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A Bullwhip Effect Weakening Approach Based on VMD-SVM Algorithm under the Background of Intelligent Manufacturing

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Abstract: In view of the current situation that the maturity of enterprise intelligent manufacturing capability is generally low and the information asymmetry in the upstream and downstream of the supply chain is high, taking any supply and demand link in the supply chain as an example, a group of initial demand signals that change nonlinearly over time are divided into intrinsic mode functions and noise residuals with different data characteristics by means of the variational modal decomposition (VMD) algorithm. On the basis of signal denoising and reconstruction, the support vector machine (SVM) algorithm is used to make regression prediction of the reconstructed signal with each intrinsic mode function as sample attribute. Compared with the regression prediction results of the original demand signal, it is verified that the VMD-SVM bullwhip effect weakening model can effectively filter the demand noise generated by each link in the supply chain and improve the accuracy of demand information transmission. It has a certain reference value to the weakening of the bullwhip effect and the improvement of supply chain synergy efficiency.

Keywords: intelligent manufacturing; bullwhip effect; demand forecasting; variational mode decomposition; support vector machine

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Citation: Zhang, M.; Shi, L.; Zhuo, X.; Liu, Y. A Bullwhip Effect Weakening Approach Based on VMD-SVM Algorithm under the Background of Intelligent Manufacturing. *Processes* **2021**, *9*, 1957. https://doi.org/10.3390/pr9111957

Academic Editor: Anet Režek Režek Jambrak

Received: 2 September 2021
Accepted: 29 October 2021
Published: 31 October 2021

1. Introduction

With the continuous deepening of a new round of scientific and technological revolution and industrial reform, the integrated development of digitization, networking and intelligence in the manufacturing industry is constantly breaking through new technologies and giving birth to new business forms. Intelligent manufacturing has become an important starting point to promote the transformation and upgrading of manufacturing industry and accelerate the high-quality development of manufacturing industry [1]. In 2016, China Institute of electronic technology standardization issued the *White Paper on Intelligent Manufacturing Capability Maturity Model*, which divided the enterprise's intelligent manufacturing capability maturity level from low to high into five levels: planned level, specification level, integration level, optimization level and leading level [2]. According to the latest *Intelligent Manufacturing Development Index Report (2020)* released by China Institute of electronic technology standardization, 89% of enterprises' capability maturity is at the planned level and specification level, of which the former accounts for 75% of the total [1]. In June 2020, the German national academy of engineering (Acatech) constructed the "sixth order maturity model" to measure the maturity level of enterprise intelligent manufacturing capability, and published the research results of the Application of Industry 4.0 Maturity Index in Industry at the same time. Among the respondents, four fifths of the enterprises have reached the second stage of the model and are moving towards the third stage [3]. As we all know, China's manufacturing industry has a strong influence on the world, and Germany's industrialization process has always been in the lead in the world. They can largely reflect the current development level of international advanced manufacturing industry. From the achievements of China and Germany in intelligent manufacturing, the maturity of intelligent manufacturing capability at home and abroad is generally at a relatively basic level, which is reflected in that enterprises have a certain information foundation and can realize cross equipment and cross system data sharing, but they still cannot effectively eliminate cross enterprise information asymmetry. In this case, how to use the existing technical means to improve the collaborative efficiency of such enterprises has become an important problem to be solved in supply chain management.

The bullwhip effect is a common phenomenon of demand variation and amplification caused by information asymmetry in the process of demand information transmission. It is also an important reason that leads to the low efficiency of supply chain collaboration. Generally, the order quantity received by the supplier tends to fluctuate more than the actual sales volume of the buyer, and the resulting information distortion and confusion are gradually magnified in the process of transmission from the downstream of the supply chain to the upstream inventory system [4]. There are many reasons for the bullwhip effect. Lee and Chen [5–7] attribute it to the following factors: demand forecast, batch order, delivery time, price fluctuation and short-term rationing game. Because of its complex causes and wide range of influence, it is not of practical significance to eliminate the bullwhip effect fundamentally. Therefore, it is the focus of current research to take corresponding measures to mitigate and control the negative impact. Demand forecasting is often used as an important combination point for academic circles to explore the weakening way of the bullwhip effect. The common methods include minimum mean square error (MMSE) [8], moving average (MA) [9], exponential smoothing (ES) [10] and autoregressive integrated moving average model (ARIMA) [11].

With the increasingly complex external environment of the supply chain, intelligent manufacturing has put forward high requirements for the production and operation activities of enterprises, which requires enterprises to be able to respond to the demand fluctuations brought by market uncertainty factors flexibly and timely. The traditional forecasting methods can no longer meet the current needs of enterprises in terms of prediction accuracy [12]. In recent years, with the continuous maturity of data science and artificial intelligence theory and technology, a large number of scholars who use machine learning as research fulcrum to predict demand algorithm have emerged. Jaipria et al. [13–15] constructed a hybrid prediction model by combining discrete wavelet transform (DWT), least squares support vector machine (LSSVM), artificial neural network (ANN) and intelligent technology polygenic genetic programming (MGGP). By comparing ARIMA model, it is proved that the model can effectively improve the prediction accuracy. Liu Y et al. [16] used the artificial bee colony algorithm (ABC) to optimize the fitting of polynomial parameters in the demand forecasting model of product life cycle (PLC), and realized the goal of precise ordering and reducing safety stock. Sadeghi et al. [17] used the genetic algorithm (GA) embedded with boundary operator in the meta heuristic algorithm of particle swarm optimization (PSO) as a local searcher to explore the approximate optimal solution of the constrained inventory problem. The above-mentioned scholars combined the models with different functions and characteristics to weaken the bullwhip effect, and achieved certain results. The research shows that, for the specific research background, the combined forecasting model can achieve better prediction effect than the single prediction model. It is worth noting that the construction of current demand forecasting models is generally based on the sales data of enterprises, that is, the actual demand data of downstream. However, in fact, enterprises take the lead in receiving the downstream order demand data, and then initiate orders to the upstream based on this data, so the order demand data is closer to the source of the problem. Since the bullwhip effect is usually characterized by the variance ratio of order quantity to demand quantity, the greater the ratio, the stronger the bullwhip effect. If the order quantity data can approach the demand quantity and ensure the prediction accuracy of the demand prediction model, the bullwhip effect problem can be effectively alleviated.

The existence of the bullwhip effect leads to continuous rise and fall of enterprise production and inventory, and the interval between continuous peaks and troughs produces nominal periodic fluctuations similar to the distortion response of electronic devices. Therefore, sometimes the bullwhip effect is vividly compared to the "high noise" of electronic devices [18]. The bullwhip effect is the result of the joint action of supply and demand links in the supply chain. Enterprises will gradually lose their competitiveness in the same market under its long-term continuous effect, and will face the problem of accumulated losses over time. Therefore, it is particularly necessary to find a method that can reduce the demand noise of the supply chain and accurately predict the real demand. In order to better serve demand forecasting, this paper extends the variational modal decomposition (VMD) algorithm with signal noise reduction function in the field of supply chain. By transforming the signal from time domain to frequency domain, the effective separation of useful signal and noise signal is realized. Considering that in the actual production and operation activities, the enterprise demand data is often collected in days, weeks or months, and the low sampling frequency leads to the limited number of sample points. Selecting the support vector machine (SVM) algorithm which performs well in small sample prediction can well match the solution of this problem. This study intends to build a bullwhip effect weakening model based on VMD-SVM algorithm, split, reduce noise, reorganize, train and predict the demand signals in a demand cycle, and explore new methods to alleviate the bullwhip effect and improve the collaborative efficiency of supply chain.

2. Materials and Methods

2.1. Variational Mode Decomposition

Variational mode decomposition (VMD) is a completely non recursive adaptive decomposition method proposed by Dragomiretskiy et al. [19]. This method has strong signal decomposition, feature recognition, purification and noise reduction, and is widely used in fault diagnosis [20], image processing [21], power grid monitoring [22] and other fields. VMD is established by using the variational theory in mathematical functional analysis, which has a solid theoretical foundation. It can obtain relatively stable subsequences with different frequency scales by decomposition, so as to reduce the non-stationarity and complexity of the original nonlinear time series [23]. Therefore, it is suitable for enterprise order quantity time series data. Compared with empirical mode decomposition (EMD), local mean decomposition (LMD), wavelet packet transform (WPT) and other methods with multi-scale time-frequency analysis capability, VMD can effectively overcome the phenomenon of modal aliasing and endpoint effect, and show better tolerance and robustness to sampling and noise [23–25].

The essence of VMD is to find the optimal solution of constrained variational optimization problems. This method needs to determine the number of mode decomposition and the quadratic penalty factor in advance. Through iterative search, the optimal center frequency and bandwidth length matching with each intrinsic mode function are updated continuously, and then the decomposition of the given input signal is realized. The concrete form of the objective function is as follows.

$$\begin{gathered}\min_{\{u_k\},\{\omega_k\}}\left\{\sum_k \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \\ \text{s.t.} \sum_{k=1}^{K} u_k = f(t)\end{gathered} \tag{1}$$

In Formula (1), $\{u_k\}$ is the set of mode components obtained by decomposition of input signal $f(t)$; $\{\omega_k\}$ is the set of central frequencies of each modal component; $\delta(t)$ is a pulse function; $*$ is a convolution symbol; j is an imaginary number unit. By introducing Lagrange multiplication operator and quadratic penalty factor to Formula (1), the original problem is transformed into an unconstrained variational problem to be solved, the expression of augmented Lagrange function is obtained.

$$\begin{aligned} L(\{u_k\},\{\omega_k\},\lambda) \quad &= \alpha\sum_k \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 + \\ &\left\|f(t)-\sum_k u_k(t)\right\|_2^2 + \left\langle \lambda(t), f(t)-\sum_k u_k(t)\right\rangle \end{aligned} \tag{2}$$

Then the above minimization problem can be transformed into solving the saddle point of Formula (2) iteratively by using the alternating direction multiplier method (ADMM) and Parseval formula under L^2 norm, and transforming the signal in time domain into modal component and center frequency in frequency domain by Fourier equidistant transform.

$$\hat{u}_k^{n+1}(\omega) \leftarrow \frac{\hat{f}(\omega)-\sum_{i<k}\hat{u}_i^{n+1}(\omega)-\sum_{i>k}\hat{u}_i^{n}(\omega)+\frac{\hat{\lambda}^n(\omega)}{2}}{1+2\alpha\left(\omega-\omega_k^n\right)^2} \tag{3}$$

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega\left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega} \tag{4}$$

The specific steps of the VMD algorithm are as follows.

Step 1. Initialization $n \leftarrow 0$, obtain $\hat{u}_k^1$, $\hat{\omega}_k^1$, and $\hat{\lambda}^1$, preset the maximum number of iterations N, noise tolerance τ, convergence criteria ε.

Step 2. Iteratively updates the modal components and center frequencies in Formulas (3) and (4).

Step 3. Update the value of the Lagrange Multiplier by Formula (5).

$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega)+\tau\left(\hat{f}(\omega)-\sum_k \hat{u}_k^{n+1}(\omega)\right) \tag{5}$$

Repeat the steps from Step 1 to Step 3, and the final iteration conditions are as follows.

$$\sum_k \frac{\left\|\hat{u}_k^{n+1}-\hat{u}_k^n\right\|_2^2}{\left\|\hat{u}_k^n\right\|_2^2} < \varepsilon \tag{6}$$

2.2. Support Vector Machine

Support vector machine (SVM) is a supervised machine learning algorithm proposed by Vapnik [26] in 1995, which takes recognition, classification and regression prediction as the main practice direction [27]. Its core idea is to find a compromise between the complexity of the model and learning ability according to the limited sample information, so as to obtain the best generalization ability [28]. SVM is a binary classification model, which is defined as the linear classifier with the largest interval in the feature space, and the learning strategy is to maximize the interval. For two-dimensional linear separable data, SVM can achieve optimal classification in theory. When the data is linearly separable in the original space, the original sample can be mapped to the high-dimensional feature space through the kernel function, so that the sample can be linearly separable in the high-dimensional feature space, and, finally, transformed into the solution of a convex quadratic programming problem [29].

When the sample size is large enough, the neural network algorithm based on the empirical risk minimization principle can ensure stable learning effect, so the neural network algorithm is widely used in big data processing. When the sample space is limited, the advantage of empirical risk minimization learning will be greatly degraded, and the difference between real risk and empirical risk will expand with the increase of

VC dimension of learning machine. This leads to over fitting phenomenon. The SVM algorithm based on the principle of structural risk minimization can effectively overcome this problem. The algorithm can ensure the empirical risk and reduce the VC dimension of the learning machine, so that the expected risk of the learning machine on the whole sample set can be controlled [30]. Thanks to the excellent generalization performance of SVM algorithm, it shows good accuracy in small sample, nonlinear and high-dimensional pattern recognition [31]. In recent years, it has been widely used by scholars in many fields such as network traffic prediction [32], bearing fault detection [33], handwritten digit recognition [34] and rainfall classification [35].

Set a given training sample $D = \{(x_i, y_i)\}$, $x_i \in \mathrm{R}^{\mathrm{n}}$, $y_i \in \mathrm{R}$, $i \in \mathrm{N}$. If the sample point x is mapped from the original space to the high-dimensional feature space, and $\phi(x)$ is the feature vector after mapping, then the corresponding model of hyperplane partition in the feature space can be expressed as

$$f(x) = \omega^T \phi(x) + b \tag{7}$$

Support vector regression (SVR) is an important application branch of SVM. Different from SVM classification, there is only one class of sample points in SVR. It does not maximize the distance from the nearest sample point to the hyperplane as SVM does, but minimizes the distance from the farthest sample point to the hyperplane.

The SVR problem can be formalized as [36]

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n} \ell_\varepsilon(z) \tag{8}$$

where C is the regularization coefficient and ℓ_ε is the ε-insensitive loss function.

$$\ell_\varepsilon(z) = \begin{cases} 0, & if|f(x_i) - y_i| \le \varepsilon \\ |f(x_i) - y_i| - \varepsilon, & otherwise \end{cases} \tag{9}$$

By introducing relaxation variables ξ_i and $\hat{\xi}_i$ into Formula (8), we obtain the following results.

$$\begin{array}{l} \min\limits_{\omega,b,\xi_i,\hat{\xi}_i} \frac{1}{2}\|\omega\|^2 + C\sum\limits_{i=1}^{n} (\xi_i + \hat{\xi}_i) \\ \text{s.t.} \begin{cases} f(x_i) - y_i \le \varepsilon + \xi_i \\ y_i - f(x_i) \le \varepsilon + \hat{\xi}_i \\ \xi_i \ge 0, \hat{\xi}_i \ge 0, i \in \mathrm{N} \end{cases} \end{array} \tag{10}$$

By introducing the Lagrange multiplier $\mu_i \ge 0$, $\hat{\mu}_i \ge 0$, $\alpha_i \ge 0$, $\hat{\alpha}_i \ge 0$, the Lagrange function expression of Formula (10) is obtained.

$$\begin{aligned} L(\omega, b, \xi, \hat{\xi}, \alpha, \hat{\alpha}, \mu, \hat{\mu}) &= \tfrac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n} (\xi_i + \hat{\xi}_i) - \sum_{i=1}^{n} \mu_i \xi_i - \sum_{i=1}^{n} \hat{\mu}_i \hat{\xi}_i + \\ & \sum_{i=1}^{n} \alpha_i (f(x_i) - y_i - \varepsilon - \xi_i) + \sum_{i=1}^{n} \hat{\alpha}_i (y_i - f(x_i) - \varepsilon - \hat{\xi}_i) \end{aligned} \tag{11}$$

In order to obtain the minimum of the objective function, the partial derivatives of L to ω, b, ξ_i and $\hat{\xi}_i$ should be zero.

$$\begin{cases} \frac{\partial L}{\partial \omega} = 0 \to \omega - \sum\limits_{i=1}^{n} (\hat{\alpha}_i - \alpha_i) x_i = 0 \\ \frac{\partial L}{\partial b} = 0 \to \sum\limits_{i=1}^{n} (\hat{\alpha}_i - \alpha_i) = 0 \\ \frac{\partial L}{\partial \xi_i} = 0 \to C - \alpha_i - \mu_i = 0 \\ \frac{\partial L}{\partial \hat{\xi}_i} = 0 \to C - \alpha_i - \hat{\mu}_i = 0 \end{cases} \tag{12}$$

Since the necessary and sufficient condition for the transformation between the primal problem and the dual problem with strong dual relation is KKT condition, the dual problem of SVR is as follows.

$$\begin{gathered}\max_{\alpha,\hat{\alpha}} \sum_{i=1}^{n} y_i(\hat{\alpha}_i - \alpha_i) - \varepsilon(\hat{\alpha}_i + \alpha_i) - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\hat{\alpha}_i - \alpha_i)(\hat{\alpha}_j - \alpha_j)x_i^T x_j \\ \text{s.t.}\begin{cases}\sum_{i=1}^{N}(\hat{\alpha}_i - \alpha_i) = 0 \\ 0 \le \alpha_i, \hat{\alpha}_i \le C\end{cases}\end{gathered} \tag{13}$$

The solution of SVR can be obtained by solving Formula (13).

$$f(x) = \sum_{i=1}^{n}(\hat{\alpha}_i - \alpha_i)K(x_i, x_j) + b \tag{14}$$

$K(x_i, x_j)$ is a kernel function. According to Mercer theorem, any positive semidefinite function can be used as a kernel function [37]. The common kernel functions include linear kernel, polynomial kernel, Gaussian radial basis function kernel (RBF kernel), Laplacian kernel and sigmoid kernel. In the selection of kernel function, RBF kernel is usually preferred when the situation is not clear.

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{15}$$

3. Bullwhip Effect Weakening Model Based on VMD-SVM Algorithm

A complete industrial manufacturing process can be simplified into input and output links. Enterprises invest raw materials, equipment, personnel and funds as the input of manufacturing activities, and, finally, obtain finished products as the output of manufacturing activities. The flow of input production factors in the manufacturing process is called manufacturing motion flow. At this stage, the intelligent factory divides the motion flow into four types: material flow, capital flow, labor flow and information flow. With the continuous improvement of social informatization, the volume of information and the complexity and diversity of information carrying are growing rapidly. Both the production and operation activities and production planning and scheduling of enterprises are inseparable from the support and feedback of information. The intelligent process of manufacturing industry also depends on the control of information, and the importance of information is becoming more and more obvious. The information flow in the field of industrial manufacturing is the movement process of transmitting and exchanging various data, information and knowledge between the manufacturing system and the environment and among the units within the system. Its functions are mainly reflected in communication and connection, guiding regulation, assisting decision-making and economic value-added [38,39]. Considering that there are few platforms that can supervise the flow of information and have not been popularized, and the high cost associated with the introduction of digital technology, the information distortion caused by the increase of information entropy in this process is almost inevitable. Therefore, we speculate that there is a negative correlation between the maturity level of intelligent manufacturing capability and the impact of the bullwhip effect, and then the results of a large-scale visit to enterprises also confirm the rationality of this speculation.

In the process of field investigation, we used the IMCM evaluation index system [40] proposed by Xuehong Ding et al. to evaluate the intelligent manufacturing capability maturity of five enterprises in different industries in Anhui Province. The system includes ten first-class indicators, including strategy and organization, design, production, equipment, warehouse, sales, service, network environment, network security and architecture platform. After comprehensive evaluation, the enterprise's intelligent manufacturing capability maturity is divided into level 1 to level 5 from low to high, and below level 3 belongs to the enterprise with low intelligent manufacturing capability maturity. Taking one enterprise as an example, as shown in the spline connection diagram in Figure 1, the data comes from a large lithium battery manufacturing enterprise in Anhui Province. The maturity of the enterprise's intelligent manufacturing capacity is at level 4. The black line and green line in the figure represent the sales data of the enterprise and the downstream order demand data, respectively. It can be seen intuitively through the image that the order demand and actual demand data are basically consistent in the overall trend, and there are only low range data fluctuations at a few nodes. In the interview with the managers of the enterprise, it was found that the enterprises with high capability maturity spare no effort in the construction of their own soft power, allocate funds for system renewal and development year after year and, also, invest a lot of human and material resources in the maintenance of new digital platform. The purpose is to help the planning department of the enterprise narrow the gap between planned and actual procurement, and strive to eliminate the demand information asymmetry in the upstream and downstream of the supply chain to the greatest extent. It can be inferred that enterprises with high capability maturity level have good ability to resist the risk of market demand fluctuation, and can limit the impact of bullwhip effect to a limited level. As mentioned above with examples from China and Germany, the current intelligent manufacturing level of enterprises is mostly in its infancy. The survey results of enterprises also confirm this statement. Only one of the five enterprises is at a high level. Enterprises with low capability maturity level are limited by their own informatization development stage and are more passive in coping with the bullwhip effect. Therefore, this paper will focus on putting forward a universal action plan to reduce the bullwhip effect for enterprises with low intelligent manufacturing capability maturity level.

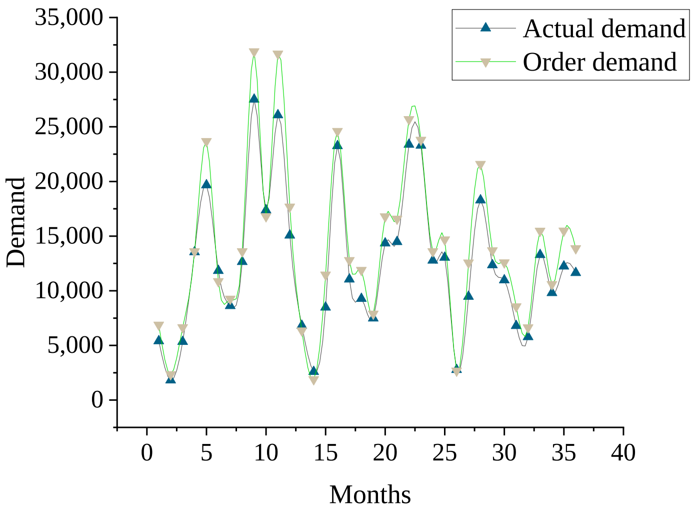

Figure 1. Demand data of enterprises with high capability maturity.

This paper combines the advantages of VMD algorithm and SVM algorithm, and proposes a bullwhip effect weakening model based on VMD and SVM algorithm. The model selects any supply and demand link in the supply chain. With the help of VMD, a group of initial demand signals with nonlinear relationship over time are divided into intrinsic mode functions with different data characteristics and signal remainder terms including noise. On the basis of signal denoising reconstruction, the original demand signal and reconstructed signal are predicted by SVM regression using the intrinsic mode function obtained by decomposition as sample attributes. It should be noted that the initial demand signal mentioned here is the order quantity data of a demand cycle obtained by the enterprise. Because the downstream enterprises in the supply chain will have different frequency when they place orders with the upstream enterprises due to the different production cycle conditions of the enterprises themselves, a unified sampling frequency can be formed by taking the standard set by the upstream enterprises as the demand data sampling frequency. The program operation steps of the VMD-SVM bullwhip effect weakening model can be described by the flow chart in Figure 2, and the specific steps are as follows.

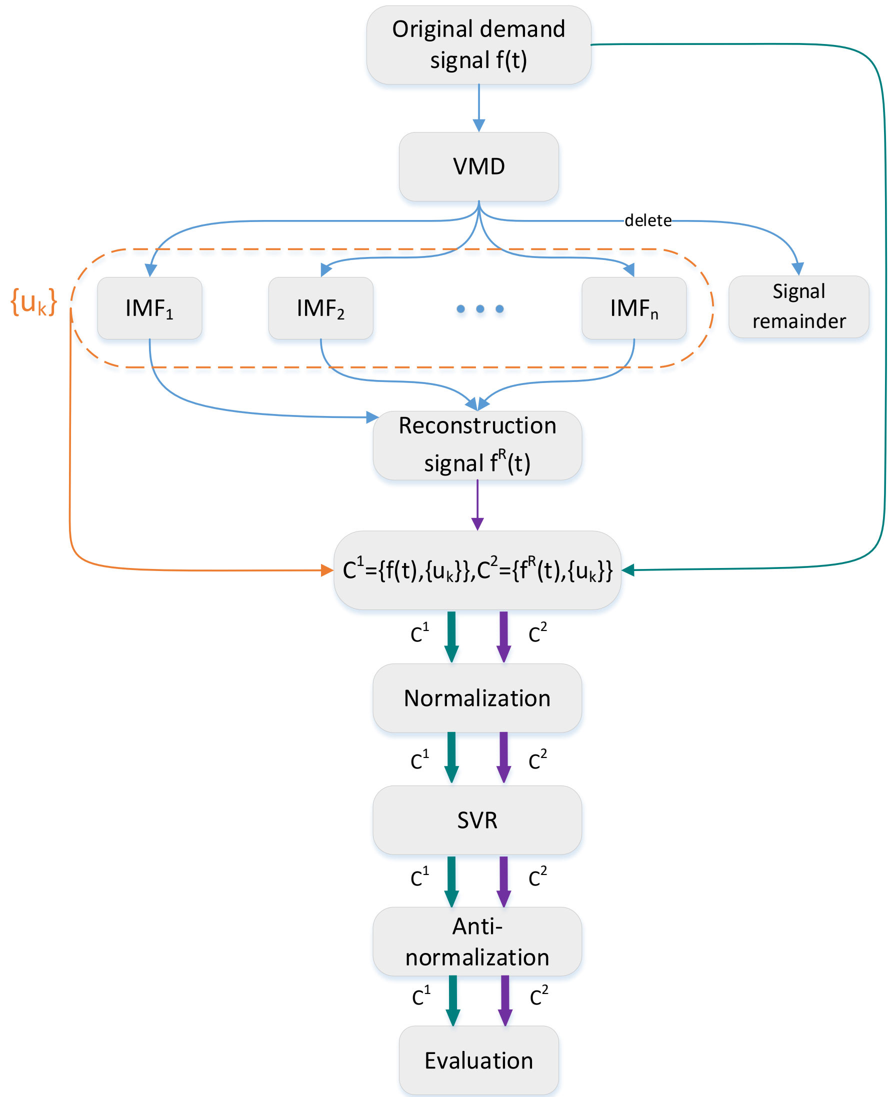

Figure 2. Flow chart of demand forecast.

Step 1. Acquisition of original demand signal data $f(t)$.

Step 2. The modal extracted by VMD can be divided into two categories: one is the intrinsic mode function (IMF_n) with different characteristics, which is represented by the se $\{u_k\}$, and the other is the signal remainder with noise.

Step 3. Eliminate the signal remainder. The remaining IMF_n are superimposed to obtain the reconstructed signal $f^R(t)$. This step realizes the noise reduction of the original demand signal.

Step 4. The IMF_n is taken as a sample attribute to form sample space $C = \{C^1, C^2\}$ with original demand signal data $f(t)$ and reconstructed signal $f^R(t)$, respectively, where $C^1 = \{f(t), \{u_k\}\}$, $C^2 = \{f^R(t), \{u_k\}\}$.

Step 5. Normalize the sample space C. The demand is normalized to the numerical range from one to two.

$$\mathrm{nor}Y = \frac{1}{\max Y - \min Y}(Y - \min Y) + 1 \quad (16)$$

Step 6. Before regression prediction, the value range of input independent variable and output dependent variable should be determined. Because the accuracy of medium and long-term demand forecasting will be affected by uncontrollable factors in the future, the trend of demand curve obtained from forecasting is often far from the real situation, which has little reference significance for the actual business activities of enterprises. Therefore, it is a common choice for enterprises to adopt short-term demand forecast. Without losing its generality, in this paper, the demand of the next s days will be regressively predicted and analyzed based on the demand of the enterprise on that day. The prediction principle is shown in Figure 3.

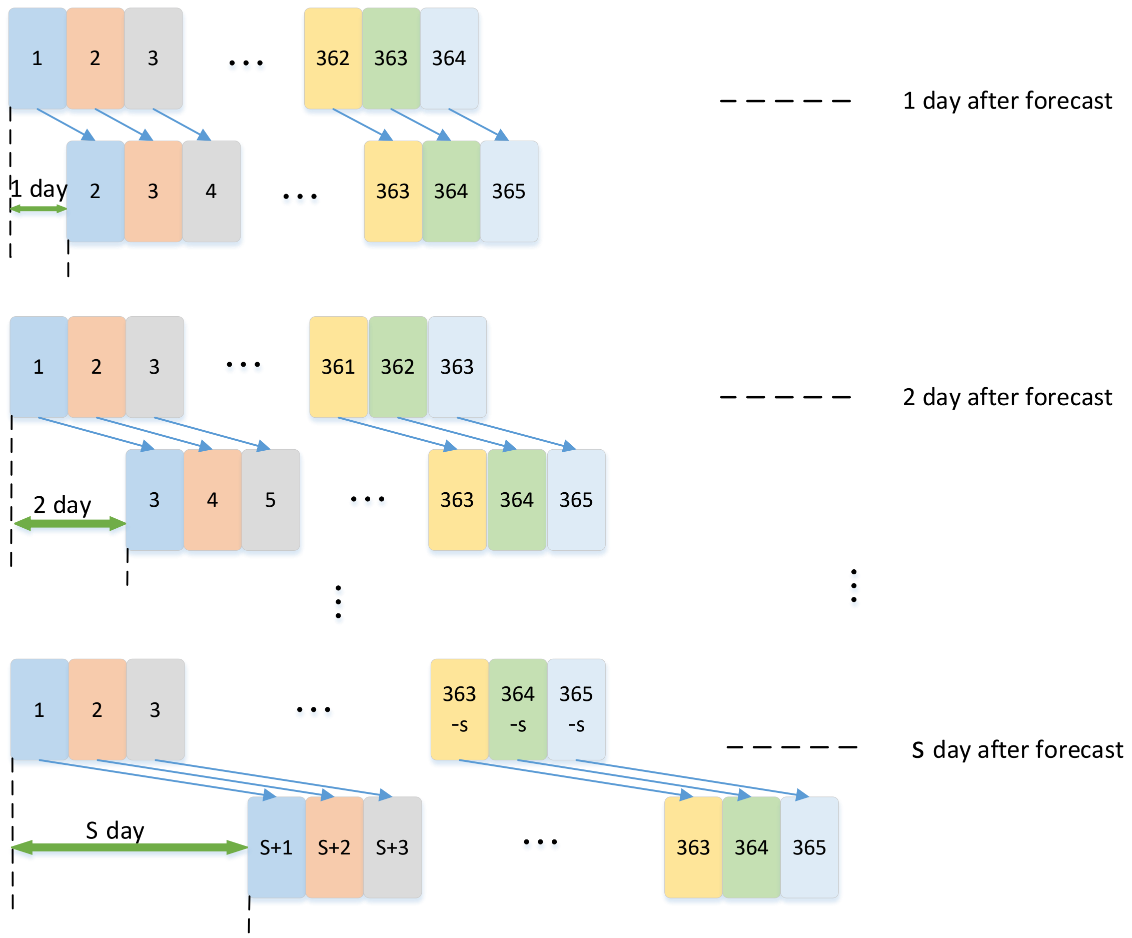

Figure 3. Schematic diagram of regression prediction principle.

Let sample space C^i be a matrix of m rows and n columns, m is the number of samples and n is the attribute of samples. The first column of the matrix is the regression prediction object, namely demand signal data.

$$C^i = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}_{mxn}, \ i = 1,2 \tag{17}$$

Let I be input and O output, then C_I is the input independent variable and C_O is the output dependent variable.

$$C_I = {C^i}_{[1:(m-s)]xn}, \ C_O = C^i_{[(s+1):m]x1} \tag{18}$$

Step 7. The SVR model is used to predict the demand signal data.

Step 8. Reverse normalizing the sample space to obtain the demand forecast value.

$$Y = (\mathrm{nor}Y - 1)(\mathrm{max}Y - \mathrm{min}Y) + \mathrm{min}Y \tag{19}$$

Step 9. The prediction results are analyzed and evaluated by error index. Common indicators for evaluating demand forecasting methods include mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and correlation coefficient square R^2 [16]. In this paper, *RMSE*, *MAPE* and R^2 are selected as the criteria to test the accuracy of the VMD-SVM bullwhip effect weakening model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{20}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \times 100\% \tag{21}$$

$$R^2 = \rho^2(y, \hat{y}) = \left(\frac{\sum_{i=1}^{n}(\hat{y}_i - \overline{y})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \overline{y})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}}\right)^2 \tag{22}$$

where y_i is the actual demand of the i-th prediction point, $\hat{y}_i$ is the forecast demand of the i-th prediction point and n represents the total number of prediction points.

4. Case Analysis

With the continuous penetration and promotion of lean production and just-in-time (JIT) ideas in the field of logistics and distribution, the circular pickup mode with single buyer and multiple manufacturers has gradually formed. This procurement mode has the characteristics of short order lead time and a small amount of multiple frequency. The collection of multi category products can be realized through a single transport vehicle through multiple stations, which is widely applicable to the automobile manufacturing industry, electronic manufacturing industry and retail industry [41].

In order to test the rationality and feasibility of the VMD-SVM bullwhip effect weakening model, and put forward valuable decision-making suggestions to enterprises based on the comprehensive analysis model, this paper takes a battery manufacturing enterprise in Anhui Province, which establishes a circular picking mode with purchasers and presents a low level in the maturity characteristics of intelligent manufacturing capacity, as the research object. As shown in Figure 4, take the power battery order demand data of the enterprise from January 2019 to January 2020 as the test sample, namely the original demand signal in the figure, and the sampling interval of data sample points is one day. There are 365 sample points in this period, and the measurement unit of order quantity is ton. Considering that the lead time of the production plan made by the enterprise's actual production activities is about one week, without losing its generality, in this paper, the demand of the next 1~7 days will be regressively predicted and analyzed based on the demand of the enterprise on that day.

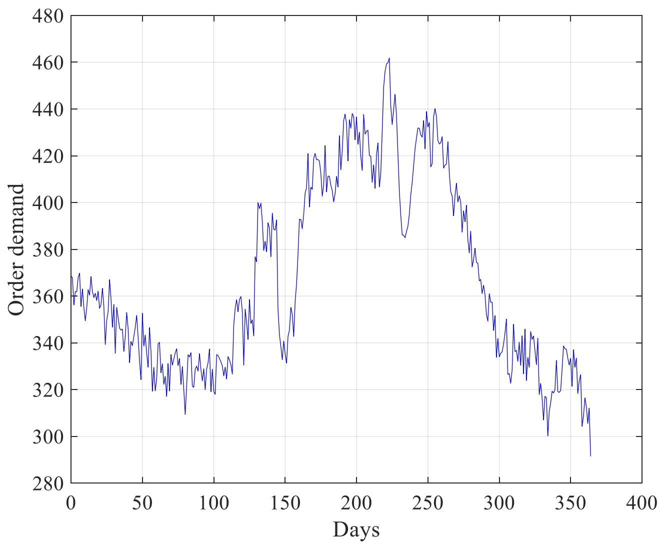

Figure 4. Original demand signal diagram.

The VMD process uses the same parameter settings as the original code written by dragomiretskiy, who proposed the method. The quadratic penalty factor $\alpha = 2000$, the initial center frequency $\omega = 0$ and the convergence criterion $\tau = 10^{-7}$. Since the number of modal decomposition K needs to be defined in advance, but it can be readjusted through Fourier transform analysis, $K = 4$ is preset here. The parameters of SVR are set by default in LIBSVM3.22 software package of MATLAB.

The information obtained from the above experimental procedure is as follows. The pictures below are the prediction results of the demand for the next day based on the demand of the enterprise on that day. The original demand signal in Figure 4 is analyzed by Fourier transform to obtain the frequency amplitude diagram in Figure 5 and the frequency amplitude diagram in double logarithmic coordinates after transformation. It can be seen that the number of frequency points with large amplitude is about five to six, that is, K can be taken as five or six. Adjust the preset K value, and $K = 5$ was selected in this paper. Thereby, the original demand signal in Figure 4 is decomposed into five intrinsic mode functions and a signal remainder in Figure 6 under the action of VMD, and the reconstructed signal of Figure 7 is obtained through step 3 in Section 3 of the article.

As can be seen from Figure 7, the VMD decomposition and reconstruction method preserves the useful information well, such as peaks and troughs in the original demand signal, and effectively removes the noise in the signal, laying a foundation for the correction of market demand forecast and the weakening of the bullwhip effect.

Figure 8 is realized by superimposing the original demand signal of Figure 4 and the reconstructed signal of Figure 7. Through comparison, it is found that except for a few discrete sample points at the left end, the amplitude of the reconstructed signal in the figure decreases in varying degrees at each sample point, and most of them converge to the interior of the original demand signal. In addition, it can be clearly seen that the trend of the reconstructed signal tends to be smooth on the whole. In a practical sense, the jitter of the original demand signal is reduced by eliminating the demand noise, making the order demand data closer to the actual demand. The reason why a few sample points in the reconstructed signal deviate greatly from the original signal trajectory may be due to the limitations of VMD itself, which is associated with the use of L^2-based smoothness stage. In this stage, the jumping of domain boundary and interior is excessively penalized, resulting in the boundary effect and burst signal [19].

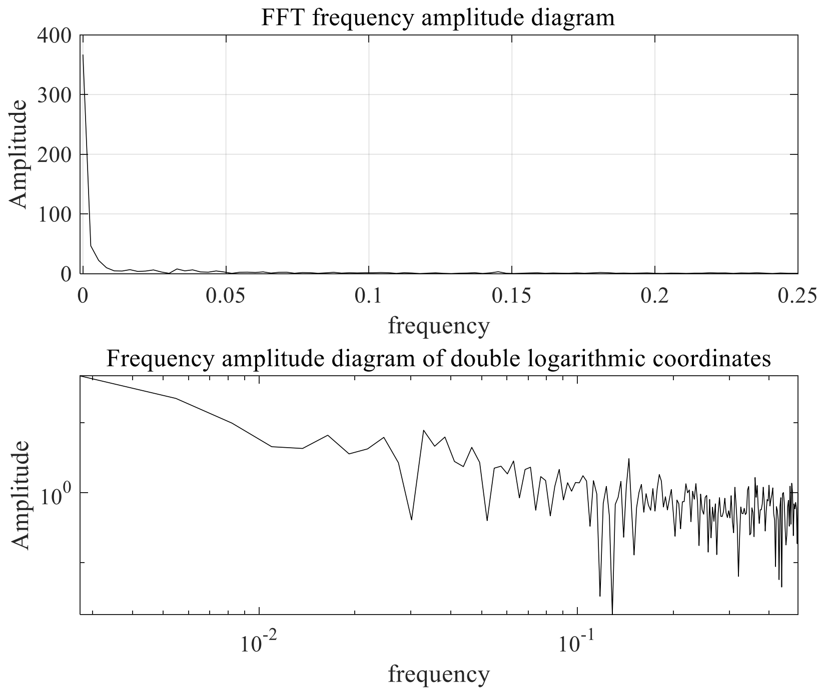

Figure 5. Fourier transform analysis. (Note: since the frequency points with large amplitude in the frequency amplitude diagram of the original demand signal obtained by Fourier transform are not obvious, the frequency amplitude diagram under double logarithmic coordinate is selected for analysis.)

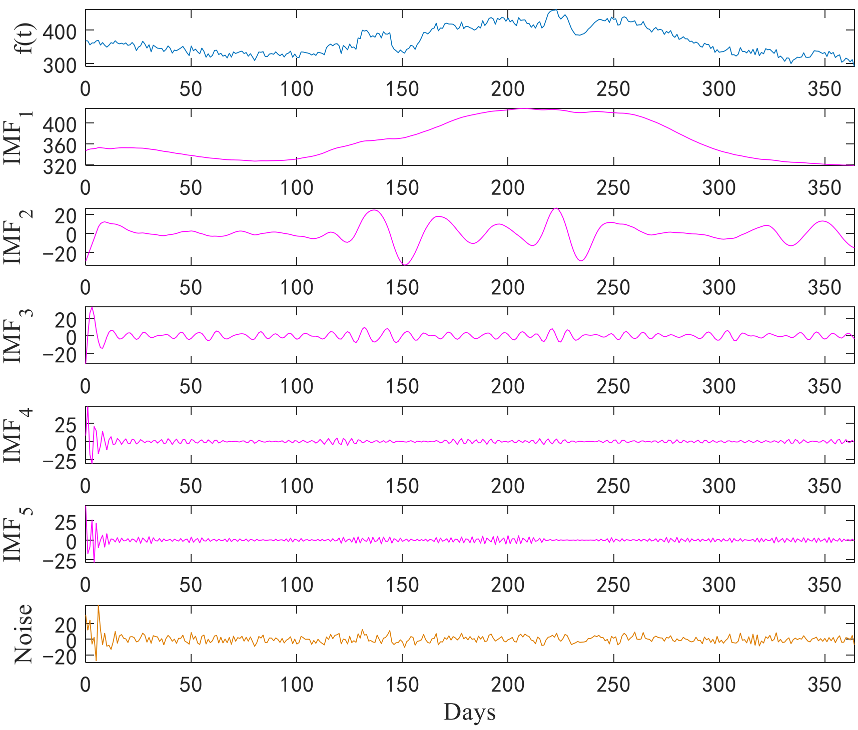

Figure 6. Original demand signal and mode decomposition diagram.

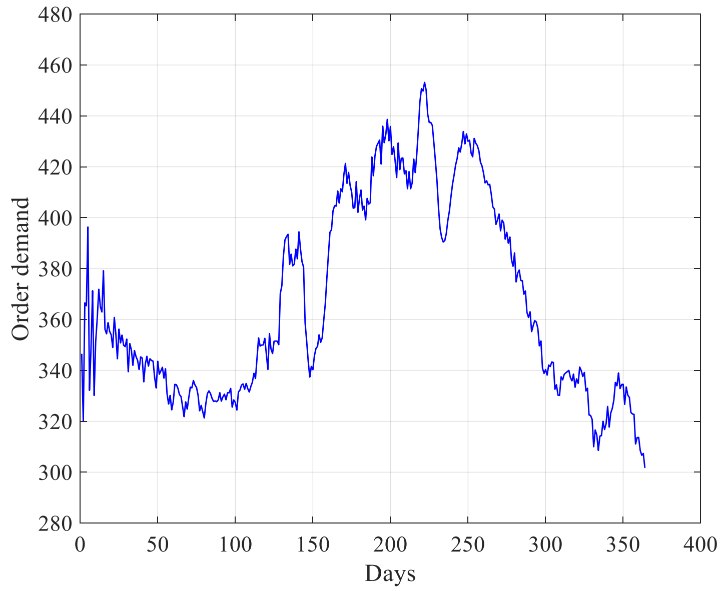

Figure 7. Reconstructed signal diagram.

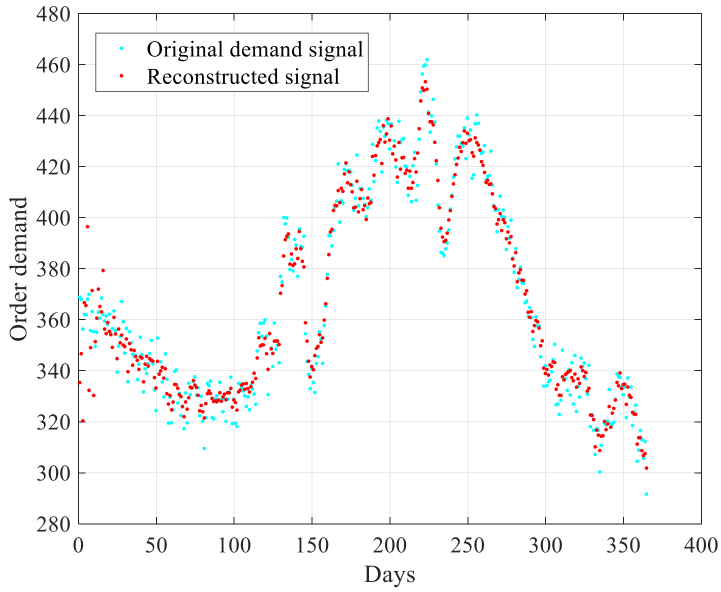

Figure 8. Comparison of original signal and reconstructed signal.

Figures 9 and 10 show the regression prediction results of the model on the original demand signal and reconstructed signal, respectively. The comparison between Figures 9 and 10 can reflect the accuracy difference between the original demand signal and the reconstructed signal. On the whole, the prediction of the original demand signal has been relatively stable, but the prediction performance in the high-frequency oscillation section is poor due to the interference of demand noise; The prediction of reconstructed signal has a large jitter in the first ten days, and then it always maintains a stable and good prediction effect.

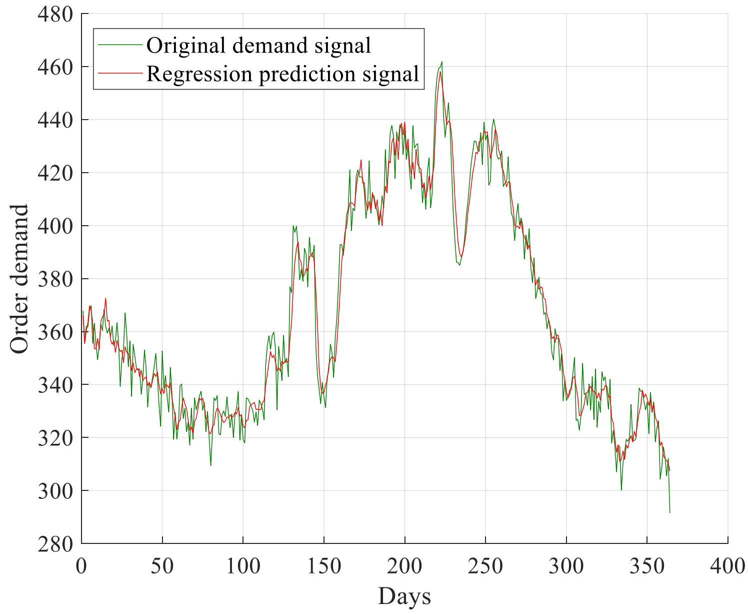

Figure 9. Regression forecast of original demand signal.

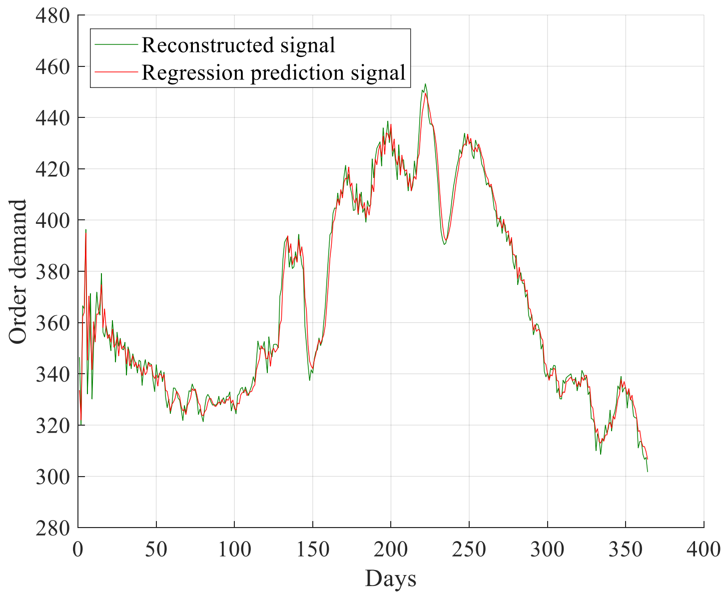

Figure 10. Reconstructed signal regression prediction diagram.

Figures 11–14 present the prediction results of the original demand signal and reconstructed signal from the specific numerical level. The specific calculation method of the error is as follows:

$$\text{Regression prediction error} = \text{predicted value} - \text{actual value}$$

$$\text{Relative error} = (\text{predicted value} - \text{actual value})/\text{actual value}$$

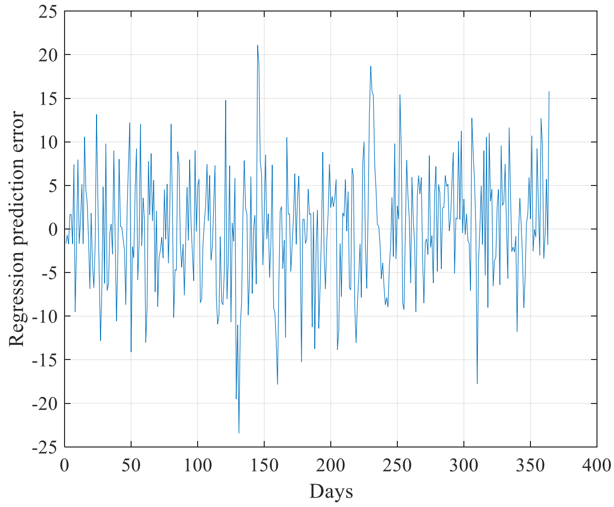

Figure 11. Regression prediction error chart of original signal.

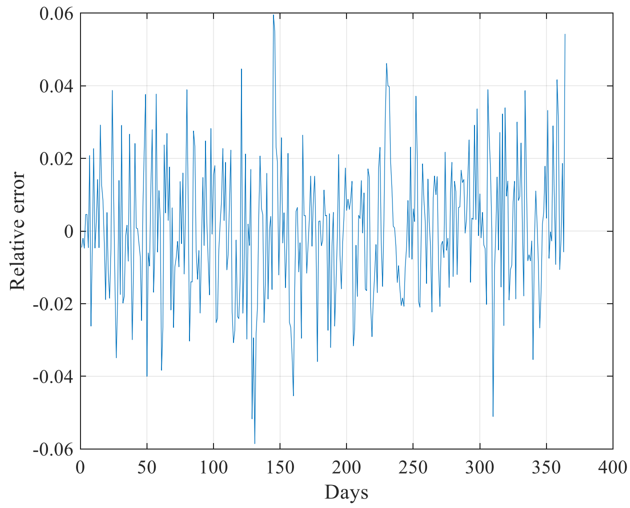

Figure 12. Relative error diagram of original signal.

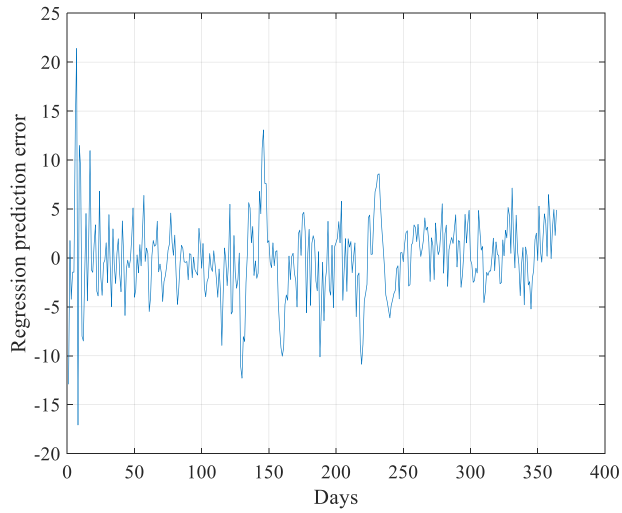

Figure 13. Error chart of reconstructed signal regression prediction.

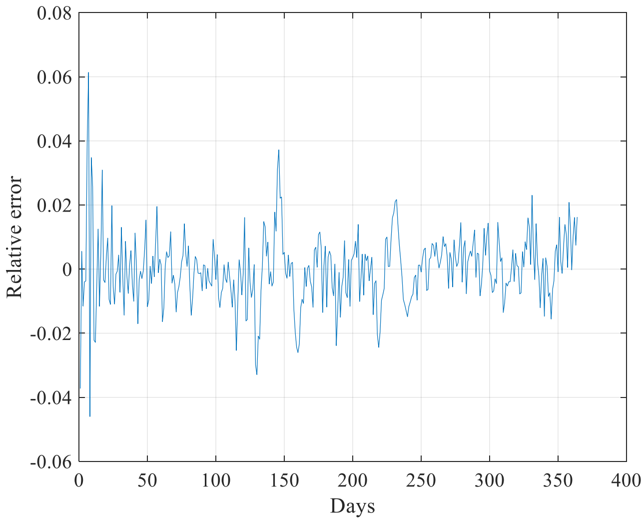

Figure 14. Relative error diagram of reconstructed signal.

It can be seen from Figures 11 and 12 that the prediction error of the original demand signal is relatively stable on the whole. Except that the errors of individual sample points on days 131, 145, 230 and 310 are large, the average error of regression prediction is about 10 tons and the relative error is about 2%. As can be seen from Figures 11 and 12, compared with the prediction result of the original demand signal, the error value of the reconstructed signal is smaller, and the points with large error are generally concentrated in the front of the data. The mean regression error of the reconstructed signal is about 5 tons, and the relative error is controlled at about 1%.

It can be seen from the data in Table 1 that when the demand of the next 1~2 days is predicted based on the demand of the enterprise on that day, the square correlation coefficients R_1^2 and R_2^2 exceed the 95% confidence level, showing a good fitting effect. However, from the root mean square error (RMSE) and absolute percentage error (MAPE), the demand prediction error of the reconstructed signal is smaller. With the extension of forecast days in the future, the prediction accuracy of the original demand signal decreases obviously, while the prediction accuracy of the reconstructed signal maintains excellent stability for a period of time, and the accuracy gap between the two gradually expands with the extension of the prediction interval.

Table 1. Comparison of error index between original demand signal and reconstructed signal.

	Original Demand Signal			Reconstructed Signal		
s	$RMSE_1$	$MAPE_1$	${R_1}^2$	$RMSE_2$	$MAPE_2$	${R_2}^2$
1	6.8293	1.4763%	97.1253%	4.1145	0.8174%	98.8739%
2	8.6238	1.7665%	95.4208%	5.8229	1.1252%	97.7580%
3	10.2323	2.0194%	93.5644%	8.3290	1.4981%	95.3994%
4	11.4189	2.2197%	92.0077%	8.5673	1.5411%	95.1835%
5	12.9622	2.5988%	89.7294%	10.0725	1.8357%	93.3550%
6	13.0840	2.4607%	89.5881%	11.5056	2.2131%	91.3219%
7	14.2863	2.7387%	87.5996%	12.4892	2.4592%	89.7267%

To sum up, the original demand signal is not the real demand, which contains the noise caused by the bullwhip effect. Affected by the bullwhip effect, while bearing the high inventory risk, enterprises are also faced with a series of negative problems that are not conducive to the survival and development of enterprises, such as waste of resources, high cost and low utilization rate of energy production. Under the vicious circle, the efficiency of the supply chain is low [42]. At present, the different maturity of enterprise intelligent manufacturing capability is accompanied by the difference of information level. At the same time, the phenomenon of information island in the supply chain system also makes it difficult to ensure the timeliness and authenticity of information interaction. In this context, this paper proposes to apply the VMD-SVM algorithm to the weakening of the bullwhip effect. Through the comparison of the prediction results of the original demand signal and the reconstructed signal, it is found that the elimination of noise has optimized various error indexes to varying degrees. It is verified that this method can effectively reduce the noise of the demand signal and improve the prediction accuracy and robustness. It has a certain reference value for the weakening of the bullwhip effect and the improvement of supply chain coordination efficiency.

5. Conclusions

The method of demand forecasting has a strong correlation with the accuracy of final forecasting. Building a reasonable and appropriate forecasting model is of great significance to guide enterprises to make correct decisions. Based on previous studies, the research puts forward new methods to weaken and prevent the bullwhip effect of intelligent manufacturing enterprises with low capability maturity. By transforming the bullwhip effect into demand forecasting accuracy problem, the VMD and SVM algorithms can find the combination point, so as to give full play to their respective effectiveness.

It is found that after the feature splitting and noise reduction reconstruction steps of the original demand signal by the VMD algorithm, the accuracy indexes of SVR have been improved to varying degrees, that is, the bullwhip effect weakening model based on the VMD-SVM algorithm can effectively filter noise, reduce the negative impact of the bullwhip effect on the supply chain. It is helpful for enterprises to manage inventory, increase capacity utilization, optimize product cost, reduce resource waste and improve supply chain efficiency. In addition, the study also found that the model can prolong the prediction time and has good robustness against the influence of uncertain factors on the prediction. This paper takes days as the time interval for sampling, and makes a more accurate forecast on the demand of enterprises in the 1~7 days. The model is extended to the actual production activities of enterprises. Considering that the lead time of production planning of different enterprises is inconsistent, enterprises can adjust the time interval of demand sampling according to their own needs on the basis of this study, so as to more calmly respond to the changes of market demand under the background of intelligent manufacturing.

VMD has a broad application prospect because of its unique ability of signal denoising and feature extraction, but there are still some shortcomings. On the one hand, the effect of VMD decomposition is related to the value of parameters in the model. Choosing different parameters will produce different intrinsic mode function and noise, which may lead to the fluctuation of signal denoising effect. In this paper, only part of the situation was analyzed. In the future, the parameters can be optimized by the way of contrast test, so as to further optimize the signal noise reduction effect. On the other hand, when separating useful signal from noise, the VMD algorithm eliminates some useful signals which are mixed in noise, which affects the integrity of reconstructed signal. Therefore, in order to improve the fidelity of the signal, the useful signals in the noise mode can be deeply mined from the perspective of algorithm improvement in the future.

Author Contributions: Conceptualization, M.Z.; methodology, M.Z.; software, M.Z.; validation, M.Z.; formal analysis, M.Z. and L.S.; investigation, M.Z. and Y.L.; resources, L.S.; data curation, M.Z. and Y.L.; writing—original draft preparation, M.Z.; writing—review and editing, M.Z.; visualization, M.Z.; supervision, L.S. and X.Z.; project administration, L.S. and X.Z.; funding acquisition, L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China [grant numbers 71801108, 62006091, 62006092]; the Overseas Visit Program for Outstanding Young Backbone Teachers in Colleges and Universities [grant number gxgwfx2020038].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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