Regional Express Business Volume Forecasting Based on Combinatorial Modelling

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Abstract. With the booming development of the tertiary and e-commerce industries, the volume of business in the express delivery industry also maintains a high growth rate. In order to further improve the prediction accuracy of regional express business volume and provide more accurate data support to the local government and express enterprises, this paper follows the idea of "decomposition followed by integration" modelling and proposes a combined prediction model based on variational modal decomposition (VMD) and grey wolf optimization (GWO) support vector regression (SVR), and analyzes the monthly data of the express business volume in Liaoning Province as an example. Furthermore, the combination of the prediction model and the other four models to do a comparison test, the results show that the prediction accuracy of the model is significantly higher than other comparative models, can effectively solve the non-linear and seasonal regional express business volume, and more accurately predict the trend of changes in the regional express business volume.

Keywords: variational modal decomposition, support vector machine regression, express business volume, combined forecasting

1 INTRODUCTION

The volume of express delivery business is an essential indicator for measuring the size of a country or region's postal market and evaluating the development of the express delivery industry. Scholars at home and abroad have conducted much research on the prediction of express business volume; initially, based on the statistical prediction method, Yang Zhou[1] et al. used the R language to establish the SARIMA sliding window model to predict the daily express business volume of a courier company. However, the model predicted that the prediction accuracy decreases with the postponement of the prediction time. Subsequently, scholars proposed artificial intelligence prediction methods based on neural networks, such as BP and RBF neural networks. Fadong Zhang[2], in the context of air-rail intermodal transport, chooses the BP neural network model to predict the express business volume of 28 major cities in China

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according to the characteristics of express volume and the actual situation of different cities. The predictive effectiveness of the method has improved, but the results still need improvement. In recent years, support vector machine prediction methods have powerful nonlinear processing capabilities, greatly simplifying the problem. Pengfei Li[3] analyses the characteristics of monthly express business volume, establishes trend-adjusted and seasonally-adjusted RBF-SVR prediction models, and improves the situation, such as the decline in the prediction accuracy of express business volume due to uncertainties. Support vector regression machines have a clear advantage when solving problems with small samples and nonlinearities. Scholars have introduced intelligent algorithms to optimise further the model's performance, including penalty parameter C and kernel parameter g. The grey wolf optimisation algorithm has the characteristics of fast parameter optimisation and good fitting effect, so this paper adopts the grey wolf optimisation algorithm to optimise the parameters of the SVR model.

Affected by the complexity of the internal structure of the courier system and the variability of external factors, a single prediction method only covers some of the adequate information, and the prediction results still have some room for improvement. Chenying Li[4] proposed adopting the CEEMD-SVM combined prediction model and introduced the idea of "decomposition before integration, " effectively solving this problem. The application of decomposition and integration methods in regional express business volume forecasting is in its infancy, with less relevant literature and insufficient framework content. Among the existing methods, the Variable Modal Decomposition (VMD), as an improved decomposition technique, can adaptively decompose the practical components of each centre frequency in the frequency domain with higher decomposition accuracy. Therefore, this paper uses the Variational Divided Modal Decomposition (VMD) method for initial data processing.

2 RESEARCH METHODS

2.1 Variational Modal Decomposition

The variational modal decomposition algorithm[5] is a novel adaptive, fully non-recursive signal decomposition method proposed by Dragomiretskiy and Zosso in 2014. The method can effectively handle nonlinear and nonsmooth signals, is highly adaptive and has advantages in solving signal noise problems and avoiding modal aliasing. The specific model is as follows:

The one-sided spectrum of the analytic signal corresponding to each modal function is computed by the Hilbert transform, followed by the addition of an exponential term to correct the estimated centre frequency of each modal function, and the spectrum of the analytic signal of each modality is modulated to the fundamental frequency band. Finally, the squared L2 parameter of the gradient of the resolved signal is calculated to obtain the estimated fundamental frequency bandwidth of each modal function, and in this way the constrained variational problem is constructed with the following expression:

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

where $\{u_k\}$ is the set of decomposed modal components; $\{\omega_k\}$ is the set of centre frequencies; k is the number of iterations; $\delta(t)$ is the Dirac function; and $f(t)$ is the original signal.

In order to transform the constrained problem into an unconstrained problem for easy computation, the quadratic penalty factor α and the Lagrange multiplier operator λ are introduced to obtain the augmented Lagrangian expression as:

$$L(\{\mu_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * \mu_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \tag{2}$$

Using the Lagrangian function to transform it from the time domain to the frequency domain and calculating the corresponding extreme values, the modal component u_k and its centre frequency ω_k are solved with the following expressions:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \tag{3}$$

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

The optimal solution of the constrained variational model is obtained by decomposing the original signal into k narrow-band modal components using the alternating direction multiplier method of alternating updates.

2.2 Grey Wolf Optimisation Algorithm

Grey Wolf Optimization Algorithm[6] is an intelligent pack optimization algorithm proposed by Seyedali Mirjalili et al. in 2014, which iteratively searches for the optimal solution by simulating the grey wolf pack hierarchy and wolf pack hunting strategy in nature. Grey wolf packs have a strict social hierarchy, and the hunting behaviour can be divided into three stages: encirclement, hunting and attacking the prey.

2.3 Support Vector Regression Machine Algorithm

Support vector machine is a machine learning method based on statistical learning theory. The regression function is implemented for regression fitting by introducing an insensitive loss function developed into the support vector regression machine algorithm. The characteristic function of SVR is defined as:

$$f(x) = \omega^T \phi(x) + b \tag{5}$$

where ωT is the weight coefficient, φ(x) is the mapping function, and b is the bias. The slack variables ξ_i and ξ_i^* are introduced to obtain the objective function and constraints as:

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$
$$\text{s.t.}\begin{cases} yi - \left[\omega^T \phi(x_i) + b\right] \le \varepsilon + \xi_i^* \\ \omega^T \phi(x_i) + b - y_i \le \varepsilon + \xi_i \\ \xi_i, \xi_i^* \ge 0, i = 1,2,3\ldots,n \end{cases} \tag{6}$$

where C is the penalty factor and ε is the insensitivity factor. Lagrange multipliers λ_i and λ_i^* are introduced and brought into the kernel function to obtain the decision function:

$$f(x) = \sum_{i=1}^{n}\left(\lambda_i^* - \lambda_i\right)K(x_i, x) + b \tag{7}$$

The Gaussian radial basis kernel function is chosen for the kernel function in this paper, which is given by:

$$K(x_i, x) = \exp(-g \cdot \|x_i - x\|^2) \tag{8}$$

3 MODEL ESTABLISHMENT

3.1 Combined VMD-GWO-SVR Prediction Model

Based on variational modal decomposition, the support vector regression prediction optimised by the grey wolf algorithm is carried out on the regional express business volume data in the following steps:

1) Data preprocessing. Read the raw data of regional express business volume, process the sample data for missing values and outliers, and then carry out normalisation to improve the accuracy and stability of the model. The training set and test set of the data are divided according to 7:3.

2) VMD decomposition. The preprocessed data are decomposed into subsequences of different frequencies and a residual component using VMD.

3) Model Training. The sets of subsequences with different frequencies are brought into the support vector regression model optimised by Grey Wolf for training, respectively. The parameters of the SVM model and the sliding time window size n are selected by Grey Wolf optimisation.

4) Prediction. According to the optimal parameters Best_c, Best_g and Best_n output after iteration, the subseries sets are predicted respectively, and finally, the predicted values are obtained by integrating the prediction results of different subseries.

3.2 Model Evaluation Index

A quantitative method is used to achieve the comparative analysis of model prediction accuracy to verify the performance of the combined VMD-GWO-SVR-based prediction model constructed in this paper. The Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Coefficient of Determination (R2) are selected as the model assessment indexes to measure the model's effectiveness in forecasting the volume of regional express delivery business.

4 Example Analysis

4.1 Selection and Pre-Processing of Data

The instance analysis takes the monthly data of the express business volume (in 10,000 pieces) of Liaoning Province in the ten years between January 2014 and December 2023 as a sample, and the data are obtained from the official website of Liaoning Postal Administration, as shown in Figure 1.

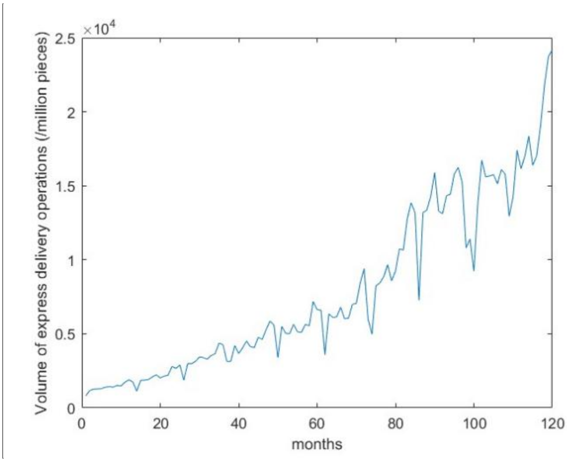

Fig. 1. Monthly express delivery volume data[1]

Figure 1 shows that the volume of express business in Liaoning Province has risen exponentially since 2014 and is seasonal. Seasonality is manifested in February, which has the lowest business volume, and November, which has the highest value of business volume. In addition, the business volume also has a 12 as the cycle of the annual cycle; each annual cycle compared to the previous annual cycle also has a significant increase in value.

The sample data were processed for missing values and outliers, for which a min-max normalisation was performed to normalise the data to between [0, 1] to improve the convergence speed of the model.

4.2 Experimental Results and Comparative Analysis

VMD Decomposition Results. The sample data were processed for missing values and outliers, for which a min-max normalisation was performed to normalise the data to between [0, 1] to improve the convergence speed of the model.

[1] Source: Official website of Liaoning Provincial Post Bureau

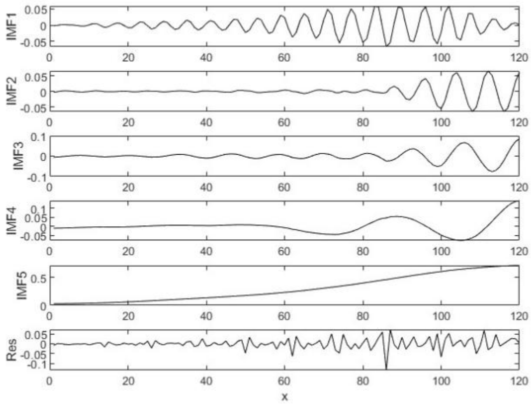

Fig. 2. Graph of VMD decomposition results[2]

The intrinsic mode function (IMF) in Figure 2 is arranged in the order of frequency from high to low, indicating the different frequencies and amplitudes of monthly express business volume in Liaoning Province in ten years. The high-frequency component reflects the short-term change of express business volume, the low-frequency component reflects the long-term change of express business volume, and the trend of the residual term (Res) is rising but levelling off in the long term, reflecting that the long-term trend of express business volume is gradually rising, which is consistent with the scenario of gradual saturation of the express market.

4.3 Optimisation of the Parameters of the Grey Wolf Optimisation Algorithm

In the process of parameter optimisation using the grey wolf algorithm for the parameters C and g and the sliding window size n of the support vector regression machine, the grey wolf algorithm is initialised with the following parameters: the wolf pack size N=50, the maximum number of iterations is 200, the values of C and g are in the range of [0.01,100], and the sliding window size $n \in [1,12]$ and n is an integer. The mean square error (MSE) is chosen as the fitness function of the grey wolf optimisation algorithm.

The four kernel functions were tested separately using the training set, and it was found that the best fit was obtained using the Gaussian radial basis kernel function. The optimal parameters BestC=8.18 and Bestg=0.041 for C and g were obtained from the training, and the sliding window size was taken as 4.

[2] Source: MATLAB plotting

4.4 Model Evaluation and Comparison

In order to verify the accuracy and effectiveness of the VMD-GWO-SVR model for the prediction of regional express business volume, this paper, in addition to the original with the SVM, GWO-SVR, EMD-GWO-SVR, VMD-PSO-SVR model to form a control model. The SVR parameters are unified in all models, the number of populations of each optimisation algorithm is set to 50, and the maximum number of iterations is set to 200. The comparison results of the four models are shown in Fig. 3, and the error analysis results are shown in Table 1.

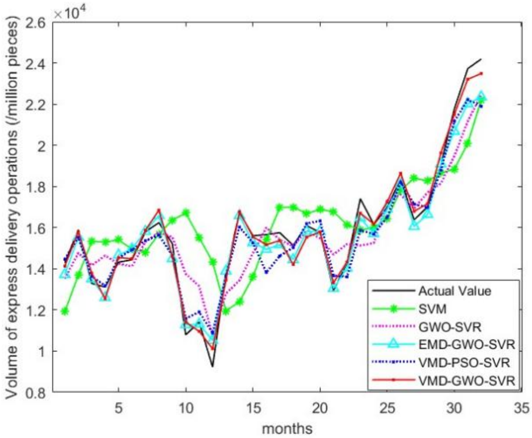

Fig. 3. Comparison of the forecasts of express business volume by model[3]

Table 1. Error analysis of the four methods[4]

modelling	R^2	MAE	MAPE	RMSE
SVM	0.817	1246	9.21	1765
GWO-SVR	0.8723	1085.03	5.87	1563.42
EMD-GWO-SVR	0.968	506.89	4.88	721.79
VMD-PSO-SVR	0.955	674.77	5.64	879.18
VMD-GWO-SVR	0.989	153.79	0.86	189.67

Figure 3 visualises the distribution and fit of the predicted and actual values of the five models, and the following conclusions can be drawn from a comparison of the results in Table 1:

The VMD-GWO-SVR model has the most significant coefficient of determination among the five models, with the highest accuracy and best fit compared with other prediction models. This model's MAE, MAPE and RMSE are lower than those of other models, which is suitable for predicting the regional express delivery business situation. It can better solve the nonlinear problem. The effect of integrated prediction after decomposition is better than the prediction of the whole time series, and the VMD

[3] Source: MATLAB plotting

[4] Source: MATLAB plotting

decomposition is better than the EMD decomposition, which can effectively overcome the problems of EMD, such as modal aliasing and minimal endpoint effects. In summary, the VMD-GWO-SVR proposed in this paper has a more significant improvement in prediction accuracy and goodness of fit and is more suitable for predicting the volume of regional express business.

5 SUMMARY AND OUTLOOK

In order to improve the prediction degree of regional express business volume and meet the urgent demand for accurate data from local governments and express enterprises, this paper proposes a combined VMD-GWO-SVR prediction model. In order to reduce the impact of data non-stationarity on the prediction results, the original series is decomposed into several IMF components and residual terms (Res) using Variable Modal Decomposition (VMD), the high-frequency part is used to predict short-term fluctuations in the volume of express delivery business, and the low-frequency part predicts the long-term trend of the volume of express delivery business, and Grey Wolf Optimization (GWO) algorithm is used to optimize the parameters of the SVR model. The high-frequency, low-frequency and residual terms are summed up to obtain the final prediction results. The empirical results show that the combined prediction model proposed in this paper is more suitable for predicting the regional express delivery business, providing accurate data reference for local governments and express delivery enterprises. However, there are still improvements in the model proposed in this paper; the initial prediction only takes into account the time-series data of regional express business volume, the timeliness and accuracy have some limitations, and other statistical indicators with vital timeliness can be expanded in the subsequent research.

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