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Railway Freight Prediction Based on Stage Segmentation and Big Data Method

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ABSTRACT

In the operation of railway transportation enterprises, having prior knowledge of future loading volumes and trends at freight stations is crucial for optimal deployment of empty cars and the development of daily operational plans. Long-term freight volumes at railway stations often exhibit cyclical patterns influenced by seasonal fluctuations, holidays and other factors. Additionally, changes in freight volume are significantly affected by the proportion of freight from various industries. To address these dynamics, this study proposes a hybrid prediction model for long-term loading volumes at railway freight stations. This model predicts by stage segmentation through peak-valley segmentation (PVS), variational mode decomposition (VMD) and an attention mechanism integrated into a temporal convolutional network (TCN). Using historical freight volumes from the Shuohuang railway freight station as a case study, we employed mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean square error (RMSE) as evaluation metrics to assess the combined predictive performance of the PVS, VMD and TCN methods. The experimental results show that the PVS-VMD-A-TCN model significantly improves the accuracy of long-term freight volume predictions. Compared to traditional methods such as ARIMA, GRU and TCN, it exhibits superior predictive performance, offering a new approach for accurately forecasting long-term loading volumes.

KEYWORDS

railway freight prediction; peak-valley segmentation method; variational mode decomposition; temporal convolutional network; attention mechanism.

1. INTRODUCTION

In the global logistics and transportation sector, railway freight serves as a critical component due to its efficiency, cost-effectiveness and environmental benefits. It is a key element of national infrastructure and plays a significant role in regional economic growth [1], [2]. Railway freight's ability to lower transportation costs, boost logistics efficiency and reduce carbon emissions makes it a foundational pillar of contemporary transportation systems. Therefore, enhancing the operational efficiency and accuracy of railway freight forecasting, particularly in predicting freight volumes, is crucial for both industry stakeholders and researchers [3].

With the rapid expansion of the railway freight industry, the volume and diversity of railway freight data have increased dramatically. This growth has made traditional freight volume prediction methods, such as autoregressive integrated moving average (ARIMA) and exponential smoothing, less effective in capturing the temporal patterns and growth trends of different freight types, thus complicating accurate long-term railway freight volume forecasts [4].

However, the advancement of big data technologies has opened new avenues for improving predictive accuracy [5]. Big data offers extensive historical datasets and enables the discovery of hidden temporal patterns and underlying factors [6]. The advancements in big data technology have introduced various machine learning and deep learning techniques, including support vector machines (SVM) [7], long short-term memory (LSTM) networks [8] and temporal convolutional networks (TCN) [9]. These methods offer improved capabilities for analysing and modelling the complex nature of railway freight data, uncovering intricate relationships between data points, and enhancing the accuracy and robustness of predictive models. Thus, integrating big data technologies with deep learning methods to explore multivariate railway freight forecasting holds substantial theoretical and practical significance.

Currently, a growing number of scholars are concentrating on using big data and machine learning techniques to forecast freight volumes. [10] employed the LSTM network to forecast the freight volume data from 2010 to 2017 for Guangzhou Railway (Group) Corporation, and compared the results with the ARIMA model and BP neural network. The results demonstrated that the LSTM model outperformed the other models. Yue-Ying Qiu and Qiong Zhang proposed a prediction method combining particle swarm optimisation algorithm (PSO) with LSTM, based on [10], and the research showed that the prediction accuracy of the PSO-LSTM model exceeded traditional LSTM prediction methods [11]. [12] proposed an ARIMA-LSTM model for daily freight volume prediction, which combines historical data to predict the future freight volume of the sorting centre to improve management efficiency. Guo Hongpeng applied the Bi-LSTM network for railway freight volume prediction and validated the accuracy of the model for monthly and daily freight volume forecasts for a railway company [13]. [14] combined the product ensemble model with an LSTM model incorporating attention mechanisms, and demonstrated that the combined model performed better in predicting railway freight volume than the single models. J Liu proposed an informer model to predict the freight volume of the main railway stations to better mine the time features by adopting an attention decoder to capture the long-term correlation of the data [15]. To deal with the non-stationarity and abruptness in the track train data, [16] proposed a multi-step fault prediction model (MTMF) based on a memory network, which dug into the different weights of long-term historical data to further improve the prediction ability for non-stationary time series. The aforementioned studies primarily operate at the level of time-series data analysis, employing conventional single-algorithm approaches. While these methods offer advantages in terms of rapid prediction convergence, they often fail to incorporate an analysis of physical cyclical patterns. Consequently, this leads to inadequate modelling of typical freight scenarios over long-term horizons. Furthermore, the prediction accuracy of these approaches is frequently susceptible to the volume of available data. Therefore, an increasing number of scholars are focusing on decomposition analysis of long-term railway freight volume temporal trend patterns. This approach aims to distinguish between diverse freight patterns by decomposing fluctuations over extended periods.

The support vector regression (SVR) model, known for its strong compatibility, is suitable for small samples and short-term forecasting, and has been widely applied in regression prediction in recent years. Liu Y and Lang X M [17] have analysed the eight major socio-economic factors influencing railway freight volume. Through normalisation processing, learning samples were selected, and testing methods were applied to validate the model's prediction accuracy. The results confirmed the effectiveness of SVR in predicting railway freight volume. Wang Zhi [18] optimised the parameters of the SVR model using a genetic algorithm and found that the combined model had smaller prediction errors compared to neural network models. Zhang Peng [19] improved Wang Z's research methodology by integrating empirical mode decomposition (EMD) and variational mode decomposition (VMD) with a genetic algorithm to build an EMD-GA-SVR model, which was able to predict the components of target values and demonstrated superior forecasting performance. [20] developed an adaptive particle swarm optimisation (APSO) least squares support vector regression model, which effectively predicted railway freight volume. The optimisation of parameters ensured the stability of predictions, enhancing the model's generalisation ability. Han Chunliang proposed an EMD-APSO-SVR model, which further strengthened the analysis of the dynamic characteristics of the railway freight volume time series in the current ever-changing environment [21]. Wang Gan considered the volatility and randomness of short-term cargo loading at freight stations and explored the application of modal decomposition in short-term cargo loading prediction, proposing the EMD-Attention-LSTM combined model [22]. However, given that freight volume fluctuations are strongly correlated with factors such as seasonality, cargo types and station categories, it remains challenging to perform a comprehensive association analysis linking the decomposed time-series data with specific freight categories and periodic peak-valley fluctuations through isolated decomposition alone.

The methods discussed earlier primarily focus on scenarios with extensive historical data on railway freight volumes, often overlooking the influence of the proportions and growth trends of various freight types across different months on long-term freight volume projections. This oversight limits their predictive performance and feature extraction capabilities for long-term forecasting involving multiple freight types. To address this gap, this study introduces a long-term railway freight volume forecasting approach based on a temporal freight cycle scenario, called VMD-A-TCN. First, we construct a scenario set by utilising clustering techniques and the inherent periodicity of railway freight to segment the data into its main components. Following this, a secondary segmentation rule is established using critical points derived from the peak-valley matrix, which helps create scenarios that capture the time series features of different freight type behaviours. This includes selecting dates with similar time series characteristics to form the scenario set. Then, VMD is applied to the freight volume data to extract multiple distinct intrinsic mode functions, which are then aggregated. The processed dataset is then fed into a TCN enhanced with a fused attention mechanism for training and prediction. Case study results indicate that this proposed method is more effective in feature extraction from various freight data, analysing periodic freight volume patterns, and achieving higher predictive accuracy compared to other methods.

2. STAGE DIVISION OF RAILWAY FREIGHT VOLUME BASED ON PEAK VALLEY SEGMENTATION METHOD

In long-term railway freight volume forecasting, sudden changes in freight volume can cause significant prediction errors due to model lag. To mitigate this issue, segmenting these moments of change is an effective strategy to improve prediction accuracy. Identifying peak-valley points in freight data, which indicate significant shifts in volume trends, is essential for capturing these abrupt changes. Thus, this paper proposes a peak valley segmentation method (PVS).

By focusing on these peak-valley moments, we can pinpoint critical transitions within the freight sequence. Given a freight volume sequence X over a specific period, these peak-valley moments are initially identified as key points. This approach divides the sequence $\boldsymbol{X} = \{x_{z0}, x_{z1}, x_{z2} \cdots x_{zn}\}$ into n+1 segments, each of which can be represented as a vector, denoted as $\bar{\mathbf{b}}_{z_k z_{k+1}}$. To gain deeper insights into the directional changes within each segment, the angles between vectors formed by the k-th moment and its adjacent moments are calculated as *Equations (1)* and *(2)*. This method provides a detailed understanding of the changes in freight volume trends, enabling the development of more nuanced and accurate forecasting models;

$$\theta_k = \cos^{-1} \frac{\bar{\mathbf{b}}_{z_{k-1} z_k} \cdot \bar{\mathbf{b}}_{z_k z_{k+1}}}{[|\bar{\mathbf{b}}_{z_{k-1} z_k}||\bar{\mathbf{b}}_{z_k z_{k+1}}|]} \tag{1}$$

$$\bar{\theta}_k = \theta_k \times \operatorname{sgn}(x_{k+1} - x_k) \times \operatorname{sgn}(x_{i+1} - x_i) \tag{2}$$

where: sgn() represents the sign function. $\bar{\theta}_k$ greater than 0 indicates that the freight volume change trend at moments k and k+1 aligns with the overall trend within the segment. Conversely, if $\bar{\theta}_k$ is negative, the trends oppose each other. A larger value $\bar{\theta}_k$ indicates a greater difference in freight volume. Therefore, it reflects the fluctuation level of the load between adjacent moments k.

$$\pi + \bar{\theta}_k < \tan^{-1}|x_{k+1} - x_k| \tag{3}$$

As shown in *Equation (3)*, it indicates significant fluctuations in freight volume before and after moment k, thereby marking k as a new important point. Important moments correspond to instances of freight volume transitions, representing abrupt changes in freight for the season.

3. CONSTRUCTION OF A LONG-TERM LOADING VOLUME PREDICTION COMBINATION MODEL FOR RAILWAY FREIGHT STATIONS

3.1 Sample entropy-based VMD decomposition

In railway freight forecasting, VMD serves as a powerful tool for analysing freight volume data by decomposing it into distinct components, thereby reducing sequence nonlinearity [23]. This technique enhances the extraction of temporal features from the data while minimising noise within the sequences. By breaking down freight data into K modes, VMD frames the task as a variational problem focused on finding the optimal solution, which is essential for improving forecast accuracy. In our study, we employ the particle swarm optimisation algorithm to fine-tune the VMD parameters. The objective function for this optimisation involves minimising the square difference between the decomposed intrinsic mode functions (IMF) and the original freight data signal, as shown in *Equation (4)*. This approach ensures that the decomposition captures the most significant temporal features essential for accurate forecasting.

$$f(x) = \left(\sum_{i=1}^{K_X} \mathrm{IMF}_i - X \right)^2 \tag{4}$$

Once the optimal parameters are established, managing the number of IMFs becomes essential, as too many can increase the computational complexity of the forecasting process. To address this, we aggregate sub-sequences by employing sample entropy as the aggregation criterion [24]. This method allows us to consolidate IMFs in a way that preserves the essential dynamics of the freight data while simplifying the model for efficient forecasting [25]. The aggregation criterion is:

$$\Delta S_E \leq \frac{\max(S_{Ei} | i = 1, \cdots, K) - \min(S_{Ei} | i = 1, \cdots, K)}{K/2} \tag{5}$$

where: $\{S_{Ei} | i = 1, \cdots, K\}$ represents the sample entropy values of the i-th IMF.

3.2 Temporal convolutional networks

In railway freight forecasting, VMD is utilised to break down freight volume data into multiple IMFs, each capturing unique patterns of fluctuation in freight activity. This decomposition is essential for isolating the underlying temporal features that drive freight dynamics. To effectively utilise these decomposed IMFs, we employ TCN, which excels at selecting convolutional layers across different time scales [26]. This flexibility allows TCN to learn and capture the temporal characteristics inherent in each IMF, thereby enabling more accurate modelling of complex patterns in freight data.

Furthermore, incorporating an attention mechanism into the model ensures that the prediction process concentrates on the most pertinent information. The attention mechanism amplifies the importance of key features, enabling the model to prioritise the most significant temporal patterns influencing freight movements. This integration of VMD, TCN and attention mechanisms creates a robust predictive framework that enhances the accuracy and reliability of railway freight forecasts.

TCN is a variant of a convolutional neural network (CNN), structured as shown in *Figure 1*. The residual block consists of two branches: one branch performs the F transformation on the input data, while the other branch conducts a one-dimensional convolution transformation on the input. The F transformation branch comprises two layers of convolution and nonlinear mapping. For the h-th residual block, the input $X^{(h-1)}$ undergoes residual network processing to yield the output X^h:

$$X^h = \mathrm{ReLU}\left(F\left(X^{(h-1)}\right) + X^{(h-1)}\right) \tag{6}$$

where ReLU denotes the activation function, defined as follows.

$$\mathrm{ReLU} = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \tag{7}$$

After introducing residual networks into the network, the phenomenon of gradient vanishing does not occur, thereby enhancing the robustness of the network. The convolution layers in the residual module are dilated causal convolutions, where the causal convolution ensures that future information does not influence past information. Dilated convolutions are a special convolutional structure, depicted in *Figure 1*. This unique structure allows for a broader receptive field with fewer network layers, improving learning efficiency. It outperforms other neural network models in analysing and learning from time series data.

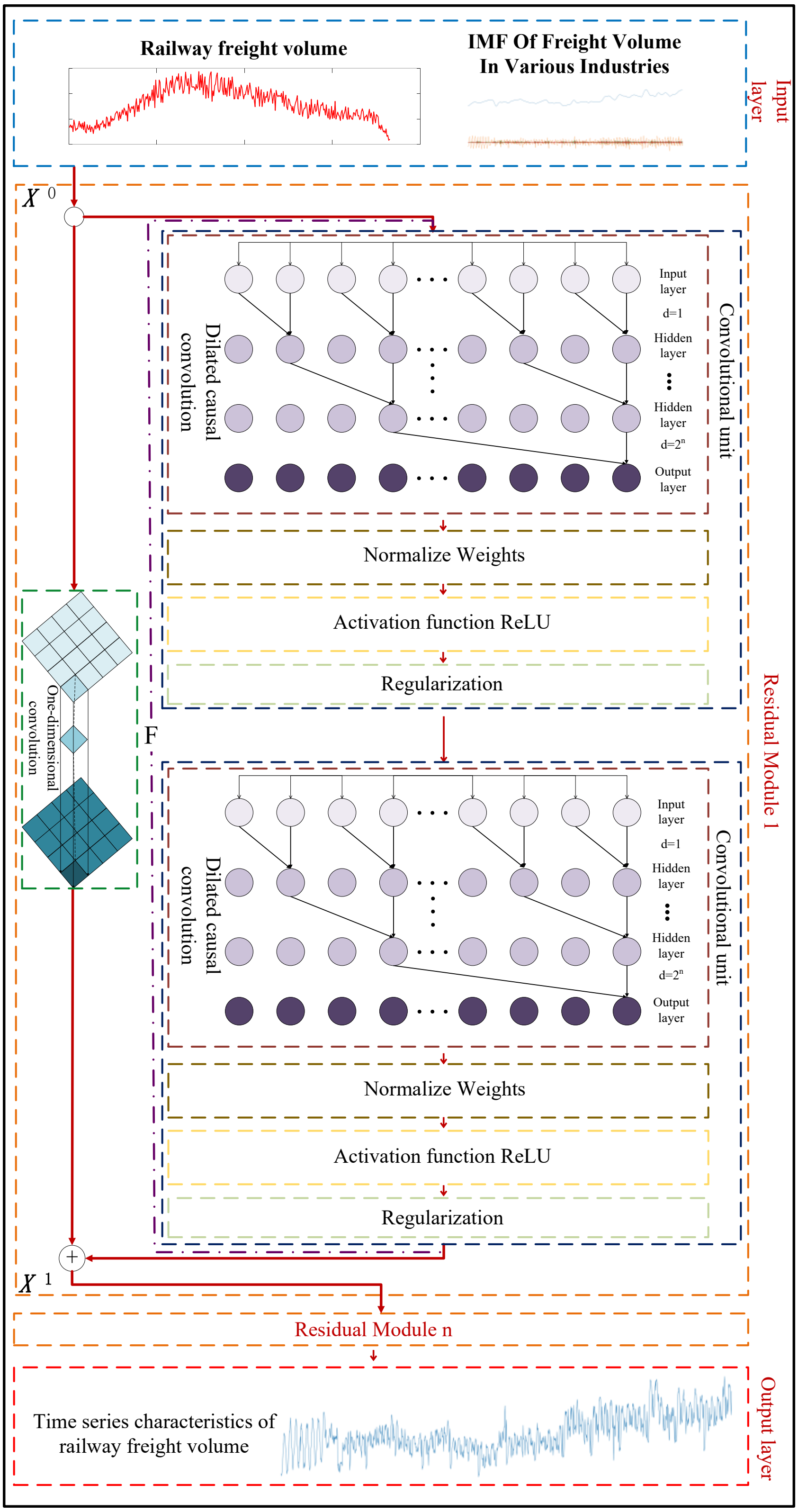


Figure 1 – TCN structure diagram

3.3 Attention mechanism

A TCN enhanced with an integrated attention mechanism can more effectively extract temporal information from railway freight data. The attention mechanism allows the model to focus on the most relevant features within the data, ensuring that significant temporal patterns are prioritised. This combination enhances the TCN's ability to analyse complex freight data, leading to improved accuracy and reliability in forecasting railway freight volumes.

The attention mechanism, first introduced by Bahdanau et al. in machine translation models [27], is inspired by the human visual neural system. It mirrors how the brain focuses on a subset of information that is deemed more important, thereby enabling more efficient resource allocation. In deep learning models, the attention mechanism calculates attention weights α between a query q and a key k using an attention scoring function f. These attention weights are then used to prioritise the selection of values v. The general computational process of the attention mechanism involves the following steps:

1) Compute the attention weight $\alpha(q, k_i)$ of a query q with respect to the i-th key k_i in the database, restricting its value to the range (0, 1) using the softmax function.

$$\alpha(q, k_i) = \text{softmax}\big(f(q, k_i)\big) = \frac{\exp\big(f(q, k_i)\big)}{\sum_{j=1}^{m}\big(f(q, k_i)\big)} \tag{8}$$

2) Perform a weighted sum of the attention weight $\alpha(q, k_i)$ and the corresponding value v_i associated with the key k_i to obtain the attention vector, where m represents the number of key-value pairs k-v in the database.

4. RAILWAY FREIGHT VOLUME PREDICTION MODEL PVS-VMD-A-TCN

The PVS-VMD-A-TCN prediction model begins by cleaning the historical daily loading volume data from freight stations, structuring it into a time series for key stations. To prevent information leakage, the historical data are divided into training, validation and testing sets instead of being decomposed all at once. Freight volumes from various sectors, such as agriculture and industry, are included in the analysis. The VMD algorithm is employed to decompose the data separately, followed by peak-valley segmentation. The decomposition results are then fed into the A-TCN model for training, producing prediction models for individual components. These models generate predictions for the test set, which are subsequently validated through comparison.

The specific steps are as follows:

1) Data processing: Gather historical loading volume data from freight stations. Address any missing data using the mean interpolation method. Then, split the data into training, validation and testing sets in a 6:2:2 ratio.
2) Segmentation and analysis: Segment the total freight volume into peak and valley periods, incorporating data from various industries to elucidate temporal growth trends. Perform VMD on these segments and conduct predictions in stages. Finally, combine the results to achieve an overall freight volume prediction.
3) VMD decomposition: Apply the VMD algorithm to break down the historical freight volume data into N intrinsic mode components along with one residual component.
4) A-TCN model prediction: Develop an attention-based TCN model, where the attention scoring function is defined as $f(q, k_i) = qk_i$, enabling efficient attention mechanisms through dot product operations. The VMD-derived prediction components, segmented using the PVS algorithm, are fed into the Attention-TCN model. Initially, a fully connected layer maps the temporal input data to high-dimensional features, followed by the TCN network extracting relevant information from the temporal data.
5) Combine prediction results: Integrate the prediction outcomes from each component and the segmented part to assess the overall performance of the model predictions.

5. CASE STUDY

This study used real historical data collected from the Shuohuang Freight Railway between 1 January 2013 and 31 December 2016 to validate the performance and effectiveness of the proposed method. Shuohuang Railway spans 242 kilometres from Shensi South Station, 21.9 kilometres from the upstream Guyue Station and 15.3 kilometres from the downstream Sanji Station. The station primarily handles various operations such as inbound and outbound freight trains, technical inspections, loading and unloading of cargoes, assembly and disassembly of ten-thousand-ton train sets, etc. [28]. The computing setup includes a Windows 10 system, 32 GB RAM, and an AMD Radeon RX 6500 XT graphics card. The programming environment is Anaconda 3, and TensorFlow and Keras are used as deep learning frameworks for building neural network models.

5.1 Predictive evaluation indicators

To demonstrate the effectiveness of the proposed method, traditional EMAE, ERMSE and EMAPE were used as evaluation indicators [28]. EMAE, ERMSE and EMAPE are employed as evaluation metrics. EMAE reflects the actual error level of the model. ERMSE indicates the impact of extreme anomalies on predictions; EMAPE represents the average of absolute errors, describing the overall performance of the prediction model. The expressions for these metrics are as follows:

$$\mathrm{E_{MAE}} = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{9}$$

$$\mathrm{E_{RMSE}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{10}$$

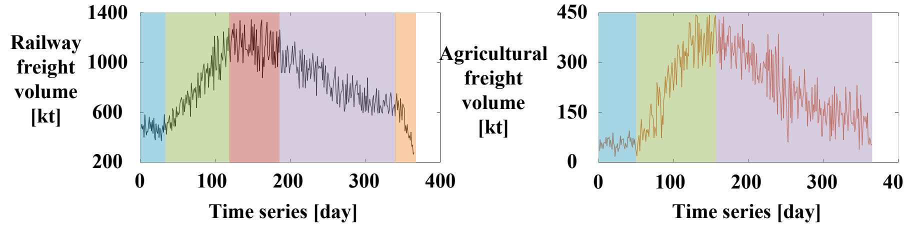
$$\mathrm{E_{MAPE}} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{11}$$

where y_i represents the real freight volume value at time series (i), $\hat{y}_i$ represents the predicted value, and n denotes the number of sampling points.

5.2 Trend segmentation of freight volume increase and decrease

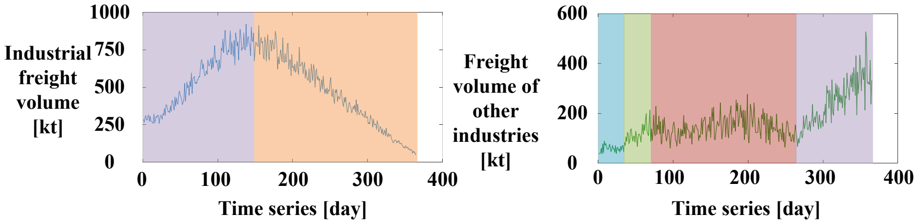
To validate the effectiveness of our proposed method for railway freight forecasting, we conducted a series of comparative experiments using the PVS-VMD-A-TCN model.

Initially, we analysed the total freight volume as well as the freight volumes from industrial, agricultural and other sectors. By employing the peak-valley segmentation method, we assessed the average trends of increase, stability and decrease in freight volume, leading to phase segmentation. For instance, *Figure 2* illustrates the total freight volume of the Shuohuang Railway, along with the freight volumes from the industrial, agricultural and other sectors that constitute the total freight volume, as well as their respective freight phase segmentation results.



(a) Total freight volume

(c) Agricultural freight volume



(b) Industrial freight volume

(d) Freight volume of other industries

Figure 2 – Stage segmentation of freight volume

From *Figure 2(a)*, we can observe that the total freight volume is divided into five segments based on trends of increase and decrease. In January and February, the volume remains stable and low, influenced by factors such as the Chinese New Year holiday. As March approaches, industrial production gradually resumes, leading to an increase in freight volume, which continues to rise until May. From June to July, the freight volume stays at a high level. Between August and November, there is a gradual decline, and in December, the volume decreases further due to year-end settlements and the onset of holidays.

In *Figure 2(b)-(d)*, the industrial freight volume exhibits two main trends because of the industry's development cycle and concentrated shipments in the first half of the year: it rises at the beginning of the year and gradually declines from mid-year toward the end. Agricultural freight volume varies with the seasons, divided into three parts: during the spring planting season, the yield of agricultural products increases, followed by a decrease in freight volume due to temperature changes. Freight volumes from other industries primarily surge at the end of the year, driven by holiday demand and year-end accounting activities.

Based on these segmented phases, we will construct a phased VMD-A-TCN model to conduct predictions in stages, ultimately combining these to produce an overall freight volume forecast.

5.3 VMD decomposition results of freight volume

By applying VMD to both the total freight volume and the freight volumes of various industries, we were able to further extract the periodic variation trends of freight volume over a long-term time scale. As shown in *Figure 3*, the freight volume of the Shuohuang Railway from 2015 to 2016 has been decomposed based on temporal scale characteristics, resulting in sequences at different time scales, including five intrinsic mode functions (IMFs). These IMFs are arranged in order of frequency from low to high, where higher frequency and shorter period fluctuations more accurately reflect the impact of random factors such as GDP, crop yields, and changes in the raw coal and steel markets on railway freight volumes.

IMF1 exhibits a smooth trend and represents the primary component of freight volume changes, acting as a key determinant of variations in railway freight volume with a distinct peak-valley pattern. The fluctuation patterns of IMF2 to IMF5 overlap with certain temporal points that correspond to the segmentation points of freight volume increase and decrease trends, which partially confirms the effectiveness of the peak-valley segmentation method.

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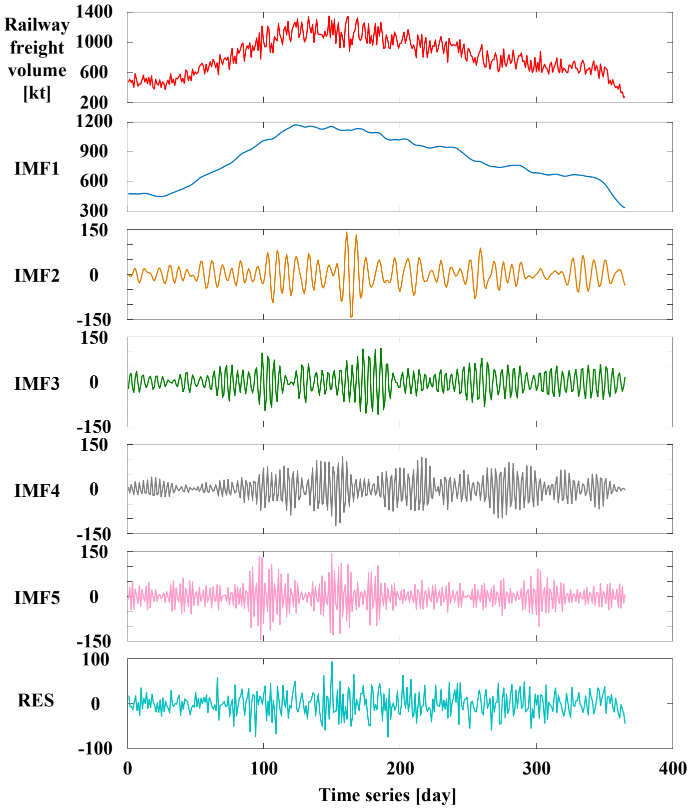

Figure 3 – Total freight volume VMD decomposition

As depicted in *Figures 4* to *6*, the VMD results for freight volumes from the industrial, agricultural and other sectors that comprise the total freight volume are presented. Notably, industrial freight volume constitutes a significant portion of the total freight volume throughout the year, resulting in a growth trend that closely mirrors the overall freight volume. After VMD decomposition, the industrial freight data produced three IMFs. During the peak freight periods in June and July, the industrial freight volume showed considerable volatility, indicating substantial uncertainty when industrial freight approaches its peak levels.

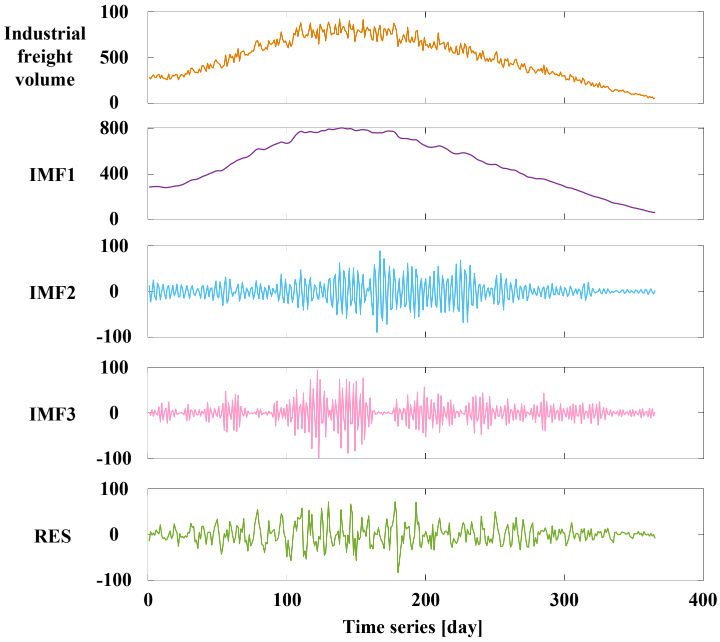

Figure 4 – Industrial freight volume VMD decomposition

The optimal number of IMFs for the agricultural freight data is 3, with IMF2 and IMF3 being particularly prominent during the autumn season. In the peak freight periods of June and July, agricultural freight also showed considerable volatility, suggesting that the uncertainty in agricultural product supplies during the autumn harvest period significantly affects railway freight operations.

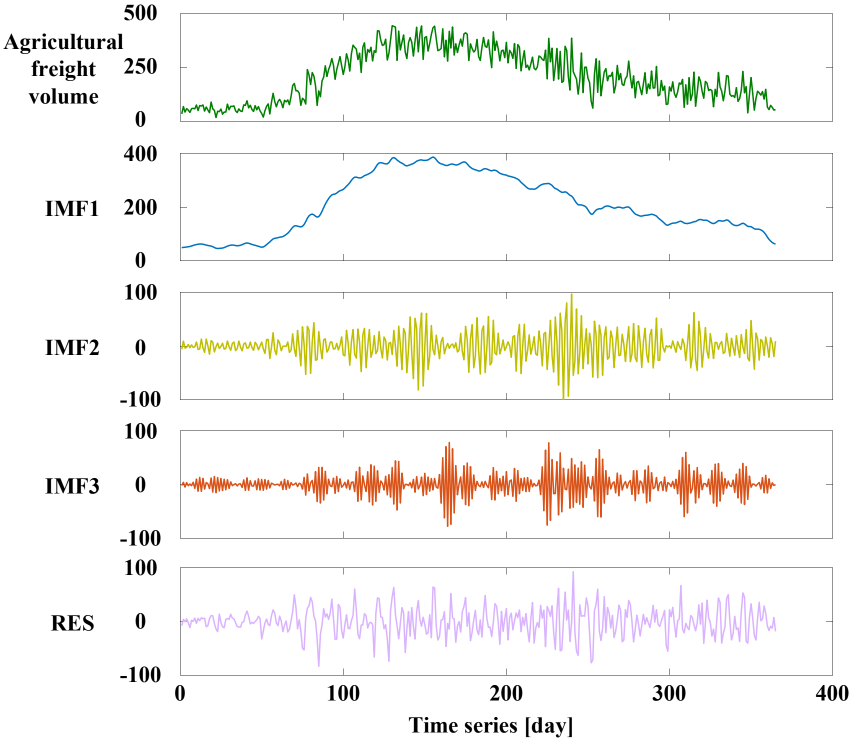

Figure 5 – Agricultural freight volume VMD decomposition

The freight data from other industries, characterised by substantial variability from various sectors, do not display the same level of regularity as the industrial and agricultural data. During the year-end growth period, these data exhibit pronounced volatility.

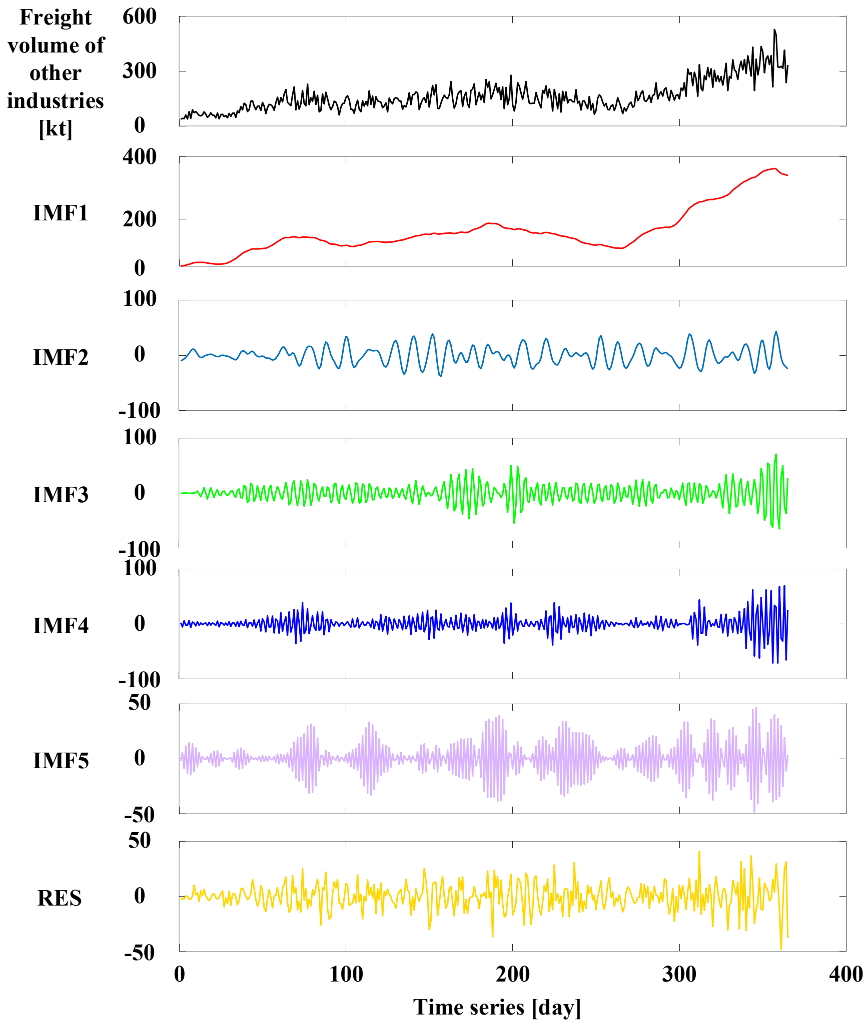

Figure 6 – Other industries freight volume VMD decomposition

5.4 Comparison and discussion of prediction results

To validate the effectiveness of the proposed method, we conducted a comparative analysis against models that exclude the PVS method, exclude the VMD method and other mainstream forecasting techniques.

First, we assessed the impact of the PK method in phased forecasting, as shown in *Figure 7*. During periods of rising and falling freight volumes, the PVS-VMD-A-TCN method demonstrates significantly better predictive performance compared to the VMD-TCN model. This enhancement is due to the peak-valley segmentation, which divides the freight volume into distinct phases with clear upward and downward trends. By forecasting each phase individually, the model can more effectively identify key features within the data.

Analysis of the simulation results shows that our model can accurately track actual railway freight volume trends, particularly during phases of increase and decrease, where predicted values closely match actual values. This accuracy is largely due to the peak-valley segmentation method, which effectively segments freight volume data according to trends, reducing data complexity and allowing the model to learn under more stable conditions. The VMD decomposition breaks down the data into modes of different frequencies, significantly reducing noise interference and highlighting important patterns within the data. This process provides clearer input features for the TCN. Additionally, the inclusion of the attention mechanism enables the TCN to better identify and focus on critical time steps, thereby enhancing the model's predictive capability over long time series and its ability to capture key information. The incorporation of the PKS stage segmentation method further enhances the model's prediction accuracy during phases of data increase and decrease.

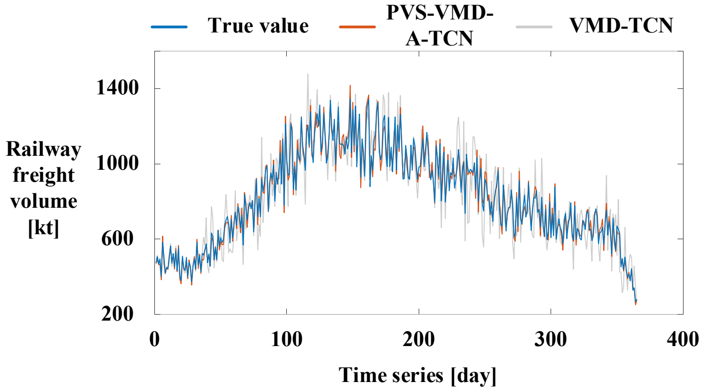

Figure 7 – Comparison of the impact of the PVS method on railway freight volume prediction

Comparing the impact of using VMD decomposition on the prediction algorithm, as shown in *Figure 8*, reveals that predictions made after applying VMD decomposition are significantly more accurate during the peak freight volume periods from June to August than those made without using the VMD algorithm. This improvement arises because VMD decomposition allows the model to analyse and predict specific fluctuating patterns, enabling it to more effectively learn and capture the variations associated with freight volume fluctuations, leading to more precise predictions.

From *Figure 8*, we can see significant differences in the performance of the PVS-VMD-A-TCN model compared to the PVS-TCN model in predicting railway freight volumes. The predictions from the PVS-VMD-A-TCN model are much closer to the actual values, especially during periods of high data volatility, demonstrating greater accuracy and stability. This advantage is primarily attributed to the VMD decomposition process, which effectively reduces noise and data non-stationarity by breaking down complex time series signals into modes of different frequencies. This allows the model to concentrate on learning the critical patterns within the data. In contrast, the PVS-TCN model, lacking the VMD decomposition step, is more susceptible to noise interference, leading to a decline in prediction accuracy during periods of high fluctuation. Overall, the introduction of VMD decomposition provides the PVS-VMD-A-TCN model with clearer and more organised data features, enhancing its predictive performance and adaptability to complex temporal trends.

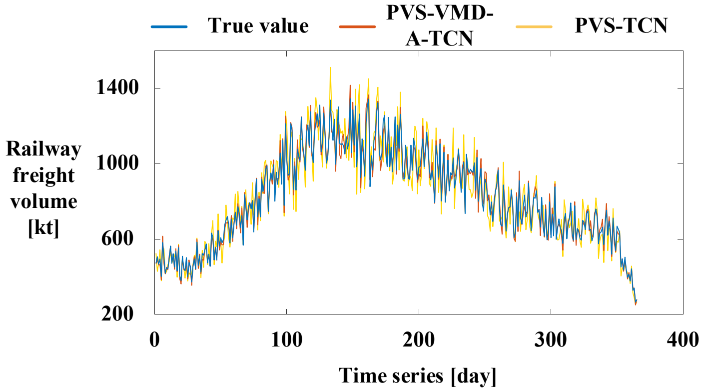

Figure 8 – Comparison of the impact of the VMD method on railway freight volume prediction

From *Figure 9*, it is clear that the PVS-VMD-A-TCN model significantly outperforms traditional GRU and ARIMA methods in predicting railway freight volumes. The prediction curve of the PVS-VMD-A-TCN model closely follows the actual values, especially during periods of high volatility, demonstrating greater stability and accuracy. Although the GRU model has certain advantages in capturing nonlinear relationships, it is susceptible to noise interference when handling complex time series signals, resulting in prediction biases. Meanwhile, the ARIMA model, as a classic linear approach, performs adequately for short-term predictions but exhibits significant weaknesses when dealing with nonlinear and non-stationary data.

The PVS-VMD-A-TCN model effectively reduces noise and complexity in the data through peak-valley segmentation and VMD decomposition, allowing the TCN to focus on learning critical patterns within the data.

Additionally, the inclusion of the attention mechanism enhances the model's capacity to capture long-term dependencies in sequences. Consequently, the PVS-VMD-A-TCN model demonstrates superior adaptability and predictive performance across various forecasting stages and complex prediction scenarios, making it particularly well-suited for predicting nonlinear and non-stationary long-cycle data.

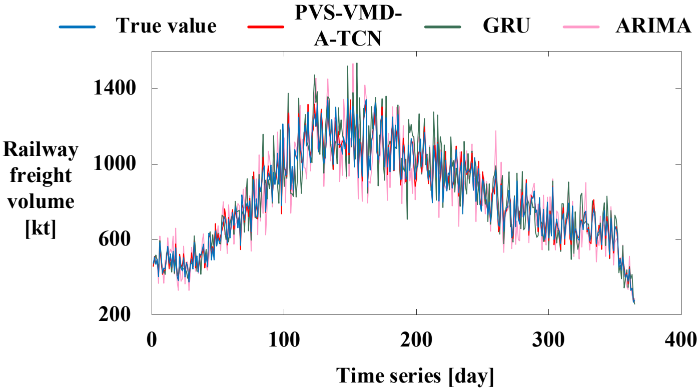

Figure 9 – Comparison of the PVS-VMD-A-TCN method with other prediction methods

Table 1 –Comparison of prediction results using different methods

	E_{MAE}	E_{RMSE}	E_{MAPE}%
PVS-VMD-A-TCN	36.68	47.02	4.51
VMD-TCN	59.01	79.11	8.62
PVS-TCN	54.5	69.20	6.69
ARIMA	77.40	96.82	9.23
GRU	70.7	90.86	9.03

As shown in *Table 1* and *Figure 10*, the radar chart illustrates that the PVS-VMD-A-TCN model excels in MAE, RMSE and MAPE error metrics, with values closest to the centre, indicating high predictive accuracy and stability. In contrast, the GRU and ARIMA models display larger error values, with ARIMA particularly underperforming in handling nonlinear and volatile data. Although the VMD-TCN model shows some improvement, it still falls short in error control compared to the PVS-VMD-A-TCN model.

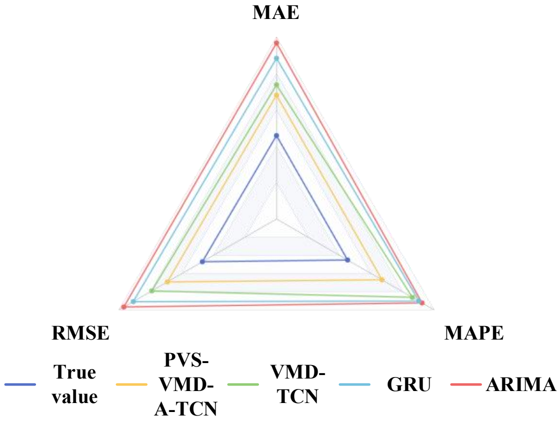

Figure 10 – Comparison of prediction methods for radar

When forecasting long-term railway freight volumes, several key considerations should be kept. First, data preprocessing and decomposition are crucial. Techniques such as VMD can effectively reduce noise and complexity. Second, model selection should prioritise the ability to capture nonlinear patterns and long-term dependencies, with attention mechanisms significantly enhancing predictive precision. Additionally, it is important to balance model complexity with computational cost to ensure efficiency and feasibility in practical applications. Finally, continuously optimising and adjusting the model based on real-world scenarios is essential for addressing dynamic changes and unforeseen events, thereby ensuring accurate and reliable long-term predictions.

6. CONCLUSION

Accurate long-term forecasting of railway freight volume presents significant challenges due to the diversity of cargo types and the multitude of influencing factors. Current forecasting algorithms often prioritise exploring potential relationships within multivariate data, sometimes overlooking the exploration of the inherent physical cyclical patterns in railway freight transportation. However, railway freight exhibits distinct seasonal characteristics and pronounced temporal and periodic patterns. Furthermore, different industries exhibit varying freight volume characteristics evolving over time. To address these issues, this paper segments the multivariate data into distinct phases to highlight seasonal variations. By identifying fluctuation patterns within these phases, long-term changes in railway freight volume can be better uncovered. Building upon this approach, this paper proposes a novel TCN-based forecasting model, PVS-VMD-A-TCN, which integrates peak-valley segmentation (PVS), variational mode decomposition (VMD) and an attention mechanism. The model first segments long-term railway freight volume data into distinct phases to capture periodic patterns. It then employs VMD decomposition categorised by industry to analyse the evolving freight volume patterns specific to different sectors. A temporal convolutional network (TCN) enhanced with a comprehensive attention mechanism is utilised for individual forecasting within these segments and decomposed components. Finally, these individual forecasts are aggregated to produce the annual railway freight volume prediction. Analysis and forecasting based on freight data from the Shuohuang Railway demonstrate that the PVS-VMD-A-TCN method achieves significantly higher prediction accuracy compared to conventional methods such as ARIMA, GRU and the standard TCN. This approach not only reflects the long-term impact of deterministic factors on freight volume but also effectively captures the influence of random factors on freight fluctuations. However, when confronted with irregular external shocks or unprecedented fluctuations, the model exhibits limitations in generalising and inferring patterns solely from adjacent temporal data. Therefore, future research will focus on further enhancing the model's generalisation capability. This will involve exploring interval probability forecasting techniques to analyse the evolution of long-term railway freight volume, aiming to meet a broader range of practical forecasting needs.

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