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AGRICULTURAL EQUIPMENT DEMAND FORECAST BASED ON DATA DECOMPOSITION AND INTEGRATION

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Abstract. *The agricultural equipment market is affected by the actual agricultural production, and the historical demand data for each month showed complex characteristics such as periodicity and nonlinearity. Traditional demand forecasting methods lack exploratory data analysis studies, making it difficult to exploit predictable information from historical data fully. Therefore, a combined prediction model based on data decomposition integration was proposed. The historical demand data was decomposed into several subsequences by empirical mode decomposition, and the periodic subsequences were extracted and reconstructed by the discrete signal spectrum analysis method. A combined prediction model of GSCV-SVR-Prophet was constructed by combining the time series model and quantitative regression model to avoid the limitations of traditional forecasting models. An example validation is carried out using a model of agricultural equipment as an example. Finally, commonly used single prediction models are selected as a comparison, and the model performance is evaluated using three metrics to validate the effectiveness of the constructed prediction method.*
Keywords: Agricultural equipment, Combinatorial prediction model, Empirical mode decomposition, Spectrum analysis of signals

1. Introduction.

Agricultural equipment as a "Made in China 2025" strategy, one of the ten key areas, is the key to changing the traditional agricultural development, to enhance the comprehensive production capacity. Compared with other machinery manufacturing products, the market demand for agricultural machinery products presents periodic characteristics, and the demand gap between peak and valley months is obvious. At present, the demand forecast of agricultural equipment enterprises is often based on the summary of historical experience, which relies too much on the analysis and judgment of enterprise management personnel and lacks a scientific basis.

Demand forecasting is a process in which the decision-making level of the enterprise is based on historical inventory information or resources, synthesizing the future development of the market, and reasonably estimating the enterprise's short-term or long-term ordering, production, and inventory. Various demand forecasting methods are widely used in actual business operations [1]. Lee et al. [2] classified the forecasting methods into three major categories: qualitative forecasting methods, quantitative forecasting methods, and combined forecasting methods.

Qualitative forecasting methods include the Delphi method [3], the market research method [4], and so on. Qualitative forecasting is usually based on observation and analysis, using logical reasoning to explain the development of the predicted object and various

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influencing factors. However, qualitative prediction methods in the prediction process rely too much on personal experience and theory as well as the ability to analyze and judge, and their prediction results are usually presented as textual descriptions or approximate value intervals, which makes the accuracy difficult to control and lacks scientific basis.

Quantitative prediction methods mainly include prediction methods based on mathematical econometric models and intelligent prediction methods based on machine learning. Quantitative prediction focuses on the quantitative analysis of prediction data, which has a strong scientific basis and operability, such as time series models [5-8], regression models [9-12], and machine learning models [13-16]. Zanfei et al. [15] proposed to develop a novel Graph Convolutional Recurrent Neural Network (GCRNN) to predict time series of water demand related to some water supply systems or district metering areas that belong to the same geographical area. Zhou et al. [16] proposed a mixed-effects segmented regression model and a new robust estimation for predicting baseline electricity consumption in Southern California, USA. Hossein et al. [17] proposed a demand prediction method based on multilayer LSTM networks. However, these quantitative forecasting methods have certain limitations when applied in practice. It is difficult for quantitative forecasting models to explain the mechanism of economic operation and fully explore the intrinsic links between economic variables, and they cannot achieve the expected results when facing a highly unstable economic environment.

Combined prediction methods [18-21] often first decompose the original sequence into multiple subsequences with different characteristics, then synthesize two or more prediction methods, input different subsequences into different models, and make appropriate combinations or improvements to obtain new prediction models. Considering the strong nonlinear characteristics of ship motion (SHM) time series, Li et al. [22] constructed a hybrid EMD-CNN-GRU (ECG) prediction model for SHM by integrating various parts of the prediction model. Aiming at the problem that the sharp changes in short-term electricity consumption make the data more complicated, Lv et al. proposed a new hybrid model based on Variation Mode Decomposition (VMD) and Long Short-Term Memory (LSTM) with seasonal factor elimination and prediction [23]. Combined prediction methods improve the prediction accuracy and enhance the interpretability of the prediction model at the same time.

The agricultural equipment market is a complex system, the market demand is the final expression of the common role of many influencing factors, its prediction is more dependent on the fusion of multi-source data, and the existing forecasting methods cannot be well applied to the agricultural equipment enterprise supply chain demand forecasting. Based on this, this paper comprehensively considers the seasonality and complexity of agricultural equipment market demand, utilizes the fully data-driven EMD to decompose the historical demand time series into a number of subsequences, and reconstructs the series based on the results of the periodicity test of each subsequence discrete-signal spectral analysis into the cyclical fluctuation series affected by actual agricultural production activities and the multifactor impact series affected by the external economic environment. A combined forecasting model with grid search-cross validation, support vector regression, and Prophet (GSCV-SVR-Prophet) is established.

The paper is organized as follows. Section 2 describes the research object and research methodology in detail. Section 3 details the example application of the demand forecasting methodology in Company Y, an agricultural equipment company. Section 4 compares the combined and single forecasting models and discusses the experimental results. Finally, Section 5 concludes the study.

2. Research Object and Research Methods.

2.1. **Research object selection and data collection.** In recent years, the tractor product structure has changed greatly, large and medium-sized tractors gradually replaced small tractors, and became the mainstream of the agricultural machinery market products. Therefore, this paper selected agricultural equipment enterprise Y company LX1604 model large tractor product family of 2021 demand as the research object for prediction.

By the customary division of agricultural production into quarters, 60 sampling points of historical monthly demand data from January 2017 through December 2021 from dealers in major sales locations were obtained based on a monthly schedule, as shown in Figure 1.

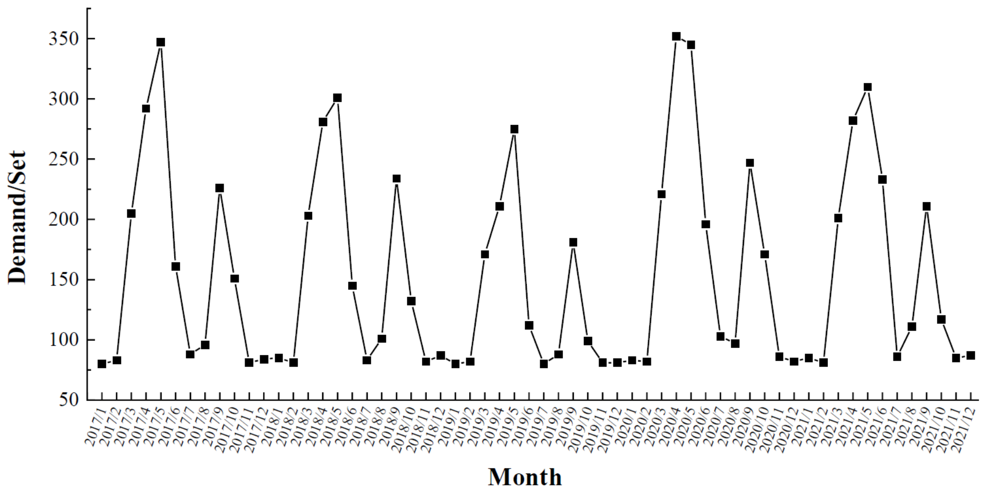

FIGURE 1. Historical monthly demand for large tractors LX1604

2.2. Data decomposition and integration method.

2.2.1. *Empirical mode decomposition.* EMD decomposes the sequence adaptively according to the time scale characteristics of the data itself [24], and can decompose the complex predicted variable sequence into subsequences with obvious characteristics. From the data-driven perspective, the fluctuation of the sequence is analyzed, and the economic and physical interpretation of the subsequence features is given, which provides a good prerequisite for the extraction and construction of features in the prediction model.

2.2.2. *Sequence periodicity test based on discrete signal spectrum analysis.* Discrete Fourier Transform (DFT) is a form of Fourier transform processing discrete signals. The DFT analysis method can transform the signal from the time domain to the frequency domain, realize the calculation of its period, and then study the spectral structure and variation law of the signal.

Let $x(n)$ be a finite discrete function, $n = 1, 2, \ldots, N-1$, and then the Fourier transform function of $x(n)$ is as shown in Formula (1):

$$x(k) = \sum_{n=0}^{N-1} x(n)e^{-i2\pi kn/N}, \quad k = 0, 1, 2, \ldots, N-1 \tag{1}$$

The inverse Fourier transform function of $x(k)$ is shown in Formula (2):

$$X(n) = \frac{1}{N}\sum_{n=0}^{N-1} x(k)e^{-i2\pi kn/N}, \quad n = 0, 1, 2, \ldots, N-1 \tag{2}$$

The imaginary units in the formula are $i = \sqrt{-1}$.

In signal analysis, the relationship between frequency and energy is expressed by spectrum, and the Power Spectral Density (PSD) function is the signal power in the unit frequency band. The auto-power spectrum can remove the random interference noise in the signal and retain and highlight the periodic signal by performing autocorrelation convolution on the measured signal. For a discrete signal that cannot describe the spectral characteristics, according to the Wiener-Khintchine theorem, a clear function representing the power spectrum distribution of the signal can be obtained by the discrete Fourier transform of its autocorrelation function, and the content of each frequency component in the random signal can be visually displayed. The periodic test and calculation of subsequences are realized.

The autocorrelation function is usually used to describe the degree of correlation between random signals at different times. It is the sum of the product of the delay of the signal and the signal. The autocorrelation function of the signal $x(n)$ is shown in Formula (3):

$$R_x, x(\theta) = \int_{-\infty}^{+\infty} x(n)x(n+t) \tag{3}$$

By performing a discrete Fourier transform on the autocorrelation function $x(\theta)$, the corresponding power spectral density function can be obtained, as shown in Formula (4):

$$P(\theta) = \lim_{N \to \infty} \frac{\left| \sum_{n=0}^{N-1} x(n) e^{-i2\pi kn/N} \right|^2}{N} \tag{4}$$

Due to the high time complexity of discrete Fourier transform and inverse transform, the huge amount of calculation leads to low computational efficiency. Therefore, FFT can be used to achieve efficient calculation of each subsequence period.

By FFT, the results of the periodicity test of each subsequence can be obtained, the subsequences with obvious periodicity are separated, and the remaining subsequences are reconstructed into sequences influenced by the input features, as shown in Formula (5):

$$\mathrm{IMF}^{\alpha} = \sum \mathrm{IMF}_j + \mathrm{RES} \tag{5}$$

A multi-factor influence sequence IMF^{α} and several periodic fluctuation sequences IMF_i^{β} are obtained, as shown in Figure 2.

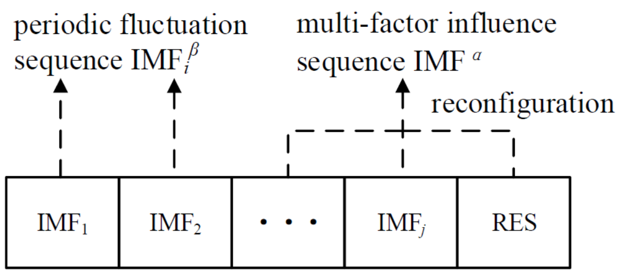

FIGURE 2. Reconfiguration of IMF

2.3. GSCV-SVR-Prophet combined prediction model.

2.3.1. *Data standardization.* Data standardization was performed to eliminate the influence of the dimension of the sample data and to make the calculation of the distance between the data more reasonable.

For numerical data, the maximum and minimum standardization is used to process the collected numerical data, and the sequence data is mapped to the range of $[0, 1]$ respectively, as shown in Formula (6):

$$\hat{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

where $\hat{x}$ denotes the normalized data value, $x_{\max}$ denotes the maximum value in the sequence, $x_{\min}$ denotes the minimum value in the sequence, and x denotes the current value.

For categorical data, One-Hot coding is used for standardization. The One-Hot encoding of categorical feature data with n feature classifications is shown in Figure 3.

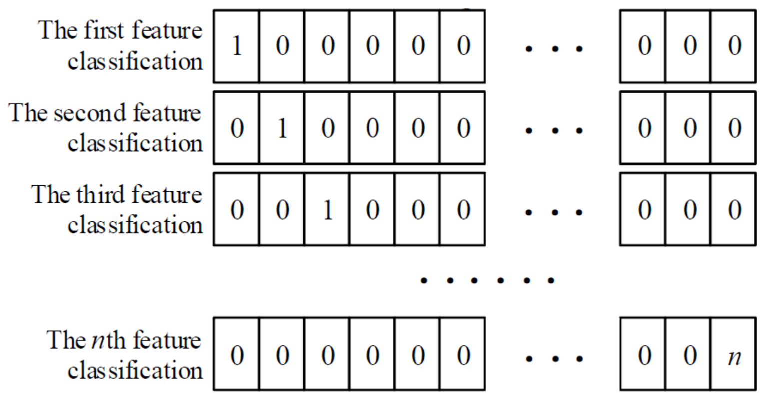

FIGURE 3. The One-Hot code of discrete feature

2.3.2. *Support vector regression based on grid search and cross-validation.*

1) *Support vector regression.* Support Vector Regression (SVR) is an application of Support Vector Machine (SVM) for the problems of small samples and nonlinearity in regression prediction [25]. It can overcome the problem of local minimum in neural network models and has advantages in high-dimensional pattern recognition.

2) *Grid Search-Cross Validation method.* Grid Search-Cross Validation (GSCV) aims at minimizing the mean square error. By setting the parameter range and search step size, it traverses each possible parameter combination, avoids the existence of a local optimal solution, effectively improves the accuracy of parameter optimization, and reduces the prediction error. In the case of fewer parameters, there is no problem with long calculation time, which is widely used in the parameter optimization of support vector machines.

The K-fold cross-validation method divides the training data into K subsets and selects any subset as the test set, and other subsets as the training set for cross-validation. Repeat K times to find the parameter combination with the smallest mean square error, and input the obtained optimal parameters into the SVR model [26], as shown in Figure 4.

2.3.3. *Prophet time series prediction model.* The Prophet can identify the trend term, seasonal term, holiday term, and noise part of the time series, and use different functions to construct the model and predict respectively, as shown in Formula (7):

$$f(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{7}$$

The Prophet has a good fitting effect on historical data with strong periodic characteristics. The algorithm uses the Fourier series to simulate the periodic transformation of

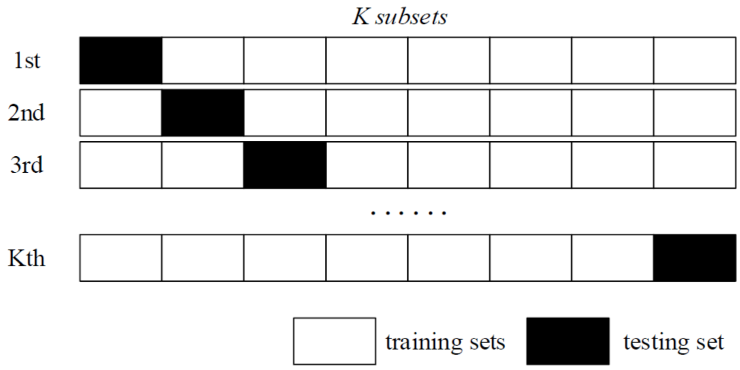

FIGURE 4. K-fold cross-validation

the time series to model the seasonal term, as shown in Formula (8):

$$s(t) = \sum_{n=-N}^{N} c_n e^{\frac{i2\pi nt}{P}} \tag{8}$$

where c_n is the coefficient to be estimated, satisfying $c_n \sim N\left(0, \sigma_c^2\right)$; P represents the period series; parameter N is the number of approximation terms used to fit the periodicity.

The historical data is input into the Prophet model for training, the prediction step is set to predict, and thus the prediction results can be obtained.

In summary, a combined prediction model based on GSCV-SVR-Prophet can be obtained. The specific steps of prediction are as follows.

Step 1. Sequence decomposition. EMD is used to perform empirical mode decomposition on the standardized predicted variable data to obtain several IMF subsequences and an RES subsequence.

Step 2. Periodicity test and subsequence reconstruction. FFT is used to test whether the subsequences obtained by EMD decomposition have obvious periodicity. The subsequences with obvious periodicity are classified as periodic fluctuation sequences, and other sequences are added and reconstructed into multi-factor influence sequences.

Step 3. Combine model training. The constructed model input matrix and the multi-factor influence sequence were input into the GSCV-SVR model as the training set to obtain the SVR prediction model under the optimal parameter combination. The Prophet prediction model is obtained by inputting the periodic fluctuation sequence into the training set Prophet model.

Step 4. Combined model prediction. Set the prediction step and input the feature vector of the data to be predicted into the GSCV-SVR-Prophet combined prediction model to get the final prediction results.

The specific prediction process is shown in Figure 5.

3. Verification of Demand Forecasting Method Example.

3.1. **Large tractor historical demand sequence decomposition.** The data is standardized and transformed into a time series signal including 60 scalar data. The EMD method is used to decompose the signal to obtain four IMF components and one RES component, as shown in Figure 6.

3.2. **Selection of influencing factors and sequence reconstruction.** The discrete signal spectrum analysis of each subsequence obtained by decomposition is carried out, and the power spectrum diagram with a single sampling point as the measurement unit is drawn by using a fast Fourier transform, as shown in Figure 7.

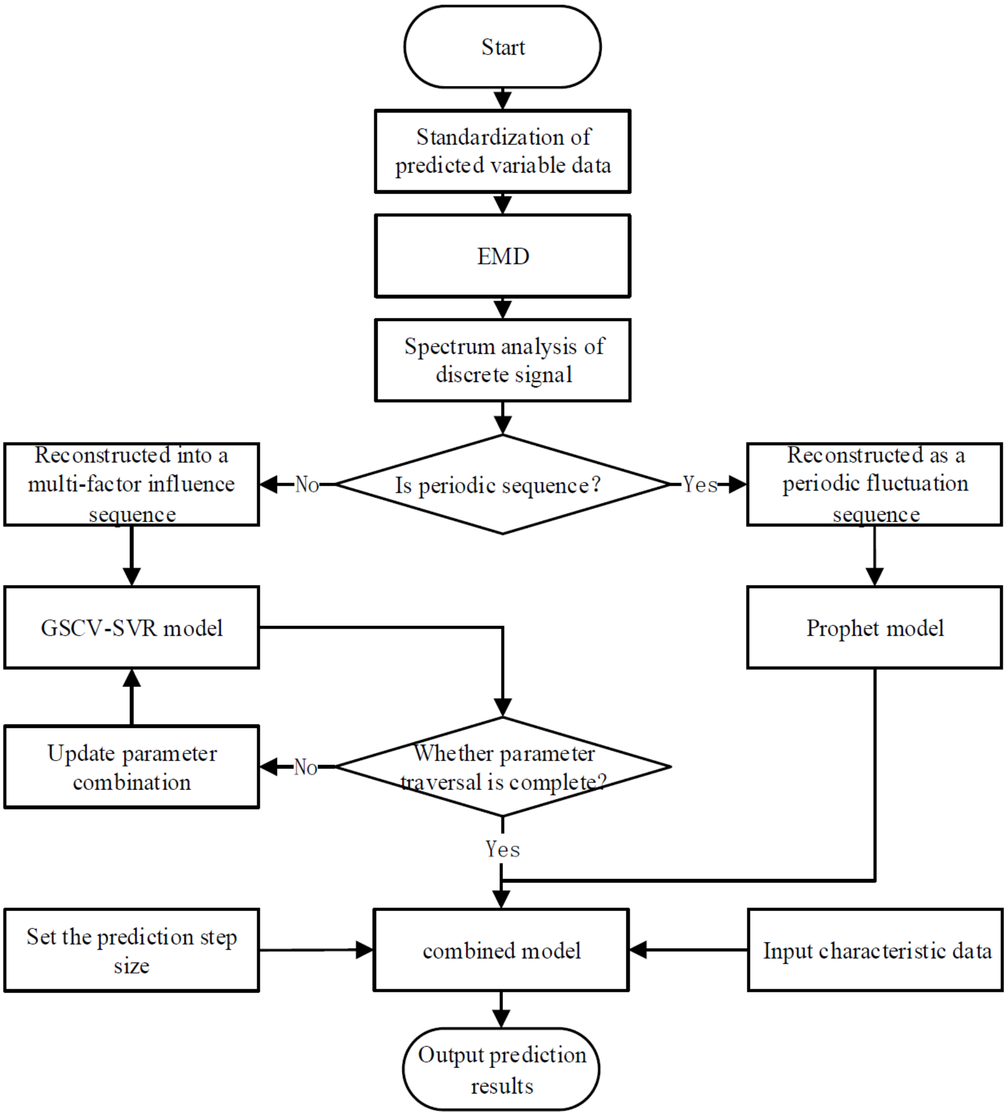

FIGURE 5. The prediction process of the combined prediction model

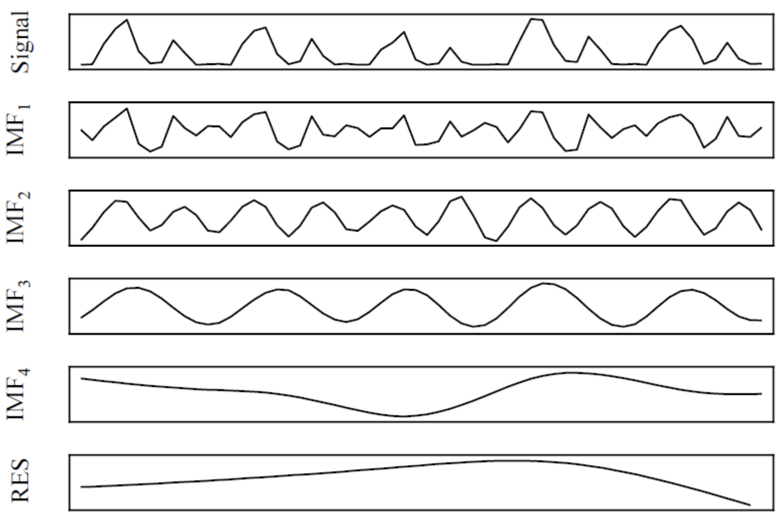

FIGURE 6. EMD decomposition result of historical monthly demand

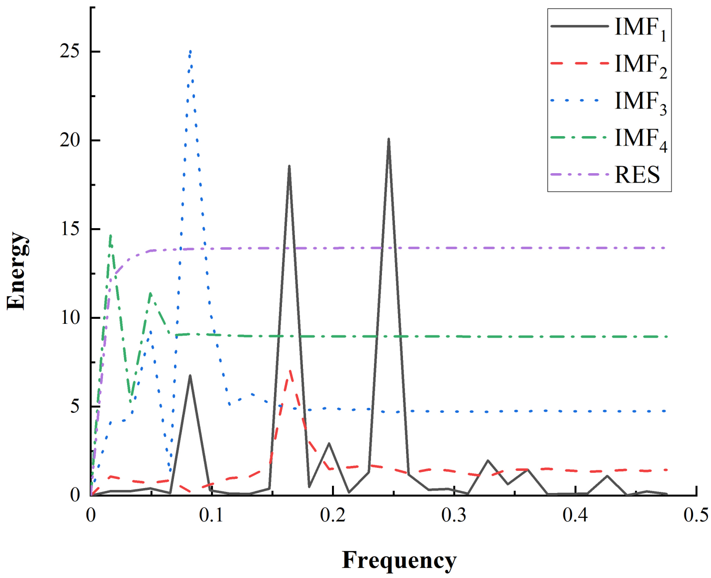

FIGURE 7. Freq-power graph of IMFs

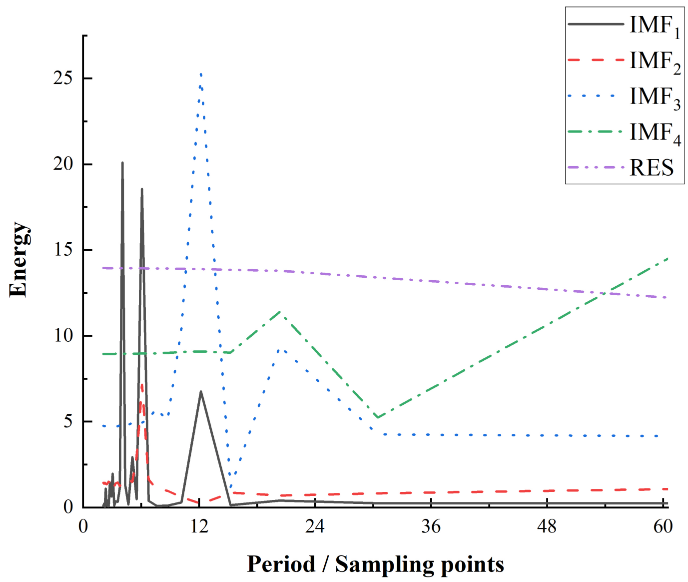

FIGURE 8. Period-power graph of IMFs

To observe and calculate the period of each subsequence more intuitively, the power diagram is drawn in the form of a periodic function with the number of sampling points per cycle as the measurement unit, as shown in Figure 8.

The calculation of the variance contribution ratio and correlation coefficient between each subsequence and the original sequence was carried out, and the analysis results of each subsequence were summarized, as shown in Table 1.

According to Table 1, Figures 7 and 8, the results of sequence analysis can be obtained as follows.

1) IMF_1 has the highest frequency, reflecting the imbalance of the short-term market for this model of large tractors under the influence of the external economic environment; the variance contribution ratio and Pearson correlation coefficient of IMF_1 are ranked first,

Table 1. Summary of IMF analysis results

Sequences	Variance	Variance contribution rate	Pearson correlation coefficient	Kendall correlation coefficient	Period
IMF_1	0.037	0.383	0.750	0.399	
IMF_2	0.008	0.086	0.694	0.506	6.33
IMF_3	0.0292	0.306	0.560	0.437	12.67
IMF_4	0.001	0.014	0.197	0.138	
RES	0.2×10^{-5}	0.2×10^{-4}	−0.016	−0.002	

indicating that IMF_1 contains more information about different scales in the original series.

2) IMF_2 and IMF_3 show more regular sinusoidal fluctuations, with two peaks in spring and fall respectively, reflecting peaks and valleys in demand influenced by actual agricultural production activities; the Kendall coefficients of IMF_2 and IMF_3 are ranked the first and the second respectively, suggesting that cyclicality is the most important feature in the original series.

3) IMF_4 has the characteristics of no significant periodicity and low vibration frequency. Its up and down vibration is related to major events in the agricultural machinery market: From 2017 to 2019, the total annual demand for this type of large tractor decreased year by year due to the change of agricultural machinery subsidy policy affecting consumers' willingness to purchase; In 2020, due to the impact of the product renewal cycle and the temporary population movement restrictions under the epidemic, the demand for agricultural equipment market has increased significantly, which has led to the growth of demand for this type of large tractor; In 2021, the market demand will return to normal levels and enter a normalized downward channel. The variance contribution rate, Pearson correlation coefficient, and Kendall correlation coefficient are not high, which have limited influence on the prediction results, but they are still the key components of the original sequence.

4) The RES sequence has a slow rate of change, a small amplitude of change, and a small correlation with the original sequence.

Referring to the existing research results [27], considering the availability of data, several predictive variables as shown in Table 2 are selected as the external influencing factors of the model. Considering the lag of market impact, the previous period of some forecast variables is used as the current input. Among them, the number of employees in the primary industry, the disposable income index of rural residents, and the sown area of crops were filled with the monthly data using the linear interpolation method. The average of the beginning and the end-of-month prices of wheat, corn and diesel is taken as the price for the month.

According to the above analysis results, each subsequence is reconstructed into a periodic fluctuation sequence that changes with the actual agricultural production activities and a multi-factor influence sequence that changes with the external economic environment. The subsequence reconstruction results are shown in Table 3.

3.3. **Combined model application.** The collected historical predictive variable data are standardized to obtain 60 sampling points of the historical data of the standardized numerical predictive variables, as shown in Figure 9.

The One-Hot coding of the month for the categorical predictor is shown in Table 4.

The training set of the GSCV-SVR model was constructed by the sliding window method with the 1st to the 48th data points of IMF^{α} and standardized variable time

TABLE 2. Variable summary table

Variable name	Category	Input
Month	Categorical type	Current
The amount of agricultural machinery subsidies in main sales areas	Numerical value type	Current
Wheat price	Numerical value type	The previous issue of the current period
Corn price	Numerical value type	The previous issue of the current period
Diesel prices	Numerical value type	The previous issue of the current period
Number of employees in the primary industry	Numerical value type	The previous issue of the current period
Rural residents' disposable income index	Numerical value type	The previous issue of the current period
Sown area of crops	Numerical value type	The previous issue of the current period

TABLE 3. Reconfiguration of IMF

Sequence types	Sequence reconstruction
Multi-factor influence sequence	$\mathrm{IMF}^{\alpha} = \mathrm{IMF}_1 + \mathrm{IMF}_4 + \mathrm{RES}$
Periodic fluctuation sequence	$\mathrm{IMF}_1^{\beta} = \mathrm{IMF}_2$ $\mathrm{IMF}_2^{\beta} = \mathrm{IMF}_3$

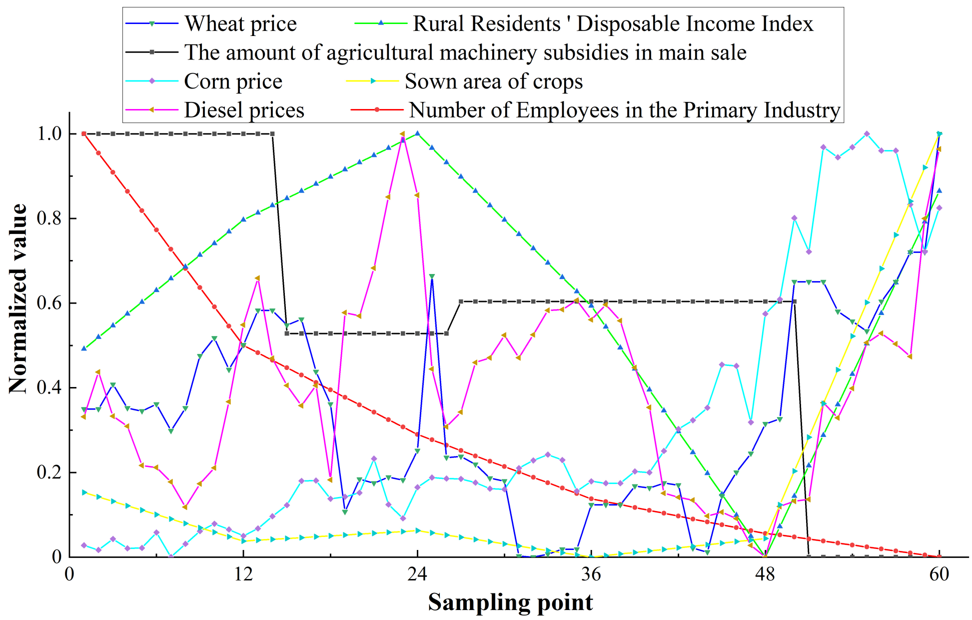

FIGURE 9. Normalized numeric variable time series

Table 4. One-Hot coding for each month

Month	One-Hot coding											
January	1	0	0	0	0	0	0	0	0	0	0	0
February	0	1	0	0	0	0	0	0	0	0	0	0
March	0	0	1	0	0	0	0	0	0	0	0	0
April	0	0	0	1	0	0	0	0	0	0	0	0
May	0	0	0	0	1	0	0	0	0	0	0	0
June	0	0	0	0	0	1	0	0	0	0	0	0
July	0	0	0	0	0	0	1	0	0	0	0	0
August	0	0	0	0	0	0	0	1	0	0	0	0
September	0	0	0	0	0	0	0	0	1	0	0	0
October	0	0	0	0	0	0	0	0	0	1	0	0
November	0	0	0	0	0	0	0	0	0	0	1	0
December	0	0	0	0	0	0	0	0	0	0	0	1

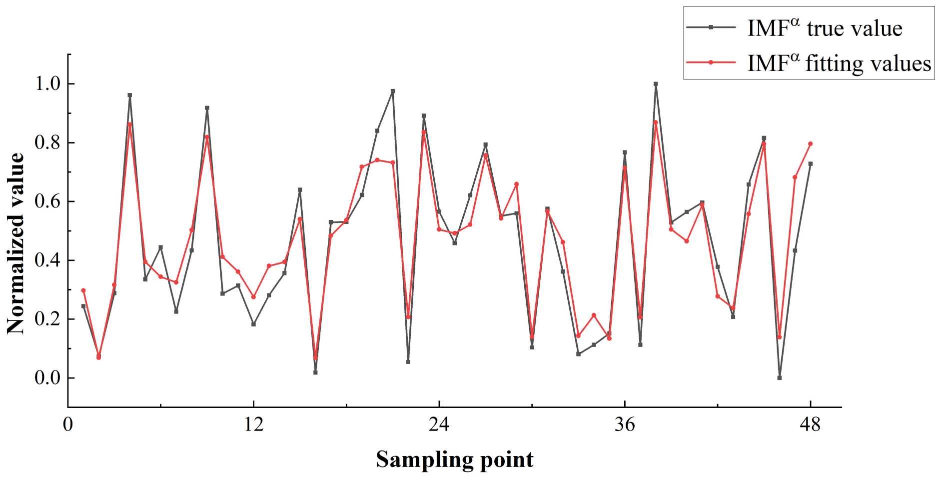

Figure 10. Multiple factors affect sequence fitting effect.

series. The Shuffle method was used to disrupt the dataset and set the SVR prediction model random seed number to take values in the range of $[0, 9999]$. Set the sliding window step size L maximum $N = 12$, GCSV initial search step size $M = 10$, fold number $K = 4$. The GCSV-SVR prediction model with optimal parameters $L = 3$, $C = 177.9755859375$, $g = 0.0009765625$ was obtained by training, and the fitting effect is shown in Figure 10.

The 1st to 48th data points and IMF_2^β were taken to construct the Prophet model training set. The fitting effect of the Prophet prediction model obtained by training is shown in Figure 11.

IMF^α, IMF_1^β, IMF_2^β and the 49th to 60th data points of the standardized variable time series were used to verify the prediction model. The prediction step size is set to 12, and the prediction effect of the model is shown in Figure 12.

4. **Prediction Effect Evaluation.** To further verify the adaptability and robustness of the demand forecasting method based on data decomposition integration proposed in this paper, it is compared with other forecasting models. The fitting coefficient (R-squared), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used to evaluate the performance of each model, and the performance of each prediction model was analyzed.

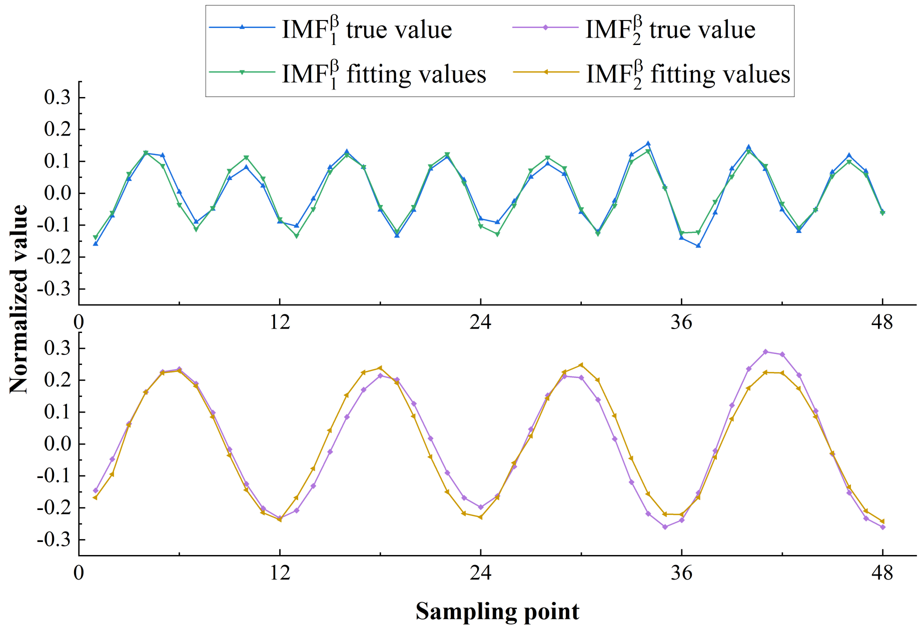

FIGURE 11. Periodic fluctuation sequence fitting effect

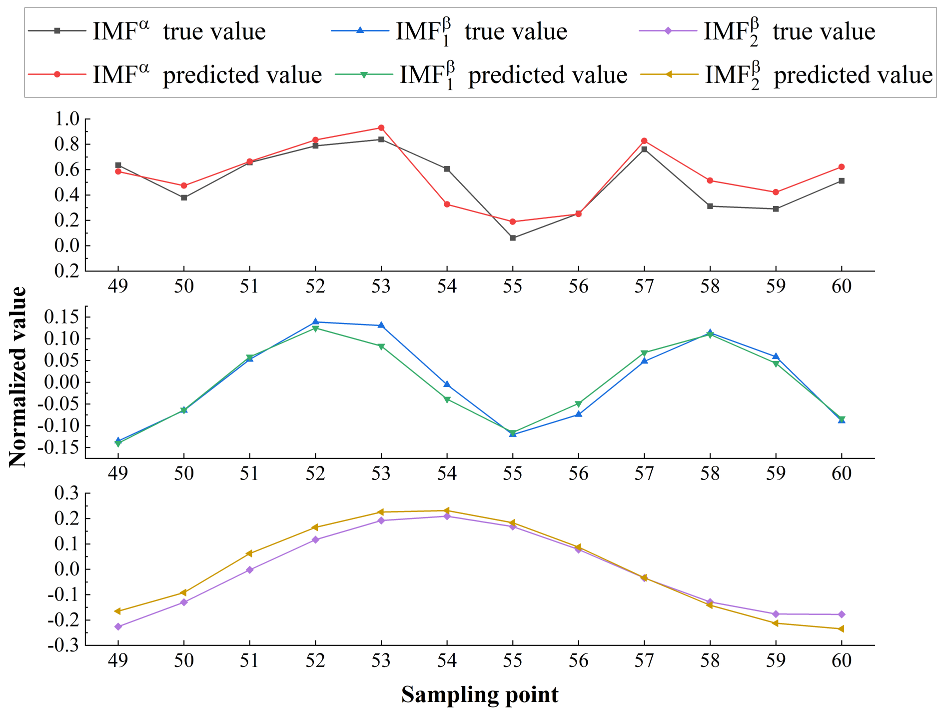

FIGURE 12. Model prediction fitting effect

The SVR model, Prophet model, and LSTM model are set as the control group. The same data preprocessing and training sample construction methods are used to predict the 49th to 60th data points of the historical demand data time series signal in turn. The performance of the prediction model is explained according to the above three performance evaluation indicators.

The prediction results of each prediction model are obtained, as shown in Figure 13. The evaluation of the prediction results of each model is shown in Table 5.

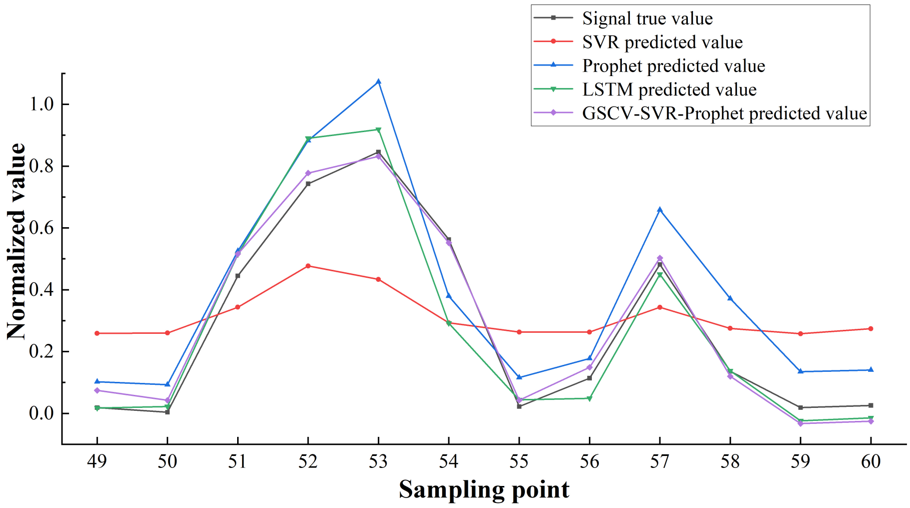

FIGURE 13. Comparison of prediction results of each model

TABLE 5. Evaluation of prediction results of each model

Forecasting model	R-squared	RMSE	MAE
SVR	−10.339	0.239	0.225
Prophet	0.873	0.111	0.097
LSTM	0.874	0.117	0.084
GSCV-SVR-Prophet	0.932	0.080	0.054

The GSCV-SVR-Prophet model proposed in this paper inherits the good periodic fitting effect of the Prophet model. Compared with the single SVR model before the combination, the prediction accuracy is greatly improved. Compared with the commonly used LSTM artificial neural network prediction model, the fitting coefficient is improved by 0.058; the root mean square error is reduced by 0.037; the average absolute error is reduced by 0.030. Through the above comparison, it can be seen that the GSCV-SVR-Prophet model is the best in the three evaluation indicators, and has better prediction performance in the demand forecasting of LX1604 large tractors.

5. **Conclusion.** In this study, based on EMD and discrete signal spectrum analysis method, the historical data sequence of large tractors is decomposed and integrated, and the GSCV-SVR-Prophet combined prediction model is constructed. Using Python language, the prediction of agricultural equipment demand is realized, and the following conclusions are obtained.

1) Theoretical aspects

a) Introducing the EMD algorithm to the decomposition of historical demand data series for a model of a large tractor. The periodicity characteristics of the subsequence were examined by using the discrete signal spectral analysis method, which reconstructed the original series into cyclical fluctuation series influenced by agricultural production activities and a multifactorial influence series influenced by the external economic environment. It provides a theoretical basis for exploratory data mining and data analysis of agricultural equipment products.

b) A combined GSCV-SVR-Prophet forecasting model combining time series model and quantitative regression model is established to forecast the reconstructed series, which effectively avoids the limitations of single forecasting models, reduces the forecasting error, and provides theoretical support for the demand forecasting of agricultural equipment products.

2) Practical aspects

The data decomposition and integration method and combined forecasting model established in this paper helps enterprises to grasp the trend of market demand changes, make decisions on production, procurement, inventory, supply, etc., and then improve economic efficiency; it can help enterprises adjust the production plan in time to avoid overproduction or underproduction; and it can also scientifically establish the reserve stock and reduce the storage cost.

The combined forecasting model established in this paper has certain advantages in demand forecasting, so it is also applicable to other industrial product areas with cyclical characteristics, such as industrial boilers, air conditioners, and clothing. In addition, with the continuous deepening of the research, the subsequent improvement of the prediction model can be considered to adapt to the accuracy of the demand prediction in the case of the explosive growth of the multivariate data volume in the era of big data and to enhance the applicability of the prediction model to the practical application.

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