Proceedings of the 4th International Conference on Mathematical Physics and Computational Simulation
DOI: 10.54254/2753-8818/2026.34453

Precise Demand Forecasting for Supply Chain Based on Machine Learning Algorithms

Zhaojun Pu*, Bo Zhong

School of Advanced Manufacturing, Guangdong University of Technology, Jieyang, China,
**Corresponding Author. Email: puzhaojun@mails.gdut.edu.cn*

Abstract. Driven by the swift expansion of the global digital economy and the e-commerce sector, the administration of supply chains has progressed into a highly refined and intelligent era. Contemporary market demands display pronounced non-stationary and non-linear fluctuating traits, making conventional statistical approaches inadequate for achieving accurate forecasts in such intricate environments. To address these challenges, machine learning offers a robust avenue for extracting complex features and modeling non-linear relationships in predicting supply chain demands. To overcome the limitations of current models regarding poor stability and sub-optimal predictive accuracy, this study introduces a novel regression forecasting algorithm based on VMD-PSO-BiLSTM. Initially, the dataset is refined using violin plot and correlation analyses. Subsequently, the proposed approach is benchmarked against diverse machine learning techniques. Findings indicate that the introduced framework delivers a substantially superior overall performance compared to standard models like BP neural networks, GBDT, Random Forest, and ExtraTrees. It achieves outstanding error regulation and fitting precision, highlighted by an MSE of 30012.063, an RMSE of 173.24, an MAE of 130.352, a MAPE of merely 4.568%, and an R2 value reaching 98.8%. This strongly validates the framework's strengths in optimizing parameters and extracting features, thereby offering dependable technical backing for exact supply chain demand projections, which is crucial for lowering operational expenses and boosting management efficiency.

Keywords: Supply chain management, VMD, PSO, BiLSTM

1. Introduction

The rapid development of the global digital economy and e-commerce industry has brought supply chain management into a refined and intelligent stage. Market demand is characterized by nonlinear fluctuation and non-stationary characteristics, and traditional statistical models are difficult to adapt to the accurate forecast demand in complex scenarios [1]. The demand of e-commerce and retail industry is affected by the coupling of multiple factors such as price, promotion, season and advertising, and the uncertainty continues to intensify. The bias of demand forecast easily leads to the risk of inventory backlog or shortage, which weakens the overall efficiency of supply chain and the market competitiveness of enterprises [2]. Building an efficient and accurate demand forecasting

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2753-8818/2026.34453

model has become the core topic of supply chain optimization and e-commerce operation decision-making, and it is also the research focus of academia and industry [3].

Machine learning provides a technical path of nonlinear relationship modeling and complex feature mining for supply chain demand forecasting. Traditional methods rely on linear hypothesis and artificial feature screening, which is difficult to capture the dynamic correlation between multi-dimensional variables. Machine learning algorithms can automatically learn the underlying laws in historical data, integrate multi-dimensional features such as price, promotion, advertisement, and season, and improve prediction robustness [4]. BiLSTM in deep learning can effectively capture the long-term dependence and bidirectional correlation characteristics of time series data, and adapt to the dynamic change law of demand sequence [5].

Aiming at the shortcomings of existing models, this paper proposes a VMD-PSO-BiLSTM regression prediction algorithm. VMD can decompose non-stationary demand sequences into multiple stationary modal components, reducing data noise and complexity, and providing high-quality input for accurate modeling. PSO algorithm is used to adaptively optimize the key parameters of BiLSTM, overcome the subjectivity and local optimal defects of manual parameter adjustment, and improve the convergence efficiency and generalization ability of the model. BiLSTM extracts depth features from bidirectional timing dimensions to strengthen the ability to capture the law of demand fluctuation.

2. Data set source

The data set used to forecast e-commerce supply chain demand covers numerous market variables and product categories, and can truly reflect the fluctuation of online market demand. Product categories recorded in the dataset include fresh foods, daily household items, clothing and footwear, and electronics. These four domains are evenly distributed in a dataset that includes 1028 validated instances, making it ideal for building accurate supply chain predictive regression models. Initially, all variables were tested for correlation, resulting in a correlation heat map as shown in Figure 1. In addition, we performed a box diagram evaluation on these variables, and the corresponding visualization results are shown in Figure 2.

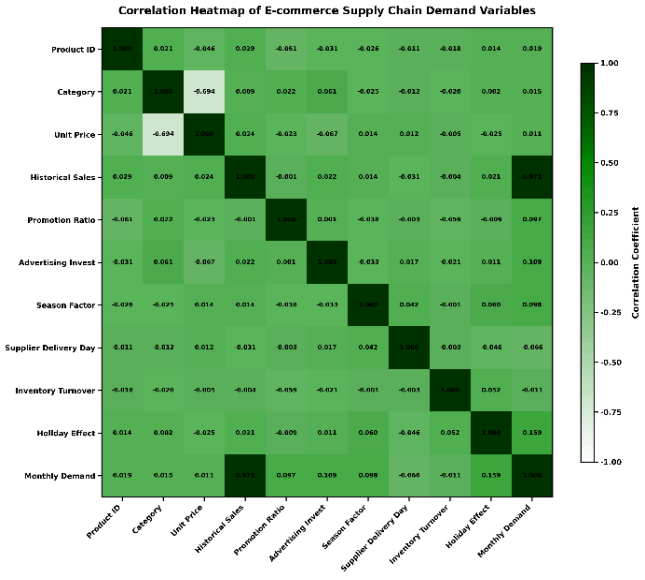

Figure 1. The correlation heat map

DOI: 10.54254/2753-8818/2026.34453

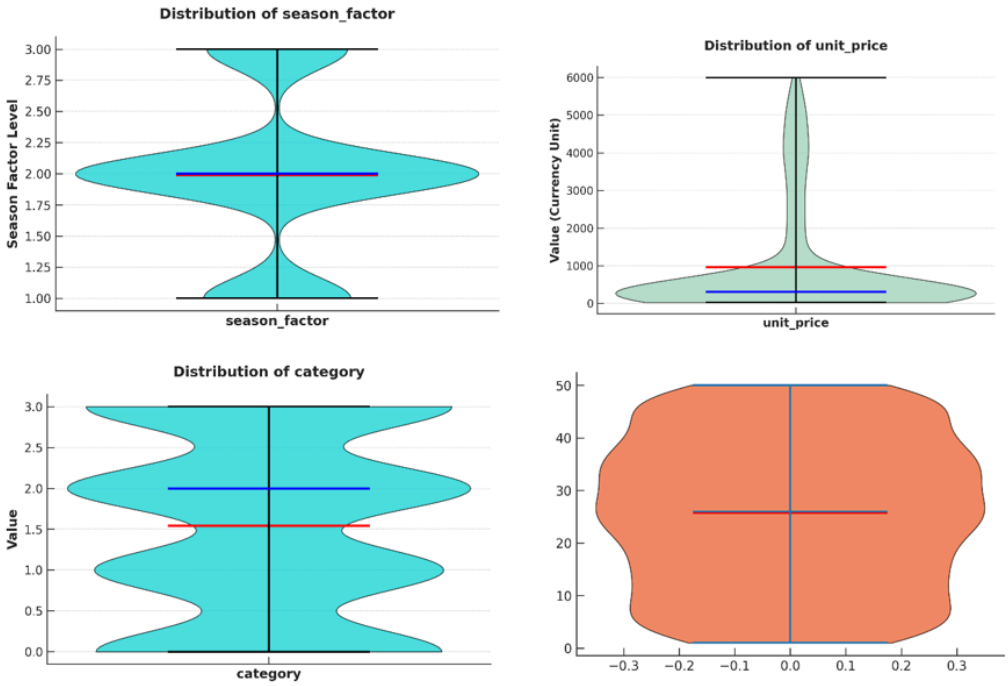

Figure 2. The violin plot

3. Method

3.1. VMD

Variational mode decomposition (VMD) is a non-recursive and adaptive signal processing technique. The basic principle is to decompose the initially complex signal into different intrinsic mode functions, each with an independent center frequency. By constructing a variational constraint framework, this mechanism transforms the signal separation task into a variational optimization puzzle [6]. As the iteration progresses, the corresponding bandwidth and center frequency of each modal element are constantly updated, so that each component can closely match the local characteristics of the original signal. Unlike classical recursive decomposition methods, VMD achieves constrained optimization through the alternate direction multiplier method. This successfully avoids problems such as endpoint effects and modal aliasing, enabling accurate extraction of various frequency band details embedded in the signal [7].

3.2. PSO

Particle swarm optimization (PSO) is a stochastic optimization technique based on swarm intelligence that is inspired by observed bird flock foraging behavior. This approach sees potential solutions to optimization problems as independent particles moving through the search environment. Each particle has two main attributes: velocity and position. These particles adjust their trajectories dynamically based on their respective best historical positions and the collective best positions determined by the entire population. Throughout the iterative adjustment phase, the particle will adjust its coordinates and velocity according to past experience, gradually approaching the optimal solution region. This method does not need to carry out complicated gradient derivation, the parameter configuration is simple, and it has strong global exploration ability [8].

DOI: 10.54254/2753-8818/2026.34453

3.3. BiLSTM

The bidirectional long short-term memory (BiLSTM) network is an advanced deep learning architecture based on the traditional LSTM architecture, which aims to solve the phenomenon of gradient explosion and disappearance common in standard recurrent neural networks [9]. The structure integrates two independent LSTM networks running in opposite directions: one running forward and one running backward. The forward path processes sequence data in chronological order to extract historical features, while the backward path runs backward to capture upcoming contextual information. By using a specialized gating mechanism to regulate information retention and discard, BiLSTM is able to efficiently understand long-term dependencies in temporal data while considering bidirectional contextual dependencies. The schematic diagram of the architecture layout of BiLSTM is shown in Figure 3.

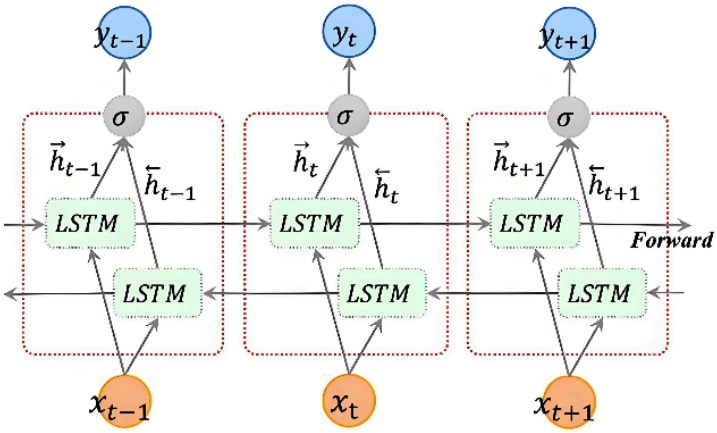

Figure 3. The violin polt

3.4. VMD-PSO-BiLSTM

The VMD-PSO-BiLSTM regression algorithm combines the advantages of signal decomposition, intelligent optimization and deep learning. First, the VMD algorithm is used to decompose the original time series data, and the complex non-stationary sequence is split into multiple stationary modal components to reduce the interference of data fluctuations on the prediction results [10]. Then, aiming at the problem that the key parameters of BiLSTM model are difficult to be optimized manually, PSO algorithm is used to optimize the learning rate of the model, the number of hidden layer nodes and other parameters, so as to avoid under-fitting or over-fitting of the model caused by unreasonable parameter setting. Finally, the optimized BiLSTM model is used for independent regression prediction of each modal component, and the prediction results of each component are superimposed and fused to get the final prediction value.

4. Result

In this study, the signal initially undergoes Variational Mode Decomposition, where the tolerance is configured to 1e-7, the target number of modes is established at 5, and the bandwidth penalty factor is assigned a value of 356. Following this, the Particle Swarm Optimization technique is invoked to refine the BiLSTM network. Here, the maximum iteration count is restricted to 15, and the swarm population size is set at 10. The hyperparameters targeted for optimization involve the number of hidden layer nodes, the starting learning rate, and the L2 regularization factor (bounded between a

DOI: 10.54254/2753-8818/2026.34453

lower limit of 1e-8 to 2 and an upper limit of 0.1 to 100). During the BiLSTM training phase, the data split reserves 70% for the training set. The maximum training epochs are capped at 500, the gradient clipping threshold stands at 1, and a learning rate drop factor of 0.2 is applied post 350 epochs. Benchmarking experiments were executed against a spectrum of machine learning frameworks, with outcomes detailed in Table 1.

Table 1. Model evaluation parameters

Model	MSE	RMSE	MAE	MAPE	R^2
ExtraTrees	64371.364	253.715	202.528	7.842	0.974
Random Forest	70928.094	266.323	214.813	7.475	0.97
GBDT	45152.155	212.49	168.802	6.419	0.982
BP neural network	48423.377	220.053	173.014	5.758	0.98
Decision Tree	129510.296	359.875	289.472	10.494	0.941
XGBoost	49024.696	221.415	173.162	6.931	0.98
AdaBoost	57538.434	239.872	197.702	7.365	0.975
CatBoost	73439.352	270.997	205.375	7.807	0.971
VMD-PSO-BiLSTM	30012.063	173.24	130.352	4.568	0.988

Output the index comparison results of the DE-Transformer-BiLSTM test set, as shown in Figure 4.

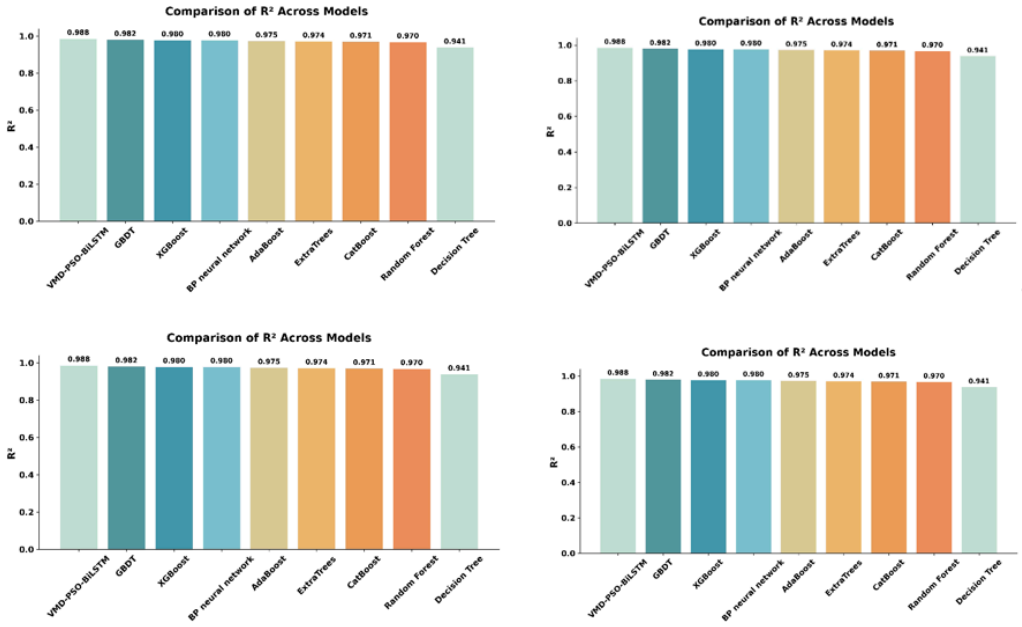

Figure 4. The index comparison results of the DE-Transformer-BiLSTM test set

From the perspective of various evaluation indicators, the comprehensive performance of the VMD-PSO-BiLSTM algorithm proposed in this paper is significantly better than that of traditional machine learning and single deep learning models such as ExtraTrees, Random Forest, GBDT, BP neural network, Decision Tree, XGBoost, AdaBoost and CatBoost. Its MSE is as low as 30012.063, RMSE is 173.24, MAE is 130.352, MAPE is only 4.568%, and R^2 is as high as 98.8%. It is optimal in error control and fitting effect. Compared with the Decision Tree model with the highest error,

DOI: 10.54254/2753-8818/2026.34453

MSE is greatly reduced, MAPE is decreased by nearly 6 percentage points, and R^2 is increased by 4.7 percentage points. Compared with the excellent GBDT, BP neural network and XGBoost models, this algorithm is also lower in various error indicators and higher in fitting goodness, which fully reflects the advantages of the BiLSTM model optimized by VMD decomposition and PSO in feature mining and parameter optimization. The overall prediction accuracy and stability are ahead of the comparison algorithm.

5. Conclusion

With the rapid development of global digital economy and e-commerce industry, supply chain management has entered the stage of refinement and intelligent development, and market demand shows the obvious characteristics of nonlinear fluctuation and non-stationarity. Traditional statistical models are difficult to meet the demand for accurate forecasting in complex scenarios. Machine learning technology provides an effective path to mine complex features and build nonlinear relational models for supply chain demand forecasting. Aiming at the shortcomings of existing models, this paper proposes a VMD-PSO-BiLSTM regression prediction algorithm, which processes the data through correlation analysis and violin graph analysis first, and then carries out comparative experiments with various machine learning algorithms. From the perspective of various evaluation indicators, the comprehensive performance of this algorithm far exceeds that of traditional machine learning and single deep learning models such as ExtraTrees, Random Forest, GBDT, BP neural network, Decision Tree, XGBoost, AdaBoost and CatBoost. Its MSE is as low as 30012.063, RMSE is 173.24, MAE is 130.352, MAPE is only 4.568%, and R^2 is as high as 98.8%. It is optimal in error control and fitting effect, fully demonstrating the advantages of BiLSTM model optimized by VMD decomposition and PSO in feature mining and parameter optimization. This algorithm can provide technical support for accurate supply chain demand forecasting, help improve supply chain management efficiency and optimize decision-making.

6. Future work

The future research will further optimize and improve the VMD-PSO-BiLSTM regression prediction algorithm proposed in this paper, expand its application scenarios and practical value, and make up for the shortcomings of existing research. First of all, at the level of feature construction, multi-source external correlation features will be introduced, including e-commerce platform promotion activities, market consumption trends, macroeconomic data, logistics and transportation efficiency and emergencies, etc., to build a more comprehensive feature input system, solve the problem that the current model can't capture external disturbance factors enough, and further enhance the model's adaptability to nonlinear and non-stationary supply chain demand fluctuations. Secondly, in the aspect of model optimization, the attention mechanism and lightweight network structure will be combined to optimize the parameter adaptive selection of VMD decomposition, and at the same time, the optimization strategy of PSO algorithm will be improved, so as to reduce the model training time and calculation cost, improve the model reasoning speed, and meet the actual needs of real-time forecasting and engineering deployment of supply chain. In addition, the model application scenarios will be expanded, from single-category demand forecasting to collaborative forecasting of multi-category and multi-supply chain nodes, and combined with federated learning technology, it will effectively solve pain points such as data islands and privacy leakage of upstream and downstream enterprises in the supply chain, and realize data security sharing and joint modeling. Finally, the robustness of the model under sudden demand disturbance and extreme

DOI: 10.54254/2753-8818/2026.34453

market environment will be studied, and the uncertainty quantification method will be introduced to improve the interpretability of the model. At the same time, it will be verified in e-commerce supply chain scenarios in different regions and scales, so as to further improve the generalization ability of the model and provide more stable, reliable and comprehensive intelligent decision-making support for refined and intelligent management of supply chain.

References

[1] Feizabadi, Javad. "Machine learning demand forecasting and supply chain performance." International Journal of Logistics Research and Applications 25.2 (2022): 119-142.
[2] Yani, Luh Putu Eka, and Ammar Aamer. "Demand forecasting accuracy in the pharmaceutical supply chain: a machine learning approach." International journal of pharmaceutical and healthcare marketing 17.1 (2023): 1-23.
[3] Zhu, Xiaodan, et al. "Demand forecasting with supply-chain information and machine learning: Evidence in the pharmaceutical industry." Production and operations management 30.9 (2021): 3231-3252.
[4] Kilimci, Zeynep Hilal, et al. "An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain." Complexity 2019.1 (2019): 9067367.
[5] Carbonneau, Real, Rustam Vahidov, and Kevin Laframboise. "Machine learning-based demand forecasting in supply chains." International journal of intelligent information technologies (IJIIT) 3.4 (2007): 40-57.
[6] Islam, MD Tanvir, et al. "Revolutionizing retail: A hybrid machine learning approach for precision demand forecasting and strategic decision-making in global commerce." Journal of Computer Science and Technology Studies 6.1 (2024): 33-39.
[7] Seyedan, Seyedehmahya. Development of predictive analytics for demand forecasting and inventory management in supply chain using machine learning techniques. Diss. Concordia University, 2023.
[8] Yu, Xiaomo, et al. "Comparison of deep and conventional machine learning models for prediction of one supply chain management distribution cost." Scientific Reports 14.1 (2024): 24195.
[9] Abolghasemi, Mahdi, et al. "Demand forecasting in supply chain: The impact of demand volatility in the presence of promotion." Computers & Industrial Engineering 142 (2020): 106380.
[10] Kamal, Esraa, et al. "Machine Learning Fusion and Data Analytics Models for Demand Forecasting in the Automotive Industry: A Comparative Study." Fusion: Practice & Applications 12.1 (2023).