



# Study on the Prediction of the Total Retail Amount of Consumer Goods Based on Deep Learning

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**Abstract.** To address the challenges of model parameter tuning and predictive accuracy in forecasting total retail sales of consumer goods, this study introduces a novel integrated forecasting model, IDBO-VMD-BiLSTM. This model enhances the traditional dung beetle optimization algorithm (DBO) with three strategic improvements: population initialization based on the Chebyshev mapping, position updating using the golden sine operator, and theft position updating guided by dynamic weight coefficients. The efficacy of these enhancements is substantiated through benchmark function testing. Subsequently, the IDBO-VMD-BiLSTM integrated forecasting model is constructed and empirically analyzed using China's total retail sales data from 2000 to 2021. The findings reveal that the IDBO-VMD-BiLSTM model delivers commendable predictive performance with an average absolute percentage error of 2.12%, outperforming four mainstream forecasting models. These insights contribute valuable, scientifically precise data support for the formulation of economic policies and business decision-making.

**Keywords:** Total retail sales of consumer goods, Deep learning, Factor identification, Prediction, BiLSTM.

## 1 Introduction

Amidst the dynamic transformation of the global economy, total retail sales of consumer goods serve as a critical macroeconomic indicator, reflecting both economic vitality and market trends. This measure encompasses the transactional volume of physical commodities and catering services intended for non-production consumption[1]. Accurate forecasting of retail sales is essential for shaping effective economic policies and market strategies but remains challenging due to the influence of complex, nonlinear factors such as economic policies, income levels, and market dynamics [2]. Traditional methods like ARIMA and regression models[3] often assume data stability and linearity, limiting their effectiveness in capturing the inherent volatility of real-world economic data. While machine learning models, such as neural networks and support vector machines, have improved predictive accuracy, they still face challenges in generalization and handling high-dimensional data[4].

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To address these limitations, this study proposes the IDBO-VMD-BiLSTM model, which integrates an improved dung beetle optimization (IDBO) algorithm, variational mode decomposition (VMD), and bidirectional long short-term memory (BiLSTM) networks. The IDBO algorithm enhances global search capabilities and convergence speed, optimizing VMD parameters for adaptive feature extraction and BiLSTM hyperparameters for robust forecasting. Using data from 2000 to 2021, the model demonstrates superior predictive performance with strong robustness and precision.

## 2 Methodology

### 2.1 The Idbo Algorithm

The Dung Beetle Optimization (DBO) algorithm, inspired by the natural behaviors of dung beetles, effectively explores the optimization space for parameter tuning[5]. To overcome its limitations, such as premature convergence and susceptibility to local optima, this study proposes the Improved DBO (IDBO) algorithm. Key enhancements include Chebyshev mapping for population initialization, a golden sine operator for position updates, and dynamic weight coefficients for theft behavior, significantly improving robustness and stability. The implementation process of IDBO is shown in Fig. 1.

#### (1) Population initialization strategy based on Chebyshev mapping

Chebyshev chaos mapping, a deterministic method in nonlinear systems, replaces random variables with chaotic ones to expand the search range and enhance population diversity. This approach improves convergence speed and flexibility, making it well-suited for optimizing the DBO algorithm[6]. The Chebyshev chaos mapping is described as shown in Eq. (1), which  $k$  denotes the order.

$$x_{n+1} = \cos(k \arccos x_n), x_n \in [-1, 1] \quad (1)$$

#### (2) Rolling position update strategy based on the golden sine operator

The Golden Sine Algorithm (Gold-SA) leverages the sine function's periodic nature to enhance global search efficiency by narrowing the solution space and approximating the optimal value. Integrating the golden sine operator into the DBO algorithm improves performance and reduces the risk of getting trapped in local optima during later phases[7].

The position update formulas with the golden sine operator added to the rolling behavior are shown in Eq. (2), respectively. Where  $R_1 \in [0, 2\pi]$  is a random number that determines the moving distance of the individual in the next iteration,  $R_2 \in [0, \pi]$  is a random number that determines the moving direction in the next iteration, and  $x_1 = -\pi + (1 - \tau) * 2\pi$ ,  $x_2 = -\pi + \tau * 2\pi$  is the coefficients obtained according to the golden section coefficient  $\tau = (\sqrt{5} - 1)/2$ , which narrows down the search space of the algorithm and leads the individual to converge to the optimal value gradually.

$$x_i(t+1) = x_i(t) \times |\sin R_1| + R_2 \times \sin R_1 \times |x_1 \times x_i^{best}(t) - x_2 \times x_i(t)| \quad (2)$$

(3) Theft position update strategy based on dynamic weight coefficients

Addressing the inadequacy of global exploration capabilities during the theft behavior phase [8], a dynamic weight coefficient based on the number of iterations is incorporated into equation. This addition aims to balance the algorithm's capabilities for global exploration and local exploitation, with the specific improvement formula presented in equation (3). where  $k_1 = 1 - \frac{t^3}{T^3}$ ,  $k_2 = \frac{t^3}{T^3}$ . In Eq. (3),  $k_1$  is larger in the pre-iteration period, enhancing the dung beetle's pre-exploration capability, while  $k_2$  gradually increasing in the later period, ensuring the dung beetle's localized exploitation capability in the later period.

$$x_i(t+1) = k_1 \times X^b + k_2 \times S \times g \times (|x_i(t) - X^*| + |x_i(t) - X^b|) \quad (3)$$

## 2.2 The Idbo-Vmd-Bilstm Model

Variational Mode Decomposition (VMD) is a robust signal processing method that decomposes signals into intrinsic mode functions by solving a constrained variational problem[9]. BiLSTM, an advanced LSTM variant, processes sequences bidirectionally, integrating forward and reverse outputs to capture temporal dependencies more effectively. Accurate forecasting relies on optimizing key parameters: VMD's decomposition levels and penalty factor, and BiLSTM's hidden units, training epochs, and learning rate[10]. Using the IDBO algorithm, these six parameters are optimized to ensure effective feature extraction by VMD and precise predictions by BiLSTM. The workflow of the IDBO-VMD-BiLSTM model is shown in Fig. 1.

Step 1: Input the raw data and conduct data preprocessing.

Step 2: Utilize the IDBO algorithm to optimize VMD, aiming to find the optimal values for VMD's penalty factor and number of decomposition modes.

Step 3: Decompose the Y series data into modal components using the optimized VMD model.

Step 4: Optimize the BiLSTM model with the IDBO algorithm, determining the optimal hyperparameter values for the BiLSTM model.

Step 5: Input various influencing factors into the BiLSTM model for prediction, forecast the individual model components, and aggregate the predicted values of each modal component to form the final forecast result.

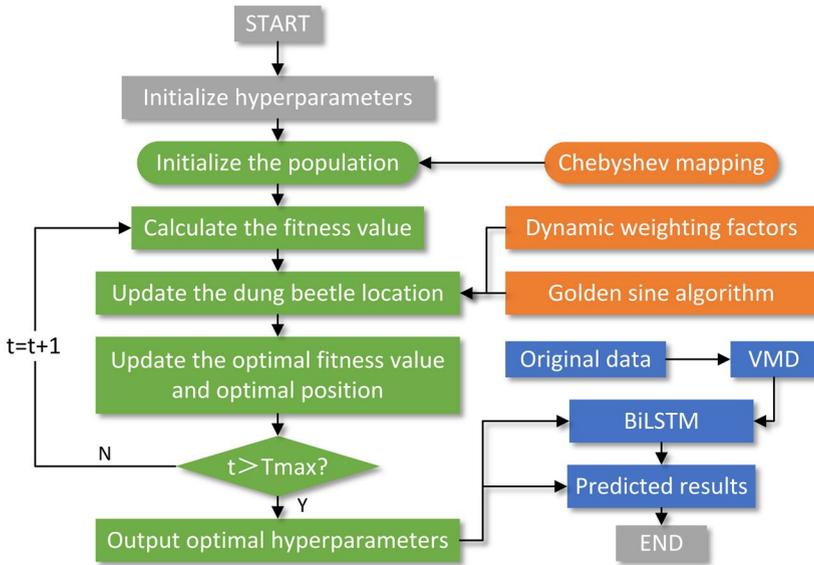


Fig. 1. Flowchart of IDBO-VMD-BiLSTM.

### 3 Empirical Analysis

#### 3.1 Data Sources and Factor Identification

This study identified seven key indicators influencing total retail sales of consumer goods, based on data from the "China Statistical Yearbook" (2000–2021) and Liu et al.[11]. These indicators include per capita GDP, consumer price index, urban residents' per capita disposable income, annual freight volume, annual import total, annual government expenditure, and money supply. Data for 2000–2019 was sourced from Liu et al.[12], and figures for 2020-2021 were supplemented from the "China Statistical Yearbook."

#### 3.2 Decomposition Results

Initially, employ the IDBO algorithm to optimize the penalty factor and the number of decomposition layers for VMD. After 30 independent trials, the penalty factor is set to 218 and the number of decomposition layers to 4, with the convergence criterion established at  $10^{-7}$ . Fig. 2 depicts the optimization curve of VMD by the IDBO algorithm. The optimized VMD is then applied to decompose the Y series, yielding modal components and residuals as shown in Fig. 3. The decomposed components encapsulate local feature signals of the original signal across different time scales.

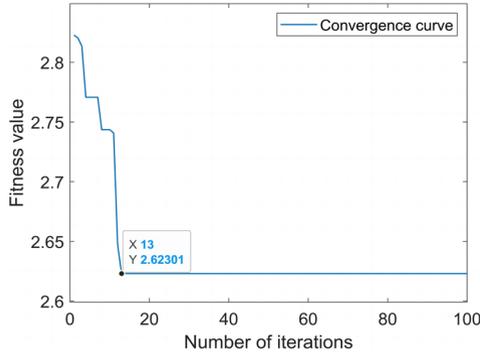


Fig. 2. Convergence curve of IDBO optimized VMD

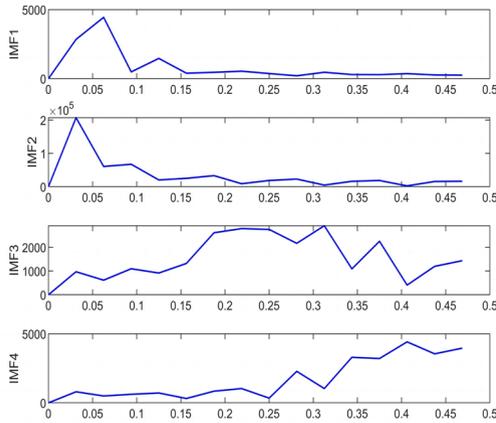


Fig. 3. Modal components of VMD decomposition.

### 3.3 Predicted Results

Utilizing data, the IDBO-VMD-BiLSTM model is applied to forecast the total retail sales of consumer goods (Y). To verify the predictive accuracy and feasibility of the IDBO-VMD-BiLSTM model, comparisons are made with four prevalent forecasting models: Multivariate Linear Regression (MLR), Back Propagation Neural Network (BP), Support Vector Machine (SVM), and Long Short-Term Memory Neural Network (BiLSTM) [9]. To mitigate the randomness in predictions, each forecasting model's optimization algorithm is set with a population size of 30 and 100 iterations, allocating the first 70% of data for training and the remaining 30% for testing. The mean results from 50 iterations of each model serve as the basis for analysis. Besides the training and testing performances, this study employs the Mean Absolute Percentage Error (MAPE) to evaluate the predictive performance of the models. A lower MAPE value indicates higher predictive accuracy.

The predictive outcomes of the models are presented in Table 1. According to Table 1, the IDBO-VMD-BiLSTM model exhibits superior predictive performance, with the

lowest MAPE for both training and testing sets among the five algorithms, recorded at 0.91% and 2.12%, respectively. Fig. 4 depicts the training and testing conditions of the five models, including IDBO-VMD-BiLSTM. From Fig. 4, it is evident that the fit and forecast results of the IDBO-VMD-BiLSTM model closely align with the actual values. Furthermore, the IDBO-VMD-BiLSTM model proficiently captures the fluctuation characteristics of total retail sales, maintaining minimal errors in areas with significant changes and closely following the predicted trends, thus demonstrating stable and precise predictive performance. This validates the effectiveness of the improvement measures adopted in this study.

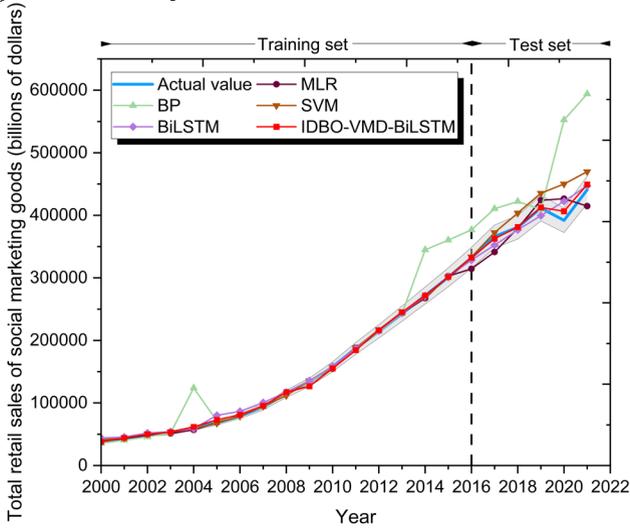


Fig. 4. Performance of model predictions.

Table 1. Prediction error of each model.

Model	Set	MAPE
IDBO-VMD-BiLSTM	Training set	0.91%
	Test set	2.12%
BiLSTM	Training set	1.77%
	Test set	4.24%
SVM	Training set	1.68%
	Test set	5.85%
BP	Training set	48.95%
	Test set	186.24%
MLR	Training set	2.33%
	Test set	5.07%

## 4 Conclusions

This study addresses the issues of model parameter tuning and predictive accuracy in forecasting total retail sales of consumer goods, proposing a novel predictive model, IDBO-BiLSTM, aimed at achieving high precision and robust prediction. The principal conclusions of this research are as follows. (1) In response to the premature convergence and susceptibility to local optima inherent in the traditional DBO algorithm, enhancements were made through population initialization strategy based on Chebyshev mapping, rolling position update strategy using the golden sine operator, and theft position update strategy with dynamic weight coefficients. These led to the development of the IDBO algorithm, forming the foundation of the IDBO-BiLSTM predictive model. (2) Based on results from benchmark test functions, the IDBO algorithm, compared to the DBO algorithm, demonstrated fewer average iterations, faster convergence, and superior real-time performance, effectively escaping local optima and consistently identifying the global optimum. (3) The IDBO-BiLSTM model outperformed the four commonly used predictive models in forecasting China's total retail sales of consumer goods, exhibiting the highest accuracy with a Mean Absolute Percentage Error (MAPE) of 2.12%.

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