A Multi-Objective Method Based on Tag Eigenvalues Is Used to Predict the Supply Chain for Online Retailers

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ABSTRACT

E-commerce has grown quickly in recent years thanks to advancements in Internet and information technologies. For the majority of consumers, online shopping has emerged as a primary mode of shopping. However, it has become more challenging for businesses to satisfy consumer demand due to their increasingly individualized wants. To address the need for customized products with numerous kinds and small quantities, businesses must rebuild their supply chain systems to increase their efficiency and adaptability. The SI-LSF technique, which employs boosting learning in the target-relative feature space to lower the prediction error and enhance the algorithm's capacity to handle input-output interactions, is validated in this study using a genuine industrial dataset. The study successfully identifies the relationship between sales and sales as well as target-specific features by applying the multi-objective regression integration algorithm based on label-specific features to a real-world supply chain demand scenario.

KEYWORDS

Ensemble Learning, Label-Specific Features, Multi-Objective Regression, Object Association, Supply Chain Demand Forecasting

With the increasingly complex supply chain structure, in the fierce market competition environment, enterprises at the core of the supply chain will face competition from all directions, so it is very important to build a perfect supply chain system (Dong et al., 2020). The most important link in the process of building the supply chain system is to select high-quality suppliers (Lin et al., 2023). With the continuous improvement of supply chain theory and the deepening of supply chain research, the selection and evaluation of suppliers are also constantly given new connotation (Chen et al., 2022), which has attracted the general attention of the business community and academia (Wu et al., 2020). By summarizing the literature, we can find that the research in this field mainly focuses on the following two aspects: (1) research on supplier selection methods and (2) research on the indicator system of

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supplier evaluation (Zhou et al., 2020). At present, with the development of the supply chain, the core enterprises in the supply chain have increasingly high requirements for their own suppliers, so the difficulty of supplier selection has also increased (Dai et al., 2021). However, most core enterprises use traditional selection methods to select suppliers (Wang et al., 2021).

Intuitive selection method enterprises analyse and evaluate suppliers based on their understanding of the supplier market, combined with their own analysis and judgment, and select their own suppliers (Chen et al., 2021). This method is simple and low cost. It is the most commonly used method for enterprises at present (Beed et al., 2020). However, this method completely depends on the company's judgment of the market, which is highly subjective, and the selection result is less scientific (Wei et al., 2020). It has certain advantages in the selection of short-term and scattered suppliers, but it is very limited in the selection of strategic suppliers (Liu et al., 2020). The bidding law can be used to select suppliers when the amount of raw materials required by enterprises is large and the competition among suppliers is fierce (Ni et al., 2021). However, the bidding procedures are cumbersome, the duration is long, and the selection is not targeted, which cannot meet the needs of urgent ordering (Hosseini et al., 2023). At the same time, there are large human influence factors in the bidding process, and there are big loopholes in the operation standardization (Tang et al., 2020). The purchase cost method is used to compare suppliers who can meet the requirements for quality and delivery date by calculating the purchase cost (Márquez-Vega et al., 2021). Purchase cost generally includes the sum of sales price, purchase expense, transportation expense, and other expenses (Zu & Liu, 2021). The purchase cost comparison method is a method to select suppliers with lower purchase costs by calculating and analysing the purchase costs of different suppliers (Zhang et al., 2022). In view of the shortcomings of the above traditional supplier selection methods, this paper uses the analytic hierarchy process (AHP) in multiobjective decision-making theory to select suppliers (Yufeng & Wan., 2021).

For the multiobjective task of supply chain demand forecasting, in practical applications or various competitions, most solutions are to split it into a simple single-objective problem (Xu et al., 2022). Some of these solutions are to preprocess the historical data and build it, to build a single-target regression model of time series based on historical data, or to use a single-target time series weighted model (Wu et al., 2022). There are two main problems with these methods: first, the correlation between targets is not considered (Sepehrzad et al., 2021). In supply chain demand, weekly sales are continuously forecasted, and there may be some correlation between weekly sales; second, most methods predict all regression targets from the same feature space, but different targets may have different characteristics unique to themselves (Qian et al., 2020).

The validity and applicability of the algorithm are determined in this paper. The main contributions of this paper are as follows:

1. Improved prediction performance. In this paper, we construct label-specific features for each target by means of lifting learning and extend the new features to the original input space. Tag-specific features consider the correlation between the input features from the original feature space and the target, as well as the correlation between the target and the target.
2. Flexibility to handle complex input and output relationships. On the basis of tag-specific features, this paper proposes an integration method based on tag-specific features, which uses a sparse aggregation function to select different types of regression methods to conduct integrated prediction of targets. Sparse integration can automatically select the appropriate model and map the input elements to the corresponding output target.
3. Availability of actual scenarios. This paper selects the practical application of supply chain demand forecasting and conducts data preprocessing, feature engineering, and modelling on the historical data of the Saudi Arabia market, so as to achieve accurate and timely prediction of long-term commodity sales, thus providing an accurate data basis for supply chain demand. The model is applied to the actual scenario of supply chain demand, and the experimental results show the availability of the algorithm.

RELATED WORK

Supply Chain and Supply Chain Design Concept

A supply chain, also known as a supply and demand chain, is defined by the national standard logistics terminology (Mohammed & Duffuaa, 2022). It will include suppliers of the chain, the online shopping supply chain mainly serves online shopping consumers, and is based on the e-commerce platform. The online shopping supply chain has relatively few nodes, mainly including suppliers, manufacturers, and end users (Chen et al., 2022).

Supply chain design refers to rationalizing the selection and setting of nodes in the supply chain and the corresponding flow changes through a certain modelling method, ultimately maximizing the operational efficiency of the entire supply chain, quickly meeting consumer needs, and improving the ability to serve consumers (Zheng et al., 2022).

From the 1980s to the present, scholars who study supply chain design problems through mathematical programming models have continuously improved the relevant conditions of the planning models to be more in line with the actual production conditions of enterprises. From the linear programming model of supply chain design to the integer supply chain planning model, modelling is becoming more and more perfect and complex.

In the transaction process, goods pass from manufacturers to distributors, to retailers, and finally reach consumers, forming the so-called forward logistics, while reverse logistics is the delivery of goods from consumers to retailers and then to distributors or manufacturers. The main reasons for the reverse process and reverse logistics are the broad return policy and market competition.

SI-label-specific features (LSFs) technology has the following advantages in personalizing consumer demand: using large-scale data to construct label-specific features to capture consumer demand and behavioural patterns; accurately selecting relevant features through independent feature selection to avoid overfitting; reducing noise interference to improve prediction accuracy, especially for complex demand; and efficiently constructing features to optimize computational efficiency when processing large-scale data.

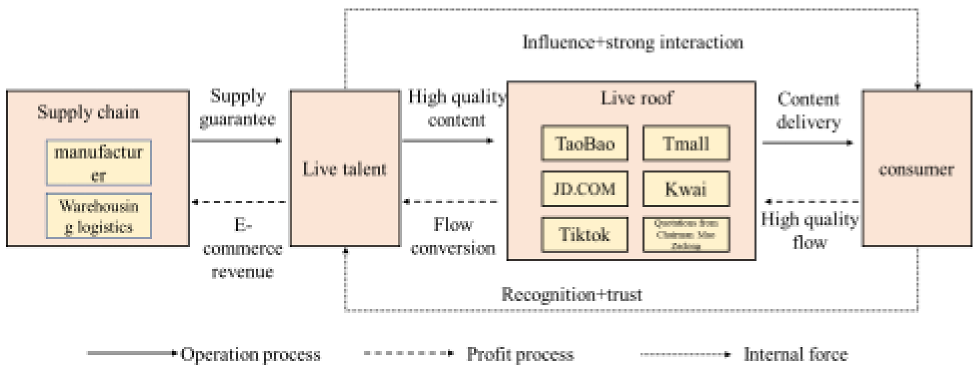
By analysing consumer buying behaviour and preferences, as well as historical data, companies can discover the correlation between specific target characteristics and sales performance. This insight helps optimize inventory management, promotional strategies, and product positioning to improve supply chain efficiency. At the same time, identifying consumers' individual needs and communicating them to supply chain teams can help adjust production plans, warehousing strategies, and logistics and distribution methods to better meet consumer demand. By analysing market trends and sales data, companies can quickly respond to market changes, adjust product mix, and predict popular products in advance, thus enhancing supply chain flexibility and adaptability. Ultimately, sales data and supply chain operation data are combined to optimize supply chain processes, reduce costs and improve delivery on-time rates to enhance customer satisfaction, increase sales, and improve enterprise competitiveness.

The Impact of Live E-Commerce on Supply Chain Operations

Live e-commerce live broadcast e-commerce can be briefly summarized by 'supply chain + live broadcast delivery': the supply chain includes manufacturers and warehousing logistics, which are responsible for producing goods and providing goods storage and delivery services; live broadcast goods are controlled by the anchor to control the traffic promotion, responsible for the display of the displayed goods. Products are sold to consumers, and the operation mode of live broadcast e-commerce is shown in Figure 1.

The live e-commerce operation mode is briefly described as 'supply chain + live delivery', where manufacturers and warehouses are responsible for production and storage, anchors promote and sell goods to attract consumers to enter the live broadcasting room to buy, and ultimately through the

Figure 1. The Operation Mode of Live Broadcast E-Commerce



supply chain to complete the product collation, packaging, distribution, and after-sales service, to achieve the delivery of goods to the consumer.

With the demographic dividend gradually disappearing, live streaming has opened up a new path for traditional platform merchants, bringing more opportunities but also facing more challenges. Because the live broadcast is only a matter of selling, that is, how to attract consumers into the live broadcast room and then use an effective way to stimulate consumers to buy. After that, the products sold through live broadcasts also need to be sorted, packaged, distributed, and after-sales service in all aspects of the supply chain, and finally delivered to consumers. In real life, the development of live e-commerce is too fast, but the development of supply chain services is relatively slow, so that in the process of live streaming, consumers have a poor service experience in terms of supply preparation, product quality, logistics speed. The current supply chain management has brought severe challenges. One is the challenge of explosive products on the supply chain, and the other is the contradiction between logistics timeliness and cost.

Driven by the live broadcast mode, the traditional platform e-commerce sales model has shifted to live broadcast e-commerce, striving to gain a share of the live broadcast e-commerce field. The most important model is the ‘factory direct sales’ model, where products can go from the direct sales of manufacturers to consumers, the characteristics of this ‘disintermediation’ are becoming more and more obvious. Due to the emergence of fragmentation in consumer demand, large-scale orders in the past will gradually be fragmented into smaller packages. Order fragmentation makes the contradiction between logistics timeliness and cost more prominent. The higher the fragmentation of the order, the more logistics lines are required to be transported together to ensure timeliness and the more operating costs that need to be invested. On the other hand, if you want to reduce costs, you need to collect orders to a certain extent and send multiple orders at the same time, so you have to endure longer delivery times, which is an inevitable challenge for supply chain management.

MATERIALS AND METHODS

Multiobjective Regression Method

Analysis of Hierarchy (AHP) is a multicriteria decision-making method by decomposing a complex decision-making problem into a hierarchical structure, comparing two by two and determining the weights, and, finally, arriving at an overall decision-making result. The hierarchical structure is first constructed, then the elements of each level are compared, and a judgment matrix is built, the weights are calculated and consistency tests are performed, and, finally, the weights of each level and the comparison results are synthesized to arrive at the optimal decision plan or trade-off decision.

Since multiobjective regression and multilabel classification problems have strong similarities, that is, they both have multiple output variables, the difference is that the output variables of regression problems are continuous values, while the output variables of classification problems are discrete values. According to the different processing methods, the existing algorithms (such as logistic regression, neural networks, decision trees.) to solve such a rule is to improve the algorithm so that it can directly deal with multilabel data. Similar to the division method of multilabel classification methods, the existing multiobjective regression methods are also divided into two categories.

This objective regression problem then builds an independent model for each target and finally connects the prediction results of all models. Predicting a single target independently leads to ignoring the correlation between the targets, which may affect the overall prediction quality. In order to explore the correlation between objects in the problem transformation method, the algorithms, two new multiobjective regression methods, namely, multiobjective regression stacking and regression chaining, are also introduced, proposing only methods based on single label regression problems and not multilabel methods based on label pairs or sets of label exemplars. Based on the problem transformation method, this section introduces several typical methods, such as the single-objective method, multiobjective regression stack, regression chain, and multiobjective support vector regression.

To predict all targets simultaneously, algorithmic adaptation is able to capture all dependencies between input features and targets as well as the internal relationships of targets. In fact, algorithm adaptation has several advantages over problem transformation methods: it is a single multiobjective model, which is more explanatory than multiple single-objective models, and it ensures better predictions when the objectives are related performance. According to the division of algorithm adaptation methods in the literature, the multiobjective regression methods have been more commonly used in recent years.

To sum up, the current multiobjective regression methods mainly focus on mining the correlation between targets and processing the complex relationship between input and output, and most methods learn from models from the same feature space to predict all regressions at the same time. At the same time, because most methods use a single model to model the complexity of the flexibility is insufficient. For example, some objects are linear with the feature space, while some objects are nonlinear. Objective regression ensemble method label-specific features mine the correlation between objects and process the complex relationship between input and output.

Multiobjective Regression Technique

Single-Target Method

This is where the training set of each single-target model is converted into a training set corresponding to a single target y_i, as shown in equation (1).

$$\mathcal{D}_i = \left\{\left(x^{(1)}, y_i^{(1)}\right), \ldots, \left(x^{(n)}, y_i^{(n)}\right)\right\} \tag{1}$$

The target variables of correlation, as found in the literature.

Since the objective regression problem can be objective subproblems, any existing single-objective algorithm can be used for prediction, as shown in equation (2).

$$X = \left(X_1, X_2, \ldots, X_m\right) \tag{2}$$

Each variable y_i is learned and predicted by a separate ridge regression method and solved by the least squares criterion, as shown in equation (3).

$$\left\{\hat{a}_{ij}\right\}_{j=1}^{m} = \arg\min_{\left\{a_j\right\}_{j=1}^{m}} \left\{\sum_{l=1}^{N}\left(y_i^{(l)} - \sum_{j=1}^{m} a_j x_j^{(l)}\right)^2\right\} + \lambda_i \sum_{j=1}^{m} a_j^2 \tag{3}$$

Single-Target Stacking

Single-objective stacking (SST) is inspired by the application of stacking generalization to multilabel classification problems and applies stacking to multiobjective regression prediction problems. SST is divided into two learning phases. The first stage is to learn *d* independent regression models in the ST framework to get the predicted value for each target. However, instead of using these models for prediction directly, a second set of d independent regression models are learned for each target y_i as the second stage. The submodels in the second stage are all learned and predicted in the converted training set. The converted training set is shown in equations (4) and (5).

$$\mathcal{D}_i^* = \left\{\left(x^{*(1)}, y_i^{(1)}\right), \ldots, \left(x^{*(n)}, y_i^{(n)}\right)\right\} \tag{4}$$

$$\hat{y}^{(n+1)} = \left(\hat{y}_1^{(n+1)}, \ldots, \hat{y}_d^{(n+1)}\right) \tag{5}$$

As a new input for the second-stage model prediction, the final prediction result is finally obtained.

Return Chain

In recent years, the regression chain (RC) method of classification chains in multilabel learning is another form of the objective model. The training process of RC consists of selecting a random combination of chains and a selected set of chains, as shown in equation (6).

$$C = \left(Y_1, Y_2, \ldots, Y_d\right) \tag{6}$$

It is relevant for predicting target Y. Then, for the target Y_d, learn and predict with the new data set. It consists of the original input vector in the training set and the actual value composition of the previous target in the chain. In the following research, it is proposed to use the estimated value of the target after cross-validation instead of the actual target value as the chain. At the same time, in order to avoid the disadvantage of being sensitive to the ordering of the selected chain, a set of different ordered chains is proposed. Regression chain model, that is, ten chains will be randomly selected, this method is called ensemble regression chain ensemble.

Multiobjective Support Vector Regression

X y can be constructed by feature vector virtualization, resulting in a new extended data set, shown in equation (7).

$$\mathcal{D}_i = \left\{\left(\left(I_i, x^{(l)}\right), y_i^{(l)}\right)\right\} \tag{7}$$

The objective function of the algorithm is defined as shown in equations (8) and (9).

$$f = \frac{1}{2} \parallel w \parallel^2 + \sum_{l=1}^{N} \frac{1}{C} \sum_{i=1}^{d} e_i^{(l)^2} \tag{8}$$

$$s.t. y_i^{(l)} = w^T \phi\left(I_i, x^{(l)}\right) + I_i b + e_i^{(l)} \tag{9}$$

In equation (9), *w* denotes the weight vector, *Ø* is the nonlinear transformation of the feature space, and the bias vector is denoted by *b*.

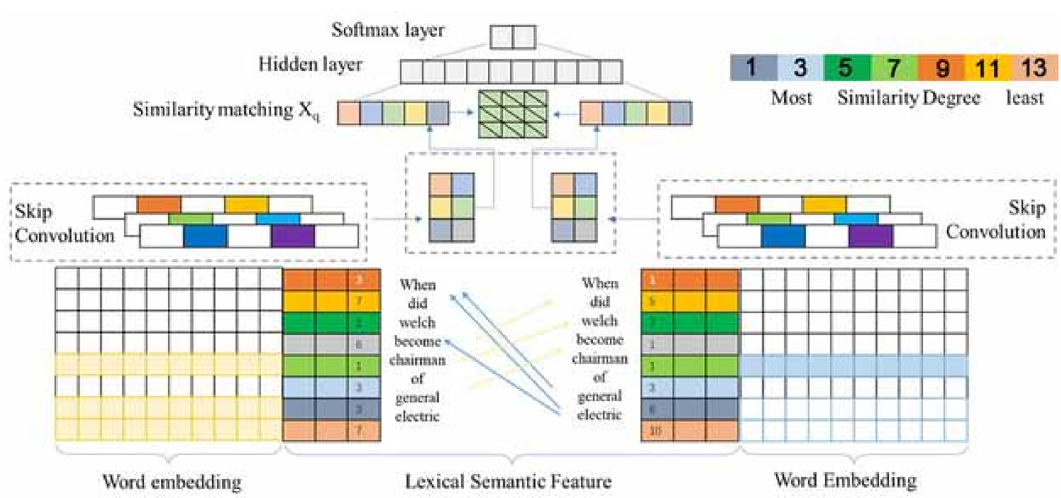
Label-Specific Features

The specific labelling method is a social science research methodology designed to reveal structures and patterns hidden in large amounts of data by systematically categorizing and labelling research objects. The method emphasises the classification of various aspects of the object of study and reveals its inner structure by analysing the classification results. The specific label approach is widely used in human behaviour research, consumer research, social network analysis and market segmentation to help understand human behaviour, consumer motivation, social networks, and market segmentation and positioning.

In order to model the correlation between targets and explore the effective features of each target to avoid the negative effects caused by redundant features, this paper proposes to construct label-specific features for each target. LSFs contain intertarget association information, as well as implicit feature information most relevant to the targets. The framework for constructing and applying LSFs is shown in Figure 2. The framework is based on the idea of SST but is different from the processing method of SST that directly uses the target prediction value as the additional input of the second stage. After obtaining the label-specific features of each target, label-specific features are used as additional features in the second stage, and regression methods are selected for training and prediction. Therefore, it can effectively reduce the noise interference caused by the predicted value of the first stage, reduce redundant features, and is more in line with the actual situation that not all targets are related.

The learning process of label-specific features is as follows. First, for each target, find its related feature TRX(Target-Related Features), in order to remove redundant features and improve learning

Figure 2. Construction and Application Framework of Label-Specific Features



accuracy. Redundant features or features irrelevant to the target will interfere with the next training and prediction. When looking for target-related features, minimize the squared error to find the feature set related *X*, as shown in equations (10) and (11).

$$R_1(\gamma, s) = \left\{ X_i \middle| x_{i\gamma} \leq s \right\} \tag{10}$$

$$\hat{c}_t = \frac{\sum_{X_i \in R_1(\gamma,s)} y_{ij}}{\left| R_t \right|} \tag{11}$$

In equation (11), *s* belongs to a certain value in X_i. Using *s*, the property of X_i can be divided into two parts, R1(γ,*s*) and R2(γ,*s*), where $1 < \gamma < X$. Secondly, for the divided two parts, the mean value of the corresponding target is calculated by formula (10), in turn, where t = 1,2. Finally, in equation (11), the best division feature and its split point *s* are found by minimizing the squared error, so as to find the relevant feature set TRX of the target and reduce the irrelevant features. The pseudo-code of the process of finding target-related features is shown in the algorithm.

The algorithmically selected target-related features can reduce redundant and irrelevant information in the feature space and can be used to build robust regression models. However, these relevant features are only a subset of features of the training set D, which may not have sufficient diversity in the feature space and may not adequately express the target. In order to increase the difference of the original feature space, this paper constructs label-specific features based on the target-related features, uses the residual of each iteration to describe the local features, and serves as an additional feature to reflect the local information in the feature space model to increase the expression ability of the model. The method is shown in the equations (12) and (13).

$$g_0\left(X'_{TR}\right) = f_q\left(X'_{TR}; Y_j\right) \tag{12}$$

$$r_t^{(j)} = -\left[\frac{\delta l\left(Y_j, g_{t-1}\left(X'_{TR}\right)\right)}{\delta g_{t-1}\left(X'_{TR}\right)} \right] \tag{13}$$

The equation (12) is to set the initial value, where f_q is the base learner, which can be linear regression or regression tree., then $g_0\left(X'_{TR}\right)$ represents the predicted value of learning the target Y_j in the input space $\left(X'_{TR}\right)$ using the base learner. Equation (13) is to obtain the negative gradient value of the current model and use this negative gradient value as the residual estimation, where *l* is the squared error loss function, as shown in equation (14).

$$l\left(Y_j, g_{t-1}\left(X'_{TR}\right)\right) = \frac{1}{2}\left(Y_j - g_{t-1}\left(X'_{TR}\right)\right)^2 \tag{14}$$

In fact, by changing the derivative, equation (14) is equivalent to equation (15).

$$r_t^{(j)} = Y_j - g_{t-1}\left(X'_{TR_{t-1}}\right) \tag{15}$$

That is the residual. In this paper, this residual value is used as the label-specific feature of the corresponding target. Equation (15) takes the residual estimation in equation (14) as the target, uses the negative gradient value to update the model, and takes it as the target of the next iteration.

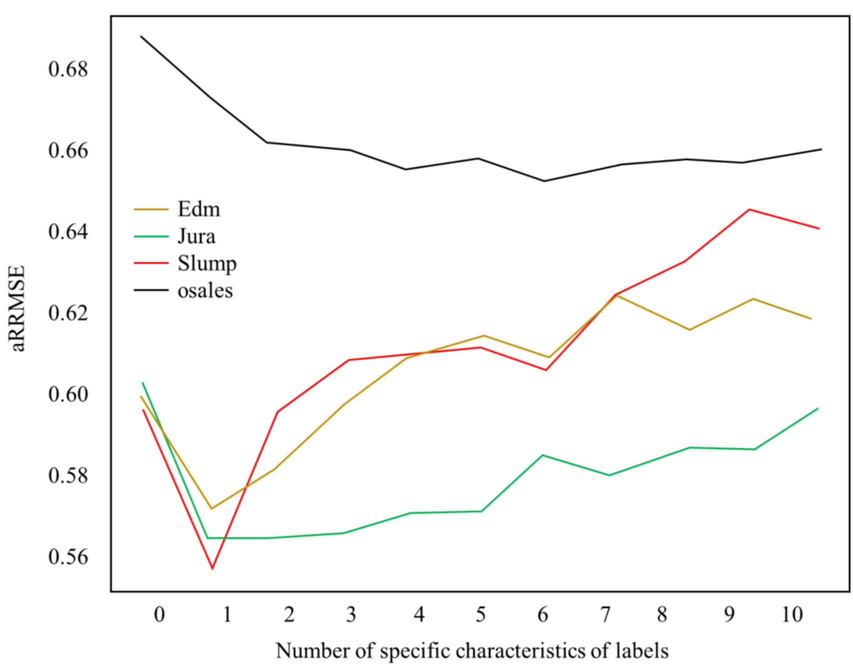
EXPERIMENTAL RESULTS AND ANALYSIS

Performance Comparison

In the experiment, the same division method was used for all multiobjective regression data sets, and aRRMSE (Relative Root Mean Square Error) was used as the evaluation index for all multiobjective regression methods. In this subsection, the performance of the algorithms was compared and analysed mainly from three aspects: prediction effect, effectiveness of label-specific features, and effectiveness of sparse ensemble.

In order to further verify the validity of specific features of labels, the Wilcoxon signed rank test of statistical test is used to determine whether SI-LSF is significantly better than SI at the significance level a = 0.05. At the same time, the original hypothesis was put forward: the mean value of the prediction results of SI and SI-LSF was equivalent, and there was no significant difference. The results of the Wilcoxon signed rank test show that the original hypothesis was rejected because *p* value < .05. This means that the mean values of the two algorithms were not equal, that is, SI-LSF was superior to SI. It was proved that the specific features of the tag cause the improvement of the algorithm, and the conclusion was drawn that the specific features of the tag can significantly improve the prediction accuracy of the algorithm. In order to verify the flexibility of SI-TSF in dealing with complex relationships between input features and output targets, aRRMSE for each target in each data set is compared on 18 data sets, and the results are shown in Figure 3.

Figure 3. Comparison of the Prediction Performance of the Comparison Algorithms for each Target Under Different Data Sets



It can be observed from Figure 3 that the relationship between input targets and output features was complex. For example, on the sf1 data set in Figure 3, both the first and second objectives were suitable for solving with linear regression, whereas the third objective was more suitable for solving with support vector regression SVR. At the same time, it can also be found that the prediction performance of SI-TSF on most targets was better than that of the comparison algorithms without sparse ensemble, which also proves the flexibility of SI-TSF to deal with multitarget problems.

RI(i) is the relative importance of the ith model in the sparse ensemble, with larger values representing higher importance. The relative importance of SVR, Linear, and RF for each target in four representative data sets in the sparse ensemble is shown in Figure 4, where longer bars represent more importance.

SVR on "Target" is the entire column, indicating that RI = 1.0, indicating that the importance of SVR in the sparse ensemble was the greatest. On "Target_5", the relative importance of Linear was 0.4, and the relative importance of RF was 0.6, indicating that the target was not suitable for solving with SVR. In Figure 4, the target "Cd" was suitable for solving with SVR, while the target "Co" was suitable for solving with RF. Further, with the different weights of the base model, SI-TSF can flexibly model the complex relationship between the feature and the target space.

Network Analysis of Live Streaming E-Commerce Supply Chain

The inventory change curve under random disturbance is shown in Figure 5. The initial values of the holdings of manufacturers, retailers, and consumers were 200, 100, and 60, respectively. After it reached all levels, the set nominal value was 300, and the consumer holdings kept fluctuating around 50. After reaching the nominal value, the inventory still fluctuated slightly, but the supply chain system had basically reached stability and was in a state of dynamic equilibrium.

As shown in Figure 5, for disturbance, which was because the set sinusoidal demand fluctuation range was relatively small, while the fluctuation range of random disturbance was relatively large; according to the simulation results, the bullwhip effect is gradually suppressed.

Figure 4. Relative Importance of Base Models SVR, Linear, RF in Sparse Ensemble

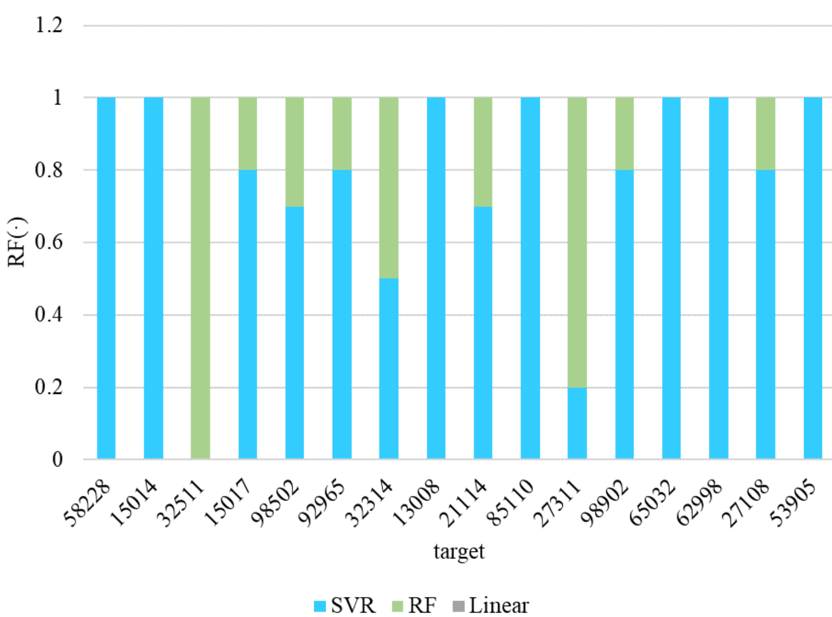
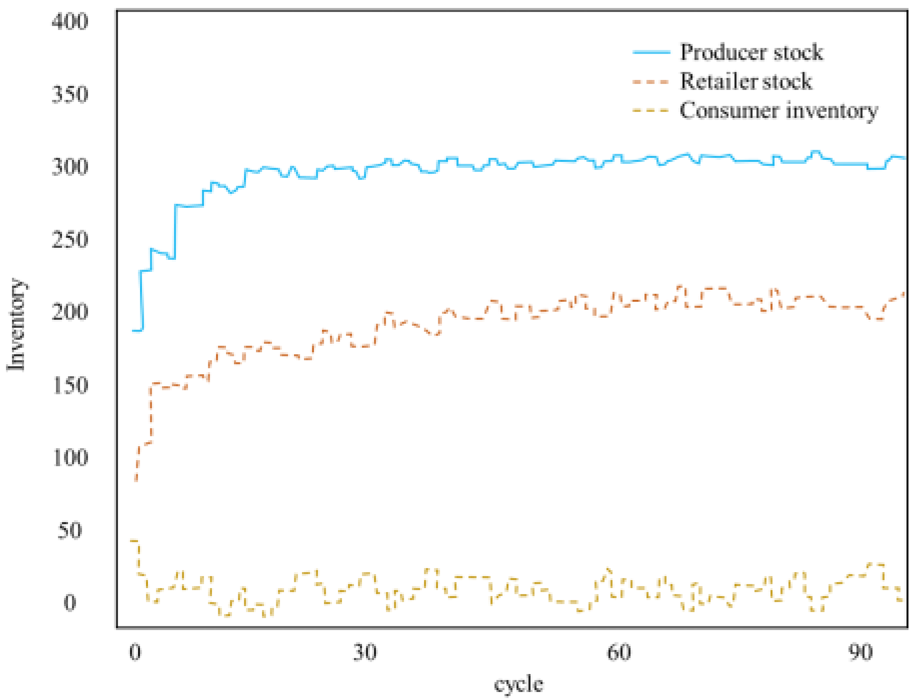


Figure 5. Inventory Change Curve Under Random Disturbance



According to the equalization results in Figure 6, the following conclusions can be drawn:

With the increase of the deferred payment period of the e-commerce trading platform, the number of product sales of small, medium, and micro suppliers on the e-commerce trading platform has gradually increased, while the number of product sales of the two suppliers on the e-commerce platform has gradually decreased. In addition, when the factoring rate of the factoring company was given, for the small- and medium-sized supplier *i*, there was always a critical time ti2 (η2) for deferred payment, when the deferred payment time of the e-commerce platform 2 satisfied t2 ≤ ti2 (η2), supplier *i* will choose to classify the accounts receivable of e-commerce platform 2 as a factoring financing business, otherwise it will not choose a factoring financing strategy.

The main function of the designed model predicting controller is that the reference input is the nominal value of the manufacturer's inventory, such nominal value of the retailer's inventory, the nominal value of the recycler's inventory, and the nominal value of the consumer's inventory. It is to control the trend of inventory changes to make it as close to the given nominal value as possible. The demand model is used to simulate consumer demand. This paper mainly used random consumer demand, sinusoidal fluctuation consumer demand, and ARMA forecast demand to simulate and test the model predictive controller. The MPC(Model Predictive Control) controller receives two input signals, one is the output of the control system, that is, the other is the reference input. During the simulation process, the two MPC controllers select which one to work by switching the signals. The outputs of the MPC controller are the control variables, which are the quantity produced by the manufacturer and the quantity ordered by the retailer from the manufacturer. The controlled object model is a discrete state space model, that is, the supply chain system model established above. The model receives two inputs, one is the control variable output by the MPC controller, the other is consumer demand, and the output is the supply of forecast of consumer demand fluctuations, as shown in Figure 7.

Figure 6. Equilibrium Profit of Small, Medium, and Micro Suppliers

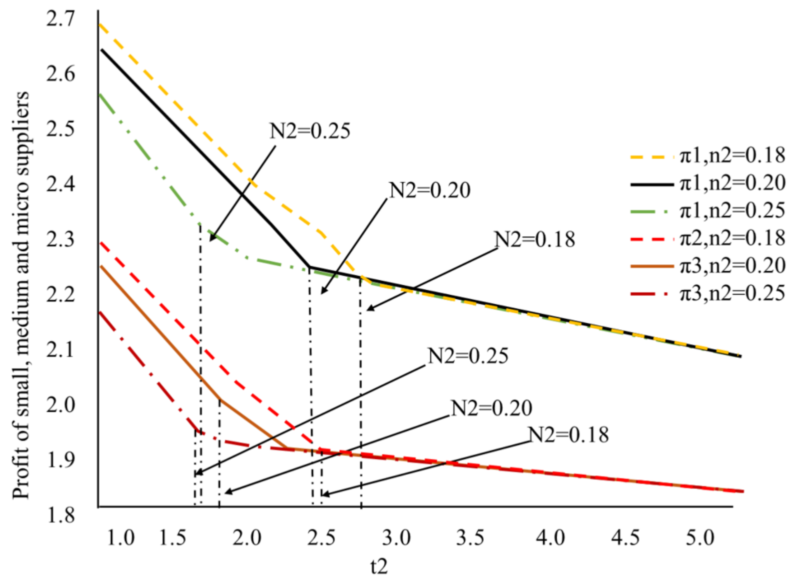
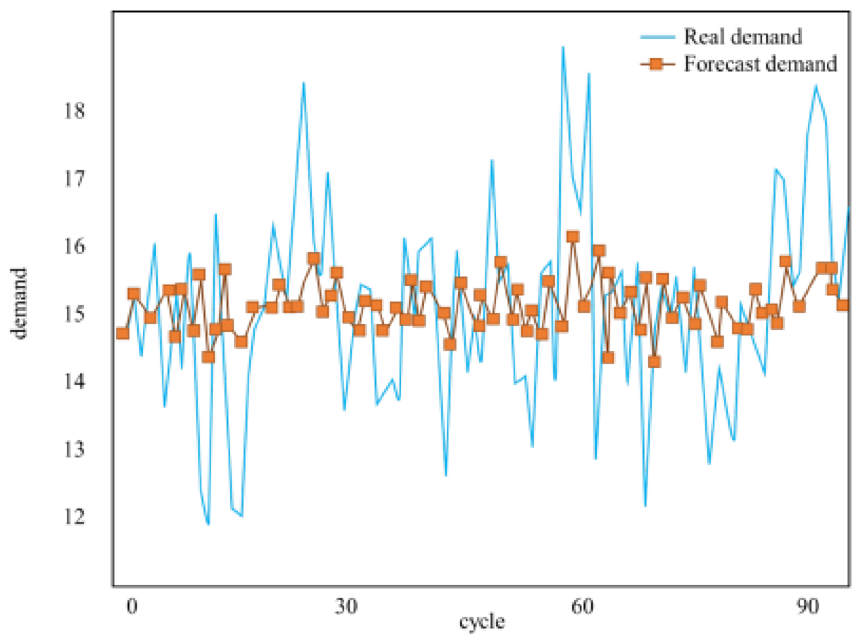


Figure 7. ARMA (Autoregressive Moving Average Model) Forecasts Demand



CONCLUSION

The multiobjective regression technique shows better performance in terms of predictive effectiveness, effectiveness of label-specific features, and effectiveness of sparse integration, and it is flexible and adaptable in dealing with multiobjective problems. The results of statistical tests can prove that label-specific features have significant advantages in improving the performance of the algorithm. The experimental results show that the multiobjective regression technique can better adapt to the characteristics of different data sets and objectives and exhibits high flexibility when dealing with complex relationships between input elements and output objectives. In terms of network analysis, the simulation results show that the supply chain system is in dynamic equilibrium, and the trend of inventory changes among manufacturers, retailers, and consumers gradually stabilises under random perturbations. Through the simulation and testing of the model prediction controller, the trend of inventory change can be effectively controlled to improve the stability and efficiency of the supply chain system. In summary, the multiobjective regression technique and the related label-specific feature modelling method have important application prospects in dealing with multiobjective forecasting and supply chain management and can provide effective support and guidance for the actual production and supply chain.

This study has several limitations. The multiobjective regression algorithm proposed in the study performs well on specific data sets, but its generalization ability may be limited on other data sets, and more extensive testing and validation are needed. In addition, the experimental results are affected by the experimental setup, parameter selection, and evaluation metrics, and more rigorous experimental validation is needed. Simplified and idealized assumptions in the model design and experimental process may impose limitations on the applicability and generalization to real-world scenarios. Therefore, these limitations need to be fully considered and more data support, experimental validation, and algorithmic improvement need to be performed in further research and practice.

DATA AVAILABILITY

The figures used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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