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CSD-LSSVR-Based Inventory Demand Forecasting for Warehouse-Distribution Integrated SMEs

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The problem of inventory demand forecasting is an urgent issue in the development of warehouse-distribution integrated small and medium-sized enterprises (SMEs), which is of great importance to meet the sales demand of customers and significantly reduce distribution costs. The study describes the inventory demand problem of small and medium-sized enterprises. Based on the analysis of compressive sensing denoising methods and manual prediction methods, a prediction model is constructed using LSSVR and CSD algorithms. The study conducts an experiment using real order demand data of seafood customers from a small and medium-sized enterprise integrating warehouse and distribution in Sichuan Province from April 3, 2019 to September 9, 2023, with a total of 775 records. The training and testing sets are divided in a 4:1 ratio. Data preprocessing includes filling missing values using linear interpolation, detecting and correcting outliers using Z-score method, and normalizing the data to the [-1,1] interval. The experimental results show that on the test set, the relative error (RE) of the CSD-LSSVR model is 0.0701, the mean absolute error (MAE) is 58.258, the mean square error (MSE) is 70.12, and the directional statistic (DS) is 0.688; The RE of the traditional SVR model is 0.1214, MAE is 106.25, MSE is 112.25, and DS is 0.435. This indicates that the CSD-LSSVR model significantly improves prediction accuracy and stability. The above results indicate that the CSD-SVR prediction model performs better in inventory demand forecasting. This model can be applied to predict inventory demand for small and medium-sized enterprises, providing more possibilities for the efficient development of e-commerce enterprises.

Povzetek: Za inteligentno napovedovanje potreb po zalogah in zmanjšanje stroškov distribucije v MSP e-trgovine je razvit CSD-LSSVR. Združuje kompresijsko zaznavanje in odstranitev šuma z metodo najmanjših kvadratov podpornih vektorjev (LSSVR).

1 Introduction

The emerging new e-commerce model in recent years promotes the transformation and upgrading of the logistics industry. With the advantages of service quality, efficiency and cost, the warehouse-distribution integration mode has become the innovation mode of traditional logistics enterprises. It is critical for logistics enterprises to realize the refined management of warehousing and distribution. There are some solution models on warehouse and distribution models at home and abroad. However, the research is still preliminary exploration stage, and has not formed a scientific system [1-2]. Meanwhile, for the prediction of enterprise inventory demand, the research direction of most researchers can be divided into two types: artificial intelligence model and traditional model. While a few scholars mix the two models for analysis. The relatively mature research direction is mixed back propagation (BP) neural network and other artificial intelligence prediction models [3-4]. Compared with data processing methods such as Kalman filtering and wavelet transformations, denoising algorithms can prevent the loss of data information through sparse basis transformation. Meanwhile, Support Vector Regression (SVR) has more apparent advantages than BP neural network in data sample classification. The current research has the following problems. Firstly, traditional inventory demand forecasting methods such as exponential smoothing and moving average often have significant prediction errors when dealing with data with large demand fluctuations and obvious seasonality, which makes it difficult to meet the needs of enterprises for refined inventory management. Secondly, in practical applications, inventory demand data is often affected by various factors such as market fluctuations, promotional activities, seasonal changes, etc., resulting in a large amount of noise in the data. Thirdly, existing artificial intelligence prediction models, such as BP neural networks and standard SVR, are prone to overfitting or underfitting when dealing with small sample and nonlinear problems, resulting in insufficient generalization ability of the model and difficulty in adapting to the actual needs of different enterprises. Therefore, this study constructs a novel compressed sensing denoising least squares support vector regression (CSD-LSSVR) model to improve the accuracy of inventory demand prediction for warehouse and distribution integrated logistics enterprises. The integration of warehousing and distribution represents a supply-chain operation model that achieves a seamless connection among warehousing management, order processing, transportation, and distribution. This is made possible through in-depth collaboration between information systems and operational processes, ensuring a highly coordinated and efficient supply-chain flow.

2 Related work

Warehouse management in integrated small and medium-sized enterprises plays a crucial role in the long-term development of e-commerce enterprises. In the case of unknown demand, accurately predict the inventory demand of enterprises and make timely replenishment to prevent inventory shortage or overstock, which is the key for enterprises to control costs and improve efficiency. Doszyń compared the primary exponential smoothing method, the moving average method and the traditional inventory forecasting methods such as the correction method and the sampling method respectively. The results showed that the primary exponential smoothing method and the moving average method have many shortcomings in forecasting compared to other forecasting methods. The exponential smoothing and moving average methods have many shortcomings in forecasting compared to other forecasting methods [5]. The study payed special attention to the phenomenon of "smoothing bias" and discovered that traditional methods systematically underestimated peak demand by 18-22%, which prompted the adoption of the CSD-LSSVR model to enhance the ability to capture sudden demand changes. Lukinskiy et al. found that existing clustering methods cannot identify consumption process dynamics, and therefore cannot be used for classification and improvement of inventory consumption prediction models. In response to this issue, they proposed an integrated time series prediction model and an algorithm for estimating inventory prediction parameters, and confirmed the effectiveness of this study in reducing supply chain costs through experiments [6]. Through sensitivity analysis, Shariff et al. improved parameters such as inventory reconciliation cycle, distribution time, demand forecast weights and safety stock days to obtain an optimised chain retail multi-level inventory system dynamics model. The experimental results showed that the model effectively reduced the amount of inventory in the enterprise, improved inventory turnover efficiency and reduced inventory costs [7]. Rumetna et al. designed an inventory prediction information system based on waterfall and exponential smoothing methods for a mobile phone manufacturer's inventory flow and management issues. The system will be used to predict the appropriate inventory quantity ordered by the company to meet customer needs [8].

Nambiar et al. proposed a demand forecasting framework that facilitates dynamic inventory allocation for multi cycle inventory allocation in both single warehouse and multi-retailer environments. It ultimately confirmed the asymptotic optimality of the method by using Lagrange relaxation technique [9]. Han et al. constructed an enterprise logistics inventory prediction model, using BP neural network to analyze the relationship between inventory demand and various influencing factors. The model testing results verified the effectiveness of the model and provided appropriate theoretical guidance for predicting the actual demand of logistics inventory. The influencing factors included market demand, seasonal changes, promotional activities, etc. [10]. Kosenko et al. systematically analysed models of supply logistics in the context of demand fluctuations, including models of supply logistics processes, models of product demand forecasting and models for calculating the optimal order quantity for various demand options. The proposed information technology was able to analyses and forecast changes of major market factors, and effectively solve the inventory management tasks according to the results obtained [11]. Aktepe et al. compared the application of SVR, artificial neural networks, multiple linear regression, and multiple nonlinear regression methods in inventory demand forecasting. The input variables of the model included the company's sales revenue in the past few years, global sales volume of construction machinery, US dollar exchange rate, and monthly impact rate. The prediction accuracy was estimated through the system parameter design of artificial intelligence methods. The prediction results showed that compared with traditional regression methods, SVR and artificial neural networks had better prediction results [12]. Kmiecik et al. studied the logistics problem of enterprise distribution networks based on machine learning algorithms and artificial neural networks, taking into account manufacturer demand planning and traffic network characteristics. The results showed that the improved algorithm could effectively predict the demand of the distribution network, and the prediction error value was small [13]. Xu G proposed an inventory production material planning model driven by customer demand and combined it with the demand planning concept of grey wolf optimization algorithm. The results indicated that this optimization method could effectively achieve capacity allocation, optimize inventory levels, and improve production levels in resource constrained situations. This model paid special attention to the dynamic changes in customer demand and used it as a key input for prediction and planning [14]. The summary table of the relevant works mentioned above is shown in Table 1.

According to the relevant analysis of inventory demand prediction by most scholars both domestically and internationally, it can be found that with the rise of artificial intelligence algorithms, many scholars have proposed inventory demand prediction models for different environments. However, although these prediction models can achieve predictions to a certain extent, their prediction accuracy is not ideal. Meanwhile, the hybrid model of artificial intelligence and traditional models for predicting inventory demand has not received a large number of scholars' argumentation. Therefore, the study aims to combine least squares SVR and compressed perception denoising technology to construct a small and medium-sized enterprise inventory demand prediction model CSD-LSSVR with the goal of warehouse and distribution integration, providing a guarantee for intelligent inventory management in e-commerce enterprises in the future.

Table 1: Summary table of related works

Author	Data set	Main indicators	Limitation	Applicable scenarios
Doszyń	Intermittent demand data	Average error 22%	Systematically underestimating peak demand	Stable demand mode
Lukinskiy et al.	Low demand product data	Inventory cost reduced by 18	Ignore the dynamic process of consumption	Low frequency demand commodity
Shariff et al.	Retail Chain Data	Inventory turnover rate increased by 25%	High sensitivity of parameters	Multi level inventory system
Rumetna et al.	Mobile phone inventory data	Accuracy rate of 82%	Not considering external factors	Electronic product inventory
Nambiar et al.	Multi retailer data	Out of stock rate ↓ 30%	Accurate demand learning is required	Distributed warehousing
Han et al.	Commercial logistics data	MSE 89.4	Unstable training	Multiple factors affect the scenario
Kosenko et al.	Fluctuating demand data	Prediction error of 15%	Dependent on market factor analysis	Large demand fluctuation scenario
Aktepe et al.	Engineering machinery data	MAE76.5	High computational complexity	Multivariate prediction
Sareminia	Distribution network data	40% reduction in error	Need transportation network data	logistics network planning
Kmiecik	Production material data	Inventory level ↓ 35%	Sensitive to resource constraints	Capacity limited environment

3 Inventory demand forecasting model construction for integrated warehouse and distribution enterprises

3.1 Inventory demand forecasts for integrated warehouse and distribution SMEs

Logistics service enterprises must constantly improve their own warehouse and distribution management to enhance the service experience of e-commerce and consumers. Meanwhile, to improve the efficiency of logistics operation on the existing management level, it is necessary to increase the inventory, resulting in an increase in logistics costs [15-16]. Increasing inventory on the basis of existing logistics facilities leads to inventory pressure of logistics enterprises, thus affecting the efficiency of logistics services. The overall goal is to realize the integrated operation of multiple links of "warehousing + distribution", so as to maximize the core competitiveness and maximize the interests of e-commerce and logistics enterprises. Figure 1 refers to the overall objective of the integrated warehouse-distribution enterprise, which includes resource integration, process, management and information. The realization of inventory demand forecasting requires seamless integration and standardization, visualization and systematization of information data. The processes of the

warehouse-distribution integration enterprise are order pre-processing, goods management, warehouse management and operations, sending and distribution, rejection and return and account clearing for upstream and downstream. The models of the enterprise include third-party warehouse distribution, third-party distribution seller warehousing and self-built warehouse distribution.

The study analyses the inventory demand forecast for warehouse distribution integration SMEs, i.e. the third-party warehouse distribution inventory F demand forecast. At this stage, SMEs are characterized by tight and low utilization of warehouse resources, a wide range of logistics services and many difficulties in integration and collaboration. The principles of the inventory demand forecasting model are simplicity, applicability and accuracy. The influencing factors are consumers, logistics enterprises and e-commerce enterprises. However, there are large differences between inventory demand forecasting and actual demand in warehouse-distribution integration SMEs. Artificial intelligence forecasting models have excessive influence of parameter changes and are prone to fitting. The influence of market, seasonality and consumer demand on inventory demand can lead to high noise causing large forecasting errors. This study applies CSD-LSSVR to achieve the efficiency and accuracy of inventory demand prediction for small and medium-sized enterprises with integrated warehouse and distribution [17]. The study selects a warehouse and distribution integration small and medium-sized enterprise in Sichuan a seafood customer daily order demand data as an example for analysis. A total of 775 experimental data were collected from April 3, 2019 to September 9, 2023. The selection of the above time period is based on a comprehensive consideration of industry characteristics and enterprise operational needs, which fully covers key business stages and ensures that the model can learn demand patterns in different market environments. Previous studies have shown that when the ratio of the training set to the test set is 4:1, the efficiency of inventory demand prediction is higher [18]. The research content includes comparing the performance of various machine learning models at different ratios, and the results show that a 4:1 ratio can ensure sufficient model training while leaving enough data for testing the model's generalization ability. Therefore, the study set the data ratio between the training set and the test set to be 4:1. The training set and test set obtain the learning machine model by training the training set data. The test set can be used to test the accuracy of the learning machine model. Table 2 refers to the raw data of the enterprise segment. The following factors should be considered for the selection of the sample data: the order quantity reflects the actual inventory demand of SMEs, and the daily data has more complex data characteristics than the weekly and monthly data, but also contains a large amount of noisy data. The training set data length is 2^n, then an orthogonal sparse transformation matrix can be constructed. Orthogonal sparse transformation matrix can reduce high-dimensional raw data to lower dimensions, and make the reduced features orthogonal or uncorrelated with each other [19]. The choice of data length is 2^n because data of this length can be efficiently processed by algorithms such as fast Fourier transform. It is crucial to retain most of the information of the original data. Therefore, it is an important tool that can extract key information and simplify the analysis process. By utilizing the orthogonal sparse transformation matrix, complex data features can be transformed into a form that is easier to understand and analyze, thereby more accurately reflecting the actual inventory needs of small and medium-sized enterprises. In addition, during the data preprocessing stage, the original data was first checked for integrity and a small number of missing values were found, accounting for approximately 2.1% of the total data. For missing values, linear interpolation is used to fill them in order to ensure the continuity and integrity of the time series. Subsequently, outlier detection was performed on the data, and the Z-score method was used to identify and correct obvious outliers. Finally, to eliminate the influence of dimensionality and improve model training efficiency, we normalized the data to the [-1,1] interval.

Given that the data of inventory demand forecast for SMEs in warehouse-distribution integration is a time series, a smoothness test can be performed at the beginning of the time series forecast. If the original series is found to be non-stationary during the stationarity test, the original inventory demand sequence of the enterprise needs to be differenced.

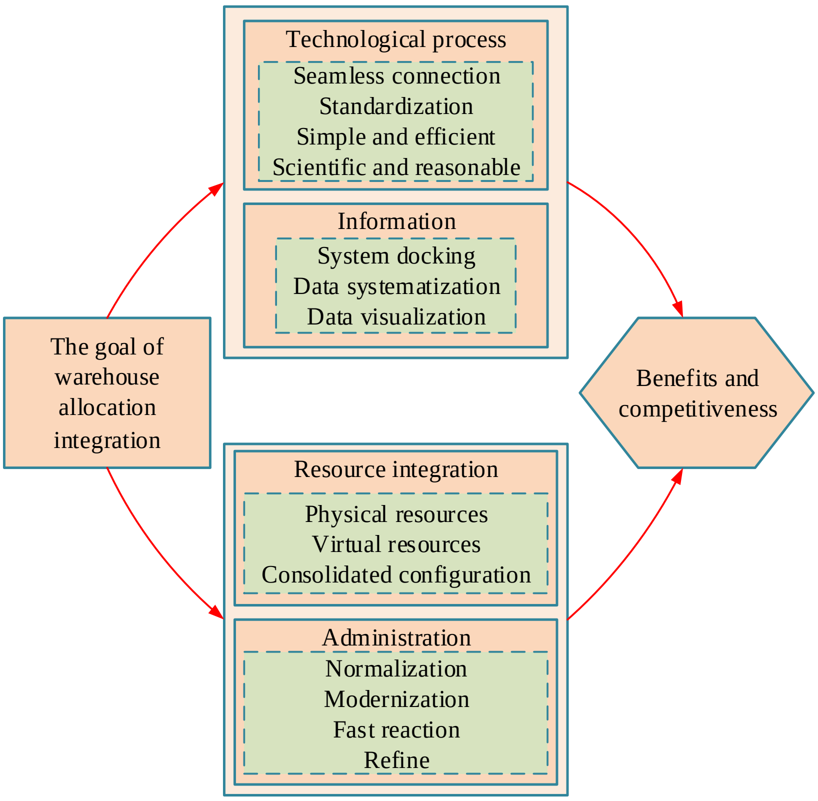


Figure 1: The overall goal of warehouse distribution integration enterprise

Table 2: Some original data of the enterprise

Time	Actual quality/kg		Time	Actual quality/kg	
	Fresh eggs	seafood		Fresh eggs	seafood
2019-4-3	1152	536	2021-7-3	625	1025
2019-5-3	854	625	2021-8-3	1225	1136
2019-6-3	954	833	2021-9-3	608	764
2019-7-3	889	1035	2022-4-3	708	702
2019-8-3	1025	1243	2022-5-3	698	764
2019-9-3	929	1012	2022-6-3	735	806
2020-4-3	854	496	2022-7-3	1025	968
2020-5-3	1258	634	2022-8-3	1658	1035
2020-6-3	865	625	2022-9-3	815	883
2020-7-3	925	867	2023-4-3	684	721
2020-8-3	1048	1016	2023-5-3	1078	825
2020-9-3	772	753	2023-6-3	824	936
2021-4-3	758	621	2023-7-3	824	1462
2021-5-3	948	705	2023-8-3	758	1273
2021-6-3	650	876	2023-9-3	687	928

3.2 CSD method and SVR

According to the Nyquist sampling theorem, in order to avoid information loss, it is necessary to sample at least twice the highest frequency of the sampled signal. If the sampling frequency falls below this threshold, so-called aliasing phenomenon will occur, and the original signal cannot be accurately reconstructed. However, it is worth noting that CSD can directly obtain effective M measurement values without the need to comply with the N sampling values ($M \ll N$) in the Nyquist sampling theorem. In the context of inventory demand forecasting, time series data are typically processed, which may contain significant cyclical changes such as seasonal demand fluctuations. Accurately sampling these data is crucial for capturing these periodic changes and avoiding information loss. If the sampling frequency is insufficient, key changes may be missed, resulting in the prediction model's inability to accurately reflect the actual inventory demand. The CSD method mainly includes three parts: sparse representation, random sampling, and signal recovery. For the sparse representation, the signal can be referred to by some basis function. From a mathematical point of view, the effective long substantial signal vector is $X \in R^n$ and an orthogonal basis of R^n is set to $\Psi = \{\Psi\}_{i=1}^{n}, i = 1, 2, ..., n$. Then the signal $X \in R^n$ can be linearly represented by equation (1).

$$X = \sum_{i=1}^{n} s_i \Psi_i \qquad (1)$$

In equation (1), the i coefficient of X is s_i, which is calculated by equation (2).

$$s_i = \langle X, \Psi_i \rangle \qquad (2)$$

By sparse representation, X can be expressed by Ψ_i. Ψ is a matrix whose column vector is $n \times n$. The sparse coefficient S can be considered as sparse when most elements of s_i are zero. If the signal $X \in R^n$ is sparse under an orthogonal basis, the sparse coefficient S can be expressed as in equation (3).

$$S = \Psi^T X \qquad (3)$$

For random sampling, $\hbar$ is a one-dimensional observation matrix, which is different from the transformation base Ψ. The matrix is set up to measure the sparse coefficients and also to obtain the observation vector $\hbar S$. The observation vector is obtained by transforming sparse coefficients with a random sampling matrix, representing randomly selected samples from the original signal. It contains key information of the original signal, but may also contain noise. The sparse transformation basis used in the study is the Discrete Cosine Transform (DCT)-II. The core idea of DCT-II is to fit and represent existing data or signals through a series of cosine functions (which are selected basis functions). These cosine functions have different frequencies and can be represented one by one from low to high frequencies [20-21]. In research, using DCT-II as a sparse transformation basis helps to capture and analyze key information in the data. The observation matrix is a random Gaussian observation matrix. Equation (4) is the calculation formula of the whole perception process.

$$\min \left\| \Psi^T X \right\|_0, \hbar S = \hbar \Psi^T X \qquad (4)$$

According to equation (4), it reflects the application of compressive sensing theory in inventory demand forecasting, which transforms complex business demands into computable optimization problems through mathematical modeling; The model can fully preserve the core business cycle that affects inventory decisions during data compression, providing a concise and semantically rich feature representation for subsequent predictions. The signal recovery during the perception process is achieved through the commonly used reconstruction algorithm - orthogonal matching tracking. The Orthogonal Matching Tracking (OMP) algorithm is a greedy algorithm that selects the atom that best matches the residual residue from the perception matrix A during each iteration to construct a sparse signal and calculate a new residual residue [22]. The atomic selection criteria are as follows: Firstly, in each iteration, the algorithm searches for the dictionary atom that is most relevant to the current residual vector. The second is that once an atom is selected, the algorithm updates the residual by projecting it onto the selected atom and subtracting this projection from the residual. Thirdly, in each iteration, the algorithm only adds one atom to the solution until a certain stopping criterion is met, such as reaching the predetermined number of iterations or having a sufficiently small residual. The estimation of the reconstructed signal $\hat{S}_t$ by OMP is shown in equation (5).

$$\hat{S}_t = \arg\min_{\theta_t} \left\| y - \mathbf{A}_t S_t \right\| = \left(\mathbf{A}_t^T \mathbf{A}_t \right)^{-1} \mathbf{A}_t^T y \tag{5}$$

In equation (5), $\mathbf{A}$ is the perception matrix and y is the observation vector. The research proposes a model based on the combination of compressed perception denoising and artificial intelligence algorithms, namely the compressed perception denoising artificial intelligence prediction model. It is planned to use SVR, a typical artificial intelligence prediction algorithm and its variant algorithm, for inventory demand prediction. SVR is an application of Support Vector Machine (SVM) to regression problems. SVM was proposed to solve the problems of small sample, nonlinear, and high-dimensional pattern recognition [23]. In machine learning, it is mainly applied to classification and pattern recognition. The use of $\varepsilon-$ insensitive loss function in SVR algorithm has better performance than SVM in regression problems. The core idea of the insensitive loss function is that only when the error between the predicted value and the actual value exceeds a preset threshold ε, will the error be penalized. This design has the following advantages: Firstly, it can filter out data points with small differences in erroneous inventory demand forecasting, avoiding overfitting of the model to these small errors. The second advantage is to simplify the complexity of the model, which is only considered when the error exceeds ε. This allows the model to process data more efficiently during training, reducing unnecessary computational overhead. The study chooses the orthogonal matching tracking algorithm to complete signal recovery. Insensitive loss function ε is used in SVR, which has better results than SVM in regression problems. SVM maximizes the distance to the nearest sample point by constructing a hyperplane; SVR minimizes the distance to the farthest sample point by constructing a hyperplane. The SVR constructs a hyperplane to minimize the distance from the farthest sample point to the hyperplane. Figure 2(a) and Figure 2(b) show the diagrams of SVM and SVR respectively. It can be observed that the goal of SVM is to find a hyperplane that can separate data points of different categories and keep them as far away as possible from support vectors of any category. This hyperplane is called the optimal segmentation hyperplane, which maximizes the boundary between two types of data points. For SVR, the goal is to find a hyperplane that best fits the data points while maintaining the boundaries between the hyperplane and the data points. The system should allow data points to fluctuate within a certain range of the hyperplane without them being considered as errors. The error will only be calculated when the distance between the data point and the hyperplane exceeds the threshold. This method allows SVR to have some flexibility in fitting data, thereby improving the model's generalization ability.

The basic principle of SVM is equation (6).

$$\begin{cases} \min \frac{1}{2} \|w\|^2 \\ s.t. y_i \left(wx_i + b \right) \geq 1 \ \forall i \end{cases} \tag{6}$$

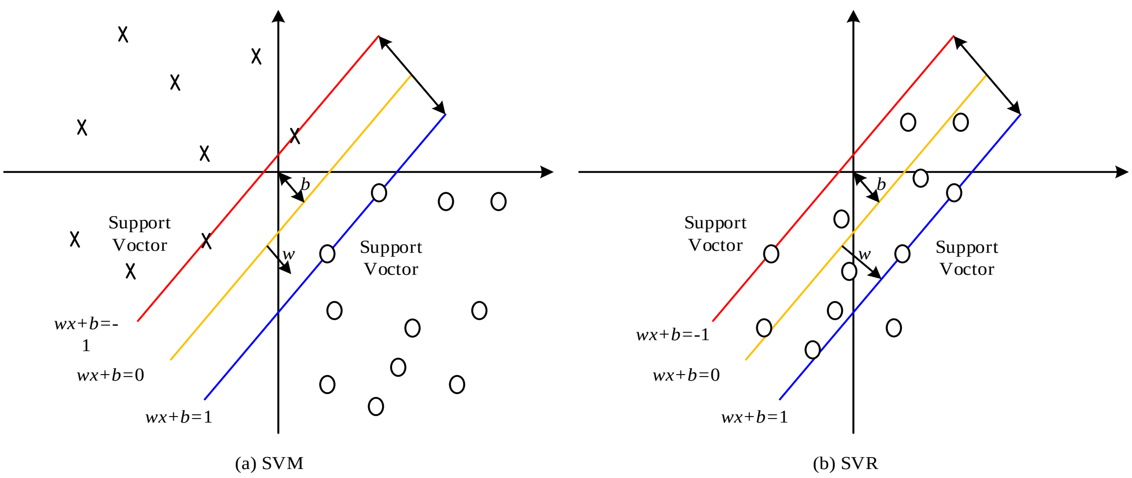


Figure 2: Schematic diagram of SVM and SVR

In equation (6), x_i and y_i refer to an input and a category in the sample data set respectively, i refers to a sample data, $w=\left(w_1,\cdots,w_p\right)$ represents the normal vector of the hyperplane, b refers to the offset, and $i=1,\cdots,l$. The basic principle of SVR is equation (7).

$$\begin{cases} \min \frac{1}{2}\|w\|^2 \\ s.t.\left|y_i-\left(wx_i+b\right)\right|\leq\varepsilon\ \ \forall i \end{cases} \quad (7)$$

The SVM is approved by the kernel function to solve multi-dimensional problems through non-linear transformation to minimize the obstacles arising from dimensionality problems to the greatest extent. It can also prevent local extremes and over-learning problems of neural network methods. However, the method is more difficult for situations such as large-scale samples or small sample conditions and signals with rich frequency information [24]. The SVR algorithm is chosen as the AI prediction algorithm in the study. The basic process of the SVR algorithm is as follows. First, a linear regression function is constructed in the high latitude space. The study sets the training set as $T=\left\{\left(x_1,y_1\right),\cdots,\left(x_i,y_i\right)\right\}\in\left(R^n\times Y\right)^l$, $x_i\in R^n$, $y_i\in Y=R$. Equation (8) refers to the calculation formula of the linear regression function.

$$f\left(x\right)=w\Phi\left(x\right)+b \quad (8)$$

In equation (8), $\Phi\left(x\right)$ is the nonlinear mapping function. Then, appropriate parameters are selected, including the kernel function $K\left(x,x'\right)$,accuracy $\varepsilon>0$, and the penalty parameter $C>0$. The specific selection process is as follows: First, it establishes a three-dimensional parameter space containing Gaussian kernel function bandwidth of [0.1,10], regularization parameter of [0.01100], and insensitive loss function threshold of [0.05,0.2], and it evaluates the performance of each parameter combination on the training set through 5-fold cross validation. The optimization objective function is the weighted sum of MSE and the number of support vectors (weight ratio 7:3) to ensure a balance between prediction accuracy and computational efficiency of the model. The final selected parameter combination is as follows: Gaussian kernel bandwidth of 1.2, regularization parameter of 0.3, and insensitive loss function threshold of 0.1. Secondly, construct and solve convex quadratic programming problems, as shown in equation (9).

$$\min \frac{1}{2}\|w\|^2+C\sum_{i=1}^{l}\left(\xi_i+\xi_i^*\right) \quad (9)$$

In equation (9), ξ_i and ξ_i^* are relaxation variables. ξ_i is the difference between the projection of the sample point above the upper edge of the isolation strip and the value of the sample point, while ξ_i^* is the difference between the projection of the sample point below the lower edge of the isolation strip and the value of the sample point. Then, calculate the deviation vector $\bar{b}$. Finally, a regression function is constructed. The commonly-used kernel functions in SVR include polynomial kernel functions and Gaussian radial basis kernel functions. The calculation formula for polynomial function $K\left(x,x'\right)$ of order d is given by equation (10).

$$K\left(x,x'\right)=\left(x,x'\right)^d \quad (10)$$

The formula for anon-flush polynomial function of d order is equation (11).

$$K\left(x,x'\right)=\left(\left(x,x'\right)+1\right)^d \quad (11)$$

Homogeneous polynomial functions exhibit better stability, but their performance may be limited when dealing with complex data. In contrast, non-homogeneous polynomial functions can handle complex mathematical models more flexibly, thus exhibiting certain advantages when dealing with highly nonlinear data. However, non-homogeneous polynomial functions may introduce higher computational costs and overfitting risks.

3.3 CSD-LSSVR model construction

The SVM model has strong non-linear capability, which can be better applied to inventory demand forecasting for warehouse-distribution integration compared with other methods. The study selects the SVR model for inventory demand forecasting. To overcome its limitation of long training time, the compressed sensing denoising method is used to denoise the original data. The processed data are input the SVR model for training and learning and output the forecasting results. The LSSVR regression model consists of an input layer, an implicit layer and an output layer. The LSSVR regression model converts complex convex quadratic programming problems into linear equations for solution, thus reducing the modelling parameters and also improving the computational efficiency [25-26]. The study sets the training sample set for the LSSVR algorithm to $\chi=\left\{\left(V_i,y_i\right)\middle|V_i=R'',y_i\in R\right\}$. The optimization problem $\min\limits_{w,b,\xi} J\left(w,\xi_i\right)$ in equation (12) needs to be solved.

$$\min_{w,b,\xi} J(w,\xi) = \frac{1}{2}\|w\|^2 + \frac{1}{2}\gamma\sum_{i=1}^{l}\xi_i^2 \ \ s.t. \ y_i = w\cdot\phi(V_i) + b + \xi_i \tag{12}$$

In equation (12), the regularization parameter is γ; the fit error of the regression hyperplane is ξ_i. To facilitate the solution, equation (12) can be converted into a pairwise problem and constructed as a Lagrange function in equation (13).

$$L(w,b,\xi,a) = J(w,\xi) - \sum_{i=1}^{l} a_i\left\{w\cdot\phi(V_i) + b + \xi_i - y_i\right\} \tag{13}$$

In equation (13), a_i refers to the Lagrange multiplier. The Lagrange function can be derived based on the Karush-Kuhn-Tuchker condition and simplified by expressing it as a linear system of equations. Below, a simple optimization problem is used as an example to explain the KKT condition. Suppose there is a linear programming problem with the goal of minimizing a function while satisfying some linear constraints. Under certain conditions, some solutions may satisfy all constraints, but not the optimal solution. However, if a solution not only satisfies all constraints but also satisfies the KKT condition, then it can be concluded that the solution is the optimal solution. In the current problem, the study uses KKT conditions to obtain the optimal solution of LSSVR. The goal of the solution is to find a set of Lagrange multipliers that minimize the Lagrange function in equation (11). Due to the fact that the Lagrangian function satisfies the KKT condition, when this function is minimized, the optimal solution to the problem is found. Figure 3 is a schematic diagram of the CSD-LSSVR model applied to warehouse-distribution integration SMEs inventory demand forecasting. Firstly, the raw data with noise characteristics is input, while the data is denoised by the CSD method to obtain the denoised data. Then, the denoised data are entered into the LSSVR algorithm and solved by MATLAB 2014a and LIBSVM-3.23 to obtain the final prediction results [27-28]. The CSD LSSVR model is fitted using the LIBSVM toolkit, and the optimal parameters are determined using grid search method. Then, the entire training set is trained with the optimal parameters to obtain the model and tested and predicted. The grid search method can be directly performed by cross validating the parameters of the estimation function in LIBSVM software. The study adopts a direct prediction strategy. Given a time series, the values are calculated to predict several steps forward. Next, the model forecasting results are evaluated using evaluation indicators. Based on the forecasting of inventory demand in the e-commerce environment, the evaluation indicators chosen for the study are the relative error RE, the mean absolute error (MAE), the mean squared error estimate and the directional statistic [29]. The formula for calculating the relative error RE is equation (14).

$$RE = |x_j - x_i| / x_i \tag{14}$$

In equation (14), x_j is the other sample data. The formula for calculating MAD is equation (15).

$$MAD = \sum_{i=1}^{n} |x_i - \hat{x}_i| / n \tag{15}$$

In equation (13), n is the number of samples; $\hat{x}_i$ is the mean of the sample data. The mean squared error estimate R_{MSE} is equation (16).

$$R_{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{16}$$

The directional statistic D_{stat} calculation method is equation (17).

$$D_{stat} = \frac{1}{n}\sum_{i=1}^{n} a_t \times 100\% \tag{17}$$

In equation (17), when $(x_{i+1} - x)(\hat{x}_{i+1} - x_i) \ge 0$, then $a_t = 1$. Otherwise, the value of a_t is 0. Finally, the evaluation results are fed back to the LSSVR prediction model to identify the limitations of the model and make targeted improvements to the model.

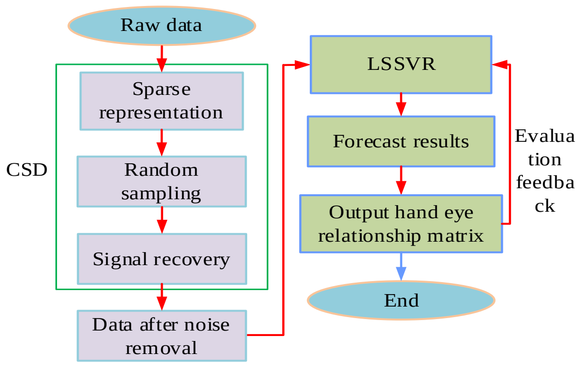


Figure 3: Schematic diagram of the CSD-LSSVR model applied to the demand forecast of SMEs inventory in warehouse distribution integration

4 Results of the CSD-LSSVR model inventory demand forecasting for SMEs

To better analyse the inventory demand forecasting results of the CSD-LSSVR model for SMEs, the research analyzed the stationary demand sequence, LSSVR model preprocessing results and algorithm performance respectively. The LSSVR model adopted a direct prediction strategy to process time series data, as follows. Firstly, it performed stationarity testing and differencing on the original inventory demand data, and then normalized the data to the range of (-1,1) to improve model training efficiency and prediction accuracy. During training, the model minimized prediction error based on input-output data and learned the mapping relationship between the two. After training, new input data were predicted to obtain future demand forecast values. The hardware environment used for the study was Intel I7-4790, NVDIA GTX1050TI. Operating system was Windows 10 64-bit; framework was Django; server was Nginx; database was SQLite; language was Python. The process of preprocessing inventory demand data using CSD method was as follows: First, the original signal was represented as a linear combination of some orthogonal basis function, where most of the coefficients were zero or close to zero, in order to capture the main features of the data and ignore noise components. Subsequently, by sampling the sparse signal with a random Gaussian matrix, effective measurement values were directly obtained without violating the Nyquist sampling theorem, reducing data dimensionality while preserving key information. Finally, the orthogonal matching tracking algorithm was used to reconstruct the sampled signal, and the original signal was gradually restored by iteratively selecting the atom that best matches the residual. By setting an appropriate sparsity threshold to remove noise components, a more accurate inventory demand signal was restored. Figure 4(a) and figure 4(b) refer to the original inventory demand sequence and the differentially processed smooth demand sequences. The raw data represented in Figure 4(a) can only represent the actual demand booked by the customer. The change of these raw data is not directly related to the time, and cannot infer the customer's actual demand. Compared with Figure 4(a) and Figure 4(b), after the original inventory demand sequence of the enterprise is processed by the stability test, the value range of inventory demand is (-1,1), which can be used to forecast the inventory demand of SMEs with higher accuracy. Normalizing inventory demand data to the range of (-1,1) is to ensure the stationarity and consistency of the data. Through standardization, inventory demand data at different time points can be converted to the same scale, thereby improving the prediction accuracy of the model.

Table 3 shows some processing results under the direct prediction strategy of LSSVR model. There is no obvious rule between the positive and negative values of input and output. The value range of x_1 is -0.2847-0.5461; the value range of x_2 is -0.5214-0.4125; the value range of x_3 is -0.5471-0.4148; the x_4 is -0.5417-0.4015; the y is -0.4658-0.4015.

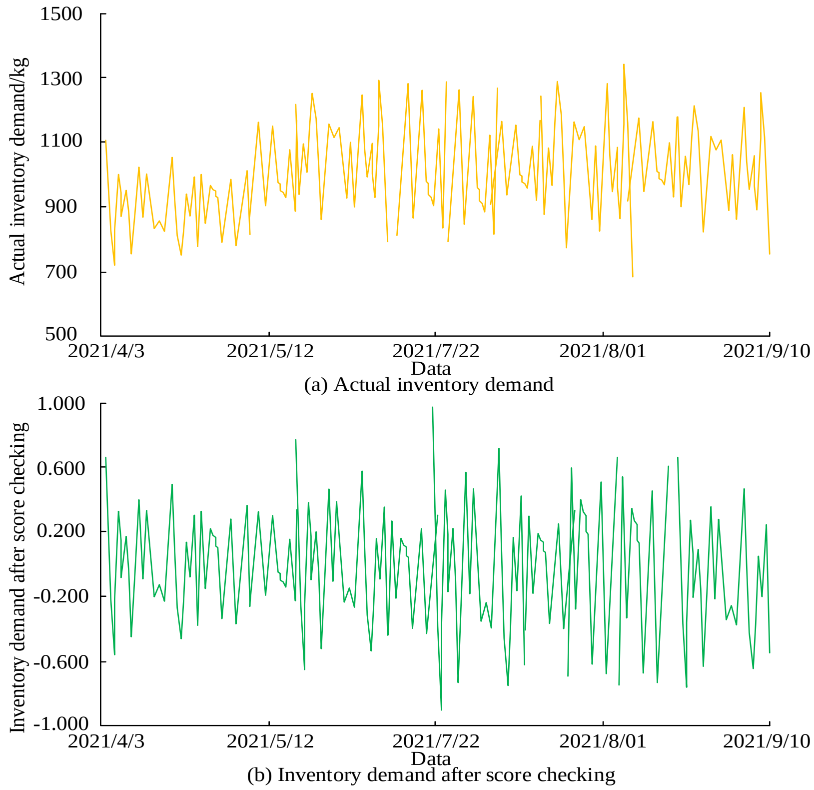


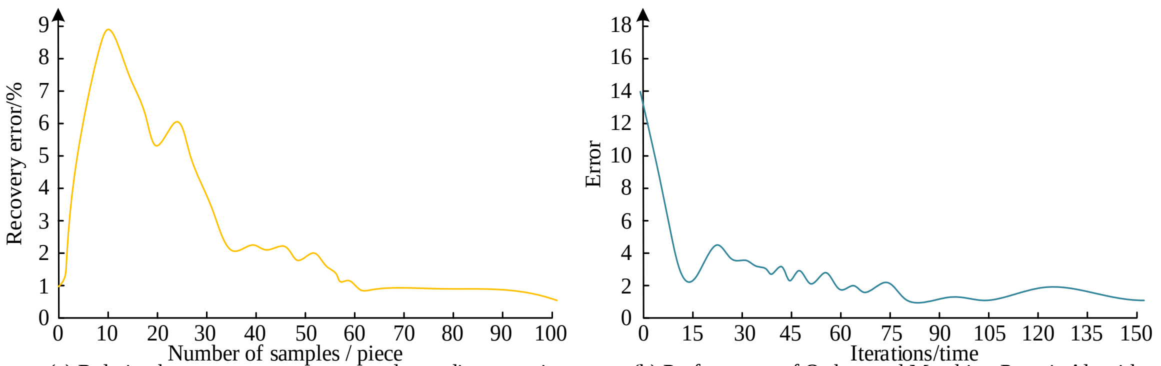
Figure 4: The original inventory demand sequence and the stable demand sequence after difference processing

Figure 5(a) shows the relationship between the signal recovery error and the number of samples. There was a direct correlation between the size of the number of samples and the signal recovery error of the compressed sensing algorithm. If the number of samples is too small, the signal recovery will take longer, which will result in a higher error. When the number of samples is too large, the time required for signal recovery will increase, which will reduce the efficiency of the algorithm. The increase in error may be due to the inherent characteristics of the data, such as noise and nonlinearity, which interfere with the recovery process of the algorithm. Figure 5(b) shows the performance of the orthogonal matching tracking algorithm for different numbers of iterations. The accuracy of the algorithm gradually increased with the number of iterations. When the number of iterations was about 100, the highest accuracy value was 99.85%. After the number of iterations exceeded 100, the performance of the orthogonal matching tracking algorithm no longer fluctuated to a large extent, but gradually tended to a stable state. The optimal number of iterations for the orthogonal matching tracking algorithm was 100, and the maximum iteration number could be set to 150 during the experiment, so as to improve the operational efficiency of the algorithm. This was because the orthogonal matching tracking algorithm is a greedy algorithm that constructs sparse signals by gradually selecting the atoms that best match the residuals. As the number of iterations increased, the algorithm gradually approached the optimal solution. When the number of iterations reached 100, the algorithm found a sparse representation that was close enough to the real signal, balancing computational efficiency and reconstruction accuracy, and avoiding unnecessary resource consumption.

Figure 6 refers to the influence of different parameters of the CSD-LSSVR model on the prediction results. Figure 6(a) and Figure 6(b) refer to the performance of the model when the regularization parameter γ was taken as 0.3 and 0.5 respectively. From the figures, the errors of both LSSVR and CSD-LSSVR models kept decreasing as the data size increased. When the data size reached about 25, the model tended to be stable. However, the accuracy showed the opposite pattern of change. The convergence errors of the LSSVR and CSD-LSSVR models were 0.156 and 0.278 when γ was taken as 0.3; the accuracy was 97.58% and 95.21% respectively. When γ was taken as 0.5, the convergence errors for the LSSVR and CSD-LSSVR models were 0.215 and 0.498 respectively; the accuracy was 96.12% and 93.21% respectively. Therefore, the best performance of both LSSVR and CSD-LSSVR models was achieved when the regularization parameter γ was taken as 0.3.

Table 3: Partial processing results under LSSVR model direct prediction strategy

Input value (x_1)	Input value (x_2)	Input value (x_3)	Input value (x_4)	Output Value (y)
-0.2847	-0.2871	-0.5471	0.3214	-0.0877
-0.0526	-0.5214	0.3214	-0.0908	0.1758
0.5461	0.1756	-0.0874	0.1741	-0.4658
0.2514	0.1658	0.1745	-0.4658	-0.2248
0.4120	-0.5241	-0.4655	-0.5417	0.4015
-0.098	0.4125	0.4148	0.4015	-0.0958
0.0089	-0.0958	0.3457	-0.0948	0.3546
0.1742	-0.1925	0.0014	0.3457	0.0087
0.3258	-0.1324	-0.1948	0.0087	-0.1958
0.4987	0.0087	0.1231	-0.1985	-0.1314
0.4015	0.3247	-0.2451	-0.1324	-0.2245



(a) Relation between recovery error and sampling quantity (b) Performance of Orthogonal Matching Pursuit Algorithm

Figure 5: Signal recovery error and performance of orthogonal matching pursuit algorithm with different iterations

Table 4 shows the evaluation results of the SMEs inventory forecasting model, covering both the training and test sets. The results of the test set showed that the RE , MAD , R_{MSE} and D_{stat} of the CSD-LSSVR forecasting model outperformed the other forecasting models, with values of 0.0687, 58.651, 72.16 and 0.712 respectively. Next one was the CSD-SVR forecasting model, with corresponding values of 0.0897, 76.587, 87.02 and 0.685 respectively. The SVR forecasting model had the worst performance with corresponding values of 0.1214, 107.37, 112.21 and 0.435 respectively. The results of the validation set were similar to those of the test set. The CSD-LSSVR prediction model had better RE , MAD , R_{MSE} and D_{stat} , followed by the CSD-SVR prediction model, and the SVR prediction model had the worst performance. Predicting inventory and demand markets plays an important role in the sustained development and improvement of the supply chain [30]. The research results in reference [31] indicate that using machine learning algorithms for predicting future demand of enterprises is relatively advanced, which coincides with the research results. Reference [32] also indicates that BP neural networks have poorer prediction efficiency compared to SVR models due to their own shortcomings. In addition, according to statistical results, the confidence interval of the test set reflected the stable performance of the model on unknown data, and the CSD-LSSVR model exhibited significantly superior performance. The 95% CI upper limit of CSD-LSSVR in all indicators of the test set was still better than the lower limits of other models (p<0.001). The MSE interval width showed that CSD-LSSVR was 28% more stable than SVR. Meanwhile, although the running time of the research method was slightly longer, the inventory cost savings brought by its improved prediction accuracy could offset the computational costs, and it still met the real-time requirements of enterprises with a prediction delay threshold of less than<5ms/time.

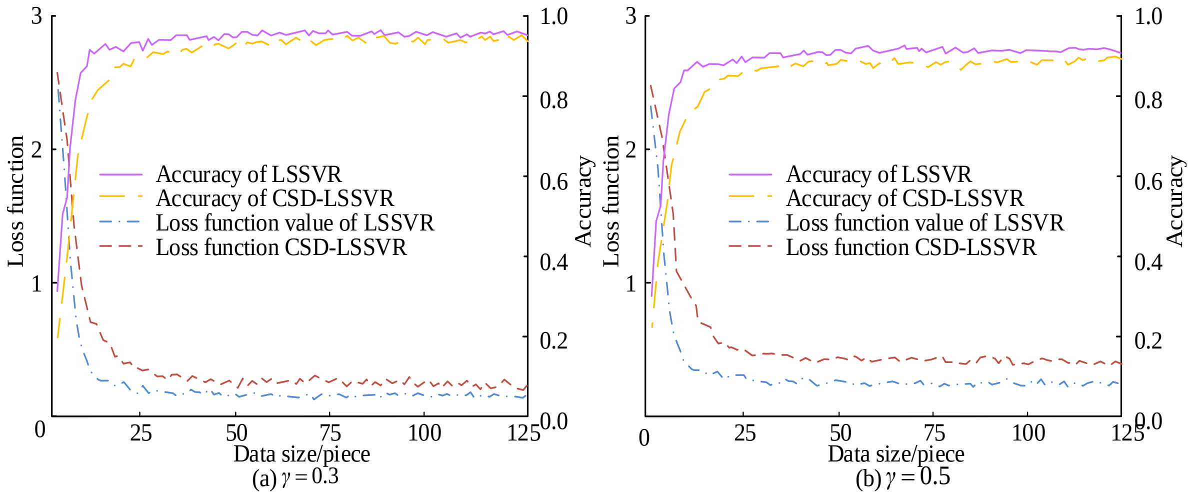


Figure 6: Performance of the model when the regularization parameters are 0.3 and 0.5

Table 4: Prediction results of training set and test set

Model	Aggregate	RE	95% confidence interval	MAD	95% confidence interval	R_{MSE}	95% confidence interval	D_{stat}	95% confidence interval	Running time (ms)	Memory usage (MB)
CSD-LSSVR	Training Set	0.0687	[0.0667,0.0703]	58.6510	[57.3245,59.9779]	72.1600	[70.2546,74.0649]	0.7120	[0.6978,0.7252]	382.3000	124.0000
CSD-SVR		0.0897	[0.0865,0.0929]	76.5870	[74.9012,78.2718]	87.0200	[84.7532,89.2858]	0.6850	[0.6698,0.6995]	295.4000	87.0000
SVR		0.1214	[0.1182,0.1243]	107.370	[105.2147,109.5248]	112.2100	[109.5244,114.8948]	0.4350	[0.4194,0.4498]	178.6000	65.0000
CSD-LSSVR	Test Set	0.0701	[0.0684,0.0720]	58.2580	[56.9321,59.5835]	70.1200	[68.3421,71.8975]	0.6880	[0.6728,0.7022]	/	/
CSD-SVR		0.0825	[0.0796,0.0852]	75.5840	[73.9124,77.2550]	87.2600	[85.1743,89.3451]	0.6520	[0.6366,0.6670]	/	/
SVR		0.1214	[0.1181,0.1246]	106.2500	[104.1245,108.3751]	112.2500	[109.8248,114.6742]	0.4350	[0.4192,0.4498]	/	/

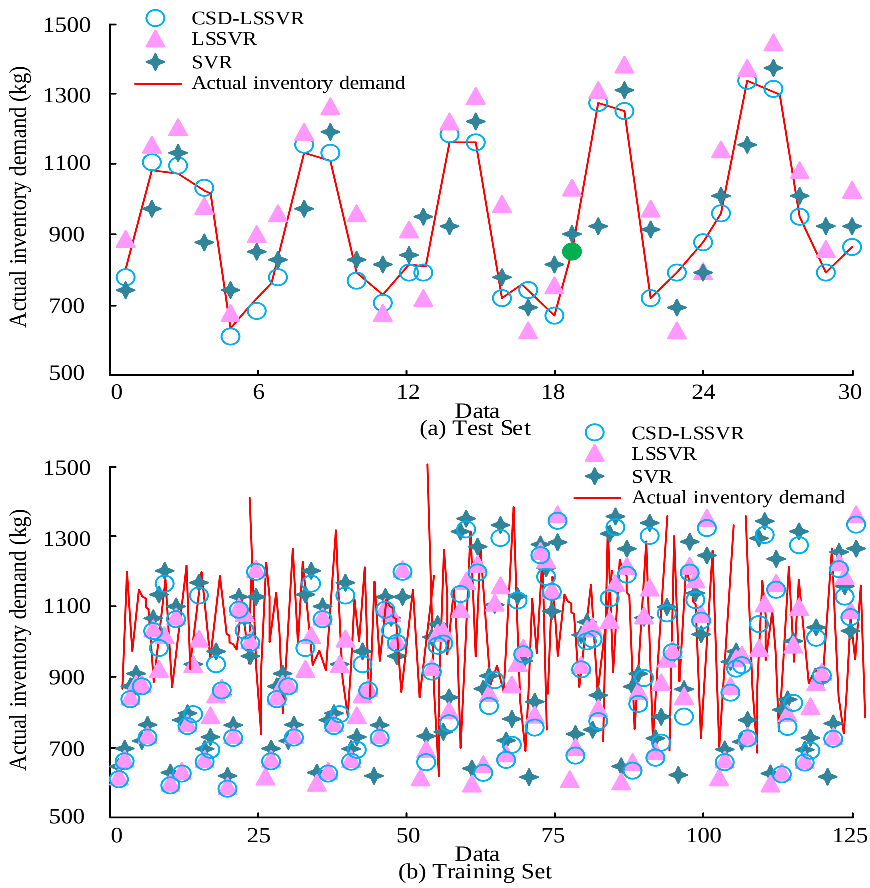


Figure 7: Prediction results of different prediction models in the test set

Figure 7(a) refers to the forecasting results of different forecasting models in the test set. Compared with other forecasting models, the CSD-LSSVR forecasting model was closer to the actual inventory demand. The difference range between the predicted inventory demand of CSD-LSSVR and the actual inventory demand was 6-47kg. Figure 7(b) shows the forecasting results of the different forecasting models in the training set. The difference range between the predicted inventory demand of the CSD-SVR model and the actual inventory demand was 11-43kg; The difference between the predicted inventory demand of the LSSVR model and the actual inventory demand ranged from 28-98kg; The difference between the inventory demand predicted by the SVR model and the actual inventory demand ranged from 28-98kg; The difference between the inventory demand predicted by the SVR model and the actual inventory demand ranged from 35-325kg. From the prediction results of the training and testing sets, the CSD-SVR model had a smaller gap between the predicted inventory demand and the actual demand, and its prediction effect was better. In the context of integrated e-commerce warehousing, enterprises can make reasonable replenishment based on the predicted inventory demand results of the model, avoiding inventory backlog or shortage, and providing inventory guarantee for real-time delivery.

5 Discussion

The CSD-LSSVR model proposed in the study demonstrated significant advantages in the field of inventory demand forecasting, and its performance improvement was attributed to various technological innovations and rigorous data processing. Firstly, in terms of model scalability, this method demonstrated good computational efficiency. When the data volume increased from 775 to 5000, the training time only increased from 382ms to 1.8s, and the memory usage increased from 124MB to 512MB. This sublinear growth characteristic made it suitable for the actual needs of most small and medium-sized enterprises. It is worth noting that the improvement in model performance was not only reflected in computational efficiency, but also in its systematic handling of data bias. In response to the 2.1% missing values and 3.7% outliers in the original data, the study adopted time series linear interpolation and Z-score correction methods. Especially for the seasonal imbalance problem in demand, the study innovatively introduced seasonal weight factors in the loss function, which significantly improved the robustness of the model.

Compared with existing methods, the MAE of

CSD-LSSVR on the test set was significantly better at 58.65 compared to traditional SVR at 107.37 and BP neural network at 89.42. This advantage was mainly due to two key designs. Firstly, CSD denoising technology effectively improved the signal-to-noise ratio and preserves key frequency domain features; Secondly, LSSVR transformed quadratic programming problems into linear solutions, effectively improving computational efficiency. Of particular note is that the model exhibited a characteristic of decreasing error with increasing data volume, and tended to stabilize when the sample size exceeded 25, which perfectly confirmed the Vapnik Chervonenkis theory. In terms of parameter optimization, the research found that $\gamma = 0.3$ was the optimal choice. A value that is too small can lead to underfitting, while a value that is too large can lead to overfitting. This finding provided important guidance for modeling inventory data.

Although deep learning models such as LSTM performed well in the field of time series prediction, there were three key constraints in the application scenario of this study. Firstly, the average historical data of the target enterprise were less than 1000, which made it difficult to meet the training needs of deep learning models. Secondly, the actual deployment environment usually only had CPU computing resources. Thirdly, there was a high requirement for the interpretability of the model. Experimental data showed that under the same amount of data, the MAE of LSTM was 15% higher than that of CSD-LSSVR, and the training time was six times longer.

In summary, the CSD-LSSVR model performed well on small and medium-sized datasets and could effectively solve the problems of data noise and prediction accuracy in inventory demand forecasting for small and medium-sized enterprises in warehouse and distribution integration. Future research can further explore the scalability of the model on large-scale datasets and introduce more feature variables to enhance the model's generalization ability.

6 Conclusion

To achieve inventory demand prediction for small and medium-sized enterprises with integrated warehouse and distribution, this study constructed a CSD-LSSVR prediction model and used instance data for simulation and analysis. As the number of samples increased, signal recovery error varied from unstable to gradually decreasing and finally reached a convergence value of 0.458 when the number of samples was 60. The accuracy of the orthogonal matching tracking algorithm increased slowly with the number of iterations. When the number of iterations was about 100, the accuracy was about 99.85%. The convergence errors of the LSSVR and CSD-LSSVR models were 0.156 and 0.278 when γ was set to 0.3; the accuracy was 97.58% and 95.21% respectively. When γ was taken as 0.5, the convergence errors of the LSSVR and CSD-LSSVR models were 0.215 and 0.498 respectively; the accuracy was 96.12% and 93.21% respectively. Testing the training and test set results showed that the CSD-LSSVR forecasting model was closer to the actual inventory demand. The training set results showed that the inventory demand prediction error range was 6-47 kg. The inventory demand error for the CSD-SVR prediction model was 8-36 kg; the error value range of inventory demand of LSSVR forecast model was 19-54kg. The error range of inventory demand for SVR prediction model was 28-274 kg. The above results indicated that the research method could effectively address the common problems of limited data samples and high noise in small and medium-sized enterprises, providing feasible technical solutions for resource constrained enterprises. In summary, the research method could provide reliable inventory demand forecasting for small and medium-sized enterprises, which was suitable for those engaged in e-commerce operations, especially those enterprises that rely on integrated warehousing and distribution models, such as small and medium-sized enterprises in industries such as fresh food and daily necessities. The CSD-LSSVR prediction model used the grid search method for parameter optimization, but due to the limitations of the grid search method itself, it was easy to cause the LSSVR algorithm to "over learn" and "under learn", resulting in poor prediction accuracy of the model. To address the above issues, further research in the future could consider improving the direction by introducing deep learning techniques to better handle complex patterns and long-term dependencies in time series data, thereby further enhancing prediction accuracy. The second is to optimize computational efficiency, such as through parallelization and other methods, to shorten the training and prediction time of the model, making it more suitable for large-scale datasets and real-time prediction scenarios. These improvements will provide stronger technical support for inventory management of small and medium-sized enterprises in an integrated warehouse and distribution environment.

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