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Short-term Load Forecasting Based on Slime Mould Algorithm Optimized Least Square Support Vector Machine Combined with Variational Modal Decomposition

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ABSTRACT

To improve the accuracy of power system short-term load forecasting and energy utilization efficiency, based on Variational Mode Decomposition (VMD), Least Squares Support Vector Machine (LSSVM), and Slime Mould algorithm (SMA), a combined load forecasting model of VMD-SMA-LSSVM is proposed. First, the load signal was decomposed by VMD. For the decomposed sub-sequences, a combined algorithm based on slime mold optimization algorithm and least square support vector machine algorithm is used to predict respectively. Then, the predicted results of each sub-sequence were superposed and reconstructed to get the final predicted value. By comparing it with other machine learning models and other decomposition methods., this research results show that the load prediction results based on this method have more excellent prediction effects than methods.

Keywords: Short-term power load forecasting, Variational modal decomposition, Slime mould algorithm, Least squares support vector machine

NONMENCLATURE

Abbreviations	
APEN	Applied Energy
Symbols	
n	Year

1. INTRODUCTION

Short-term load forecasting is of great significance for the safe, reliable, and economic operation of energy systems. Predicting the load as accurately as possible will help improve energy utilization efficiency under the premise of ensuring the safe use of energy. For the prediction of short-term load, a variety of mature and feasible methods have been developed: They include ARIMA prediction from the perspective of mathematical theory, grey prediction, and a series of machine learning and deep learning algorithms, such as BP neural network, Support Vector Machine (SVM), LSTM algorithm, Etc. On the basis of SVM, an improved model based on equality constraint, namely LSSVM Least Squares Support Vector Machine (LSSVM), was generated. In order to make the machine learning algorithm can play a better prediction effect, the selection of its hyperparameters is very important, so the combination of intelligent optimization algorithm and machine learning algorithm has become the general trend. In addition to traditional particle swarm optimization, genetic algorithm, simulated annealing, and other algorithms, a series of new and better optimization algorithms have emerged in recent years, such as the latest optimization algorithm in 2020 -- Slime Mould Algorithm (SMA) [1]. It is an intelligent application of biological phenomena based on the predation process of slime molds and has faster convergence characteristics. In addition, because the curve of load is not completely smooth, it contains some harmonic components, which may interfere with the prediction results. For this part of noise signal processing, there are also many methods, such as Wavelet Decomposition, Empirical Mode Decomposition (EMD),

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and Variational Mode Decomposition (VMD) born in 2014 [2]. The combination of decomposition, prediction, and intelligent optimization gives birth to a series of excellent combined prediction algorithms.

Based on the idea of combined prediction, a new load prediction method, VMD-SMA-LSSVM combined prediction algorithm, is proposed in this paper. Firstly, the original load was decomposed by VMD decomposition, and then the LSSVM prediction model based on slime mould algorithm was used to predict the load. Finally, the load was reconstructed and stacked. By comparing this algorithm with other machine learning algorithms and EMD decomposition results, it is proved that the prediction model proposed in this paper has good prediction ability and can accomplish load prediction tasks faster and better.

2. THEORETICAL INTRODUCTION

2.1 Variational Mode decomposition

Compared with wavelet and Fourier decomposition, the decomposed sequence by VMD is more stable. Compared with EMD series, VMD overcomes its sensitivity to noise and can extract more effective feature information by processing signal sequences. The criterion for serial decomposition of variational modal decomposition is to minimize the sum of the bandwidths of modal components [2,3,4].

2.2 Slime mould algorithm

Slime mould algorithm is the latest optimization algorithm proposed by Li et al., in 2020, by simulating the diffusion and foraging process of slime mould [1]. It is an intelligent application of biological phenomena based on the predation process of slime moulds, and has faster convergence characteristics.

2.3 Least square support vector machines

Support vector machines perform well in solving classification and regression problems [5]. On this basis, Suykens and Vandewalle reconstructed the least squares support vector machine [6]. The improved least-squares support vector machine can greatly speed up the operation and get relatively good algorithm results without excessive mining of hyperparameters.

3. VMD - SMA - LSSVM MODEL

3.1 Model structure

Combining the decomposition and algorithm proposed above ideas, this paper puts forward a combined forecasting model. First by VMD decomposition, the sequence is decomposed into multiple components of the IMF. In view of each subsequence, least squares support vector machine based on slime moulds algorithm will be trained and predicted respectively, for each sequence their prediction results are obtained. After predicting the decomposed curves, refactoring and stacking results, the final prediction curve is obtained. The main process of the prediction model is shown in Figure 1.

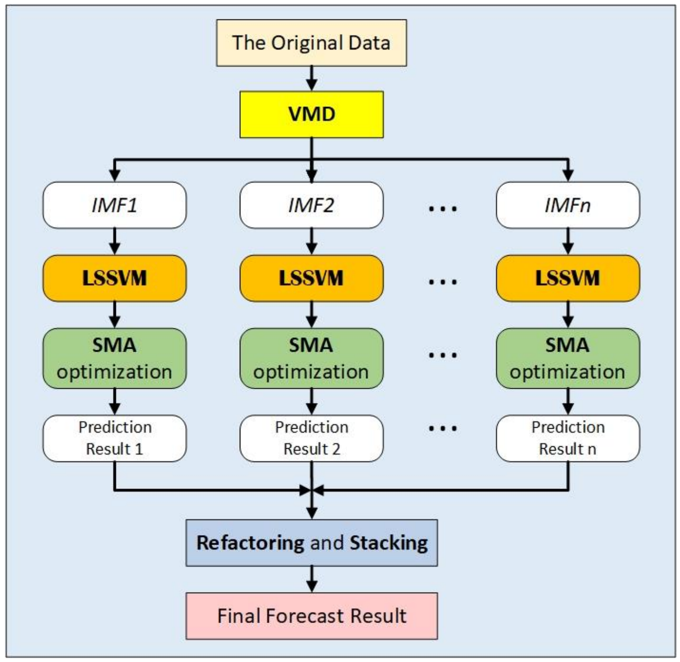

Fig. 1. Flow chart of VMD-SMA-LSSVM model

3.2 ERROR MEASURES

For the evaluation of prediction ability, it is necessary to make a quantitative comparison through error analysis. In this paper, two common error indicators are selected for analysis, and the validity of the model is verified by comparing the error size. One is the root mean square error (RMSE), the other is the mean absolute percentage error (MAPE). The expressions of these two error measures are shown in Equations (1) and (2) respectively:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \quad (1)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad (2)$$

4. THE EXAMPLE ANALYSIS

4.1 The experimental data

In order to test the reliability of the VMD-SMA-LSSVM algorithm proposed in this paper, the load data of an area in China is used as a sample to establish a data set, and the model is trained and verified. The dataset consisted of one data point every 15 minutes and 96 data points per day. 2976 data of January 2015 were extracted for analysis, in which the data of the first 30 days were used as the training set, and the data of the last day were predicted (96 data points).

4.2 Results analysis

First, the original sequence is decomposed by VMD. The number of components decomposed by VMD is relatively free, which is also a significant advantage compared with EMD. In order to improve the efficiency of operation, this paper decomposes it into five sequences. The decomposed five graphs and a graph of the initial data are shown in Figure 2. The original curve with irregular noise is decomposed into a series of sub-sequence curves with strong regularity.

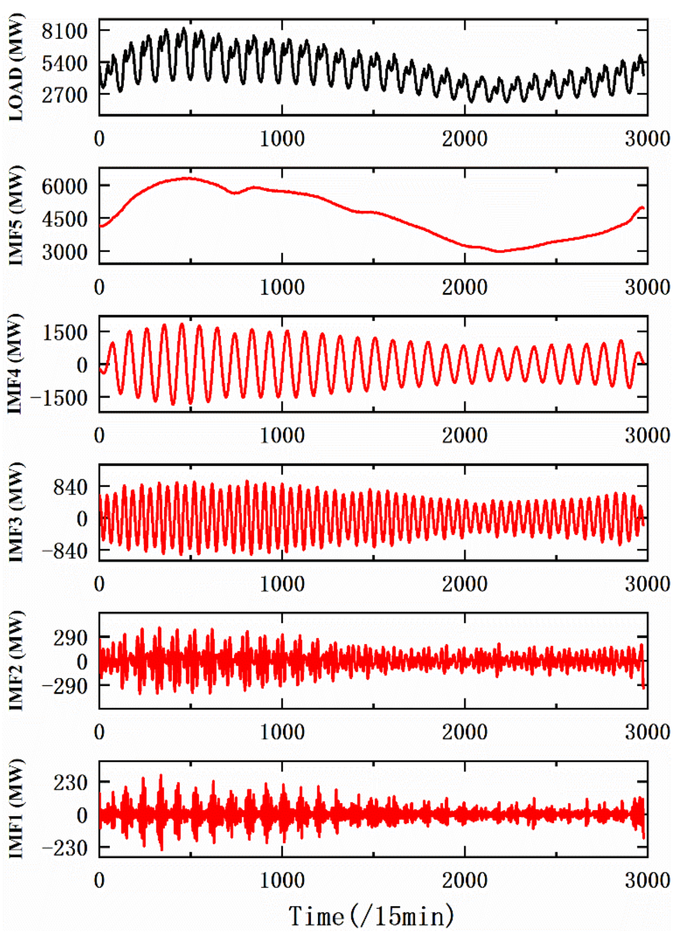

Fig. 2. Sequences decomposed by VMD

Firstly, we compared the prediction of SVM with that of LSSVM. Compared with traditional SVM algorithm, LSSVM can obtain load prediction results more quickly and effectively. However, the simple LSSVM algorithm still has some deviation from the actual load value, so the SMA optimization algorithm is introduced. The prediction effect has been further improved by SMA. Then combined with VMD decomposition, the results of VMD-SMA-LSSVM are calculated. The relevant comparison data is shown in Figure 3, which verifies the superior performance of VMD-SMA-LSSVM.

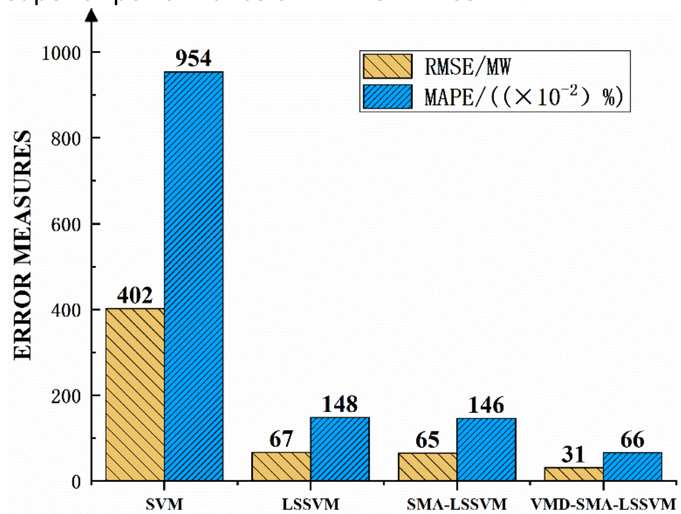

Fig. 3. Error analysis of VMD-SMA-LSSVM algorithm and related algorithms

To prove the reliability of the model, this paper also uses some other machine learning algorithms to make predictions for comparisons, such as K-nearest neighbor algorithm (KNN), random forest algorithm （RF） and gradient lifting regression (GBR). This article also compares other sequence decomposition models. After the sequence processed by EMD, its prediction results are also compared with the results of VMD-SMA-LSSVM. The specific error analysis and prediction curves are shown in Table 1 and Fig. 4(a) and Fig. 4(b). Compared with these models, VMD-SMA-LSSVM has obvious advantages in results, and the predicted value is closest to the true value.

Table 1 Comparison of prediction of each algorithm

Algorithm	MAPE/%	RMSE/MW
VMD-SMA-LSSVM	0.66	30.53
EMD-SMA-LSSVM	0.79	38.08
SMA-LSSVM	1.45	65.26
LSSVM	1.47	66.69
KNN	1.70	75.29
RF	1.79	78.69
GBR	1.95	84.68
SVM	9.54	402.22

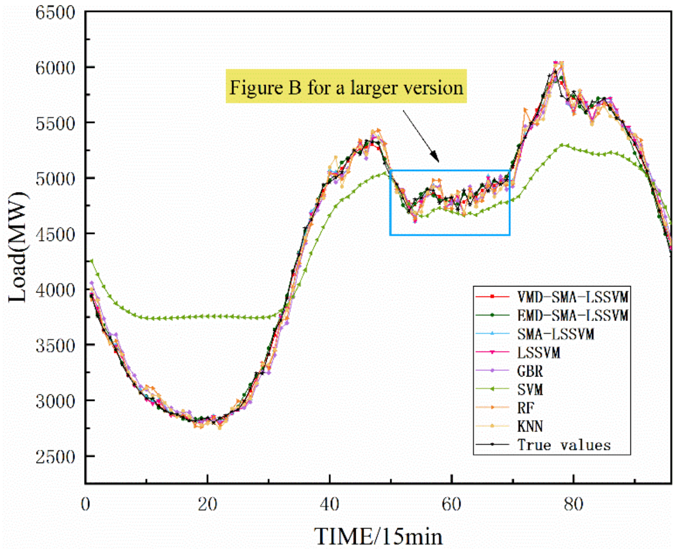

Fig. 4(a). Comparison of models' predictions

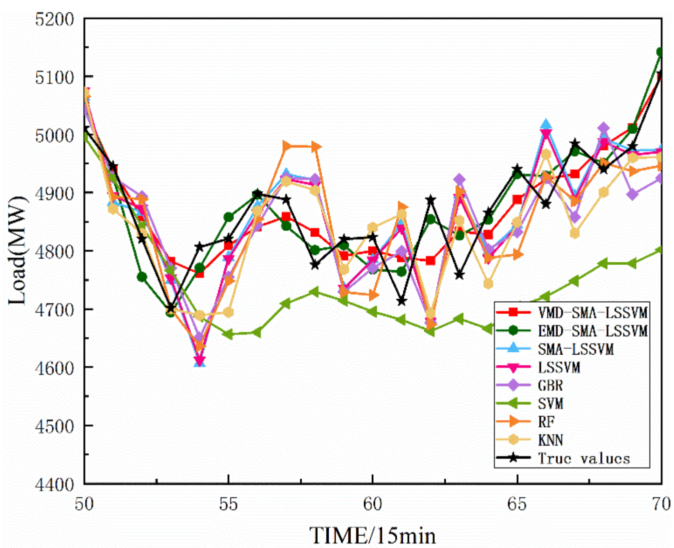

Fig. 4(b). A local enlarged view of the predicted comparison

5. CONCLUSIONS

In the experiment of short-term load prediction of power system, the VMD-SMA-LSSVM model proposed in this paper is compared with the traditional SVR, other machine learning algorithms and the prediction model after EMD mode decomposition. Through the analysis of relevant error indicators, the following conclusions can be drawn:

(1) Compared with empirical mode decomposition, variational mode decomposition has more powerful feature extraction and decomposition capabilities of timing signals, so the decomposed sub-sequence and the prediction results obtained by the algorithm are closer to the actual load.

(2) As the prediction efficiency of the traditional LSSVM model is not high, the latest slime mould algorithm can help it quickly find the optimal hyperparameter settings, to improve the prediction performance.

(3) After comparative analysis, the VMD-SMA-LSSVM algorithm proposed in this paper can predict, sum and stack respectively according to data decomposition, and has good prediction ability and prediction efficiency. The load forecast results are in good agreement with the actual values. VMD-SMA-LSSVM has obvious advantages in load forecasting applications, which is conducive to better energy distribution and utilization, and has good application prospects.

REFERENCE

[1] Li S, Chen H, Wang M, et al. Slime mould algorithm: A new method for stochastic optimization. Future Generation Computer Systems 2020, 111 aliasgharheidari.com: 300-323.

[2] Dragomiretskiy K, Zosso D. Variational Mode Decomposition. IEEE Transactions on Signal Processing 2014, 62(3):531-544.

[3] LI Wenwu, SHI Qiang, WANG Kai, et al. Runoff prediction based on variational mode decomposition and deep gated network. Journal of Hydroelectric Engineering 2020,39(03):34-44.

[4] NIU Mingfei, HU Yuerong, SUN Shaolong, et al. A novel hy-brid decomposition - ensemble model based on VMD and HGWO for container throughput forecasting. Applied mathematical modeling 2018, 57: 163-178.

[5] Vapnik V N. The nature of statistical learning theory. New York: Springer-Verlag 1995: 37-69.

[6] Suykens J A K, Vandewalle J. Least squares support vector machine classifiers. Neural Processing Letters 1999, 9: 293-300.

