parallel APSOGSA* and *NMLPNN*, all of training sets and testing sets were repeated 30 times prior to averaging. As far as we know, it is the first application of this proposed integrated method for to the *STLF*.

The remaining is organized as follows: Singular Spectrum Analysis is discussed in Section 2 and the Nonlinear Multi-layer Perceptron Neural Network will be presented in Section 3. The heuristic algorithms are introduced in Section 4 and the optimization procedure for *NMLPNN* in Section 5. The proposed integrated framework is outlined in Section 6. Experimental results obtained by three different places in Section 7. Finally, the conclusion is given in Section 8.

2. Singular spectrum analysis

Singular spectrum analysis (*SSA*) is a novel nonparametric method, which is employed to the analysis of time series and combines multivariate statistic and probability theory, and it is often used for indentifying and extracting periodic, quasi-periodic and oscillatory components from the primal data [28]. Standard *SSA* performs four steps, which include embedding, singular value decomposition, grouping and diagonal averaging. However, the first two steps are also called the time series decomposition and the three and four steps known as the reconstruction. The procedure of *SSA* is briefly depicted as below:

Step 1: Embedding. The embedding process converts the original series to a sequence of multidimensional vector. Considering a time series $Y = [y_1, y_2, ..., y_N]$ of length N. Let L be an integer and called the windows length, $1 < L < N$. The embedding process forms $K = N - L + 1$ lagged vectors (the trajectory matrix), and the trajectory matrix is written by:

$$X = \begin{pmatrix} y_1 & y_2 & y_3 & \dots & y_K \\ y_2 & y_3 & y_4 & \dots & y_{K+1} \\ y_3 & y_4 & y_5 & \dots & y_{K+2} \\ \dots & \dots & \dots & \dots & \dots \\ y_L & y_{L+1} & y_{L+2} & \dots & y_N \end{pmatrix}_{L\times K} \tag{1}$$

It is noteworthy that all the elements of the trajectory matrix along the diagonal $i + j = const$ are equals.

Step 2: Singular Value Decomposition (*SVD*). Let $S = XX^T$, denoted by $\lambda_1, ..., \lambda_L$ the eigenvalue of S taken in the decreasing order of magnitude ($\lambda_1 \geq \dots \geq \lambda_L \geq 0$) and by $U_1, ..., U_L$ the orthonormal system of the eigenvectors of the matrix S corresponding to these eigenvalues. Then the *SVD* of the trajectory matrix X can be defined as following:

$$X = X_1 + \dots + X_d, \tag{2}$$