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Green Supply Chain Demand Forecasting Based on Adaptive Decomposition and Graph Neural Networks

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Abstract. *Recently, the green supply chain management model, which integrates environmental impact and resource efficiency, has gradually received widespread attention from all sectors of society. However, owing to the serious uncertainty of product market demand in green supply chain, it will have an important impact on the supply chain management efficiency of enterprises. On the ground of this, this article designs a green supply chain demand forecasting method based on adaptive decomposition and graph neural network (GSCDF). Firstly, relied on the results of spectral division, the Variable Modal Decomposition (VMD) algorithm is optimized by calculating the number of effective components in each sub-modal state by calculating the time-domain negentropy index. Secondly, the optimized VMD decomposition method is adopted to decompose the factors affecting the inventory cost of supply chain into sub-modal IMF sequences and trend terms at different scales, and the new sequences are obtained by weighted summation. Then the dynamic attention mechanism and bidirectional mechanism are introduced into the Graph Attention Network (GAN) to fully integrate the feature information of the influencing factor indicator nodes as well as their neighbours to extract the spatial features and improve the prediction accuracy. Finally, the experimental outcome indicates that compared with the existing models, the GSCDF method has higher Accuracy, Recall, Precision and F1, and the prediction cost is almost the same as the actual cost.*
Keywords: Green supply chain; adaptive decomposition; graph neural network; graph attention networks; demand forecasting

1. **Introduction.** Recently, in the face of the serious ecological environment and resource problems, people's demand for a better life continues to rise, environmental awareness is getting stronger and stronger, and their living habits are gradually tilted in the direction of green environmental protection [1]. For the purpose of meeting the requirements of sustainable growth and reduce the dependence of products on the environment and resources, enterprises upstream and downstream of the supply chain need to actively improve the greening level of the product supply chain. However, when eco-transitioning, enterprises will invest more costs, and these additional costs will cascade down the supply chain and eventually be transferred to consumers [2, 3]. Whether consumers are willing to bear the extra costs is the main source of driving force for companies to develop green strategies. However, green products currently create uncertainty about the interests of all parties in

the green supply chain due to their own high production costs and high prices. Thus, how to forecast the green supply chain demand, in improving the green supply chain benefits of enterprises, has become a common concern of business and academic communities [4, 5, 6].

1.1. **Related work.** Hall [7] provides a comprehensive design of a green supply chain demand forecasting model to harmonise supply chain management with environmental management. Fang et al. [8] focuses on green product pricing forecasting, and uses game theory to investigate the effects of consumers' green preferences and manufacturers' output uncertainty. Hong and Guo [9] focus on environmental performance, and also introduce the effect of corresponding contracts on supply chain demand forecasting. Yang and Zhang [10] investigate the effects of manufacturers' loss aversion and product development efficiency on green supply chain demand forecasting in actual sales. Rani et al. [11] pointed out that there is a correlation between the demand for green products in actual sales, and based on this, they developed a multi-product supply chain inventory demand forecast. Currently, deep learning methods and techniques have been successfully applied to the problem of green supply chain demand forecasting. Akbari and Do [12] constructed a statistical model using the values of time series to predict future price movements. Sharma et al. [13] used machine learning components such as artificial neural networks to improve and augment validated supply chain demand forecasting models. Ghazal and Alzoub [14] used new hybrid models and neural networks to improve the performance of the above models. Ma et al. [15] used a neural network structure combining bilinear projection ideas, intelligent selection and temporal attention mechanisms to predict future cost-price trends in green supply chains.

The above-mentioned time series forecasting models cannot solve the nonlinear fitting problem well, so Graph Neural Network (GNN) based is a suitable class of model to deal with serial data [16, 17]. Wang [18] designed a green supply chain demand forecasting model based on graph theory and deep neural network. Zhu et al. [19] argued that this traditional demand forecasting method is computationally time-consuming, and aggregates k-order neighbourhood features on the Laplacian matrix of the graph to compute the forecast. Jaipuria and Mahapatra [20] combined GNN with LSTM and then introduced residual connectivity for green supply chain demand prediction. Fanoodi et al. [21] extracted the temporal features using gated convolutional neural networks but the prediction accuracy was not high. Li et al. [22] combined Graph Attention Network (GAN) with LSTM to extract features of green supply chain. However, the factors affecting the green supply chain are non-smooth time series, and modal decomposition technique is considered to be introduced to decompose the factors into a set of smooth submodalities. Rekabi et al. [23] proposed a hybrid model based on data preprocessing and analysis and combining Empirical Modal Decomposition (EMD) and neural network to predict the supply chain cost of green products. However, the prediction results were inaccurate. To improve the prediction accuracy, Nurjanni et al. [24] enhanced the EMD algorithm by wavelet transform and decomposed the indicators affecting the inventory cost of green supply chain into sub-sequences, and then predicted it by BP neural network with multi-layer perceptron type, and the root mean square error of the hybrid model was significantly reduced after comparison.

1.2. **Contribution.** The above green supply chain demand forecasting method combining EMD and neural network model does not fundamentally solve the issue of modal overlapping in the EMD algorithm, which leads to poor forecasting accuracy. To address the above issues, this article firstly enhances the variationnal mode decomposition (EVMD) algorithm by calculating the time-domain negentropy index of each sub-mode, distinguishing the singular value pairs corresponding to the effective frequency components, and reconstructing them to achieve adaptive decomposition of the original signals, and to improve the smoothness of the sequences. Then the factors affecting the green supply chain are decomposed into Intrinsic Mode Functions (IMFs) with different frequency ranges using the EVMD method, and the dynamic attention mechanism and bidirectional mechanism are introduced into the graphical attention network (GAN), which fully integrates the feature information to extract the spatial features, and the prediction accuracy can be improved. Finally, the prediction results are output through graph neural network (GNN). The results show that the GSCDF method has high prediction accuracy and can be better applied to green supply chain demand forecasting.

2. Theoretical analysis.

2.1. Graphical attention neural network.

GAN [25] adopt an attention mechanism approach to extract features from each node in the graph, adaptively assigning different weights to each neighbouring node in an attentional manner, weighted summing and updating nodes. By way of graph attention, the representation of nodes is greatly enriched, the aggregation of knowledge is achieved, and the prediction efficiency of the model is improved.

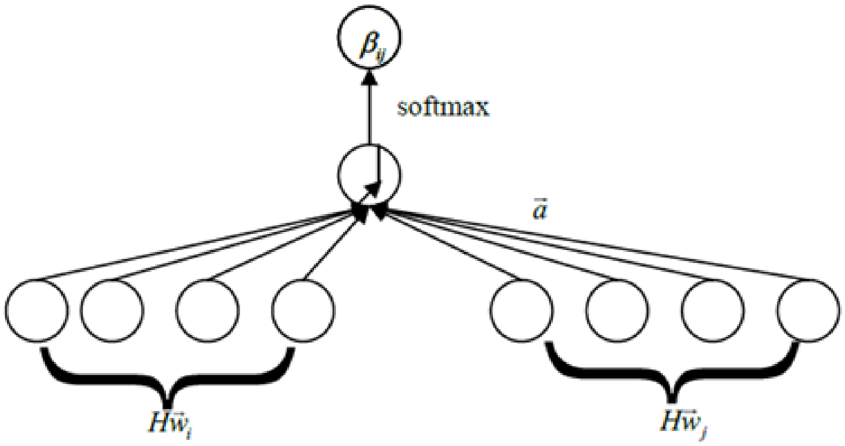

Figure 1. Graphical attention network

The input to the GAN is a collection of feature vectors of multiple nodes w. The feature vectors of all the nodes in the graph are used as inputs to the graph attention network, which is processed by the graph attention network, which results in the output w', i.e., $w' = \{\vec{w}_1, \vec{w}_2, ..., \vec{w}_M\}, \quad \vec{w}_j \in \mathbb{R}^N$, which is a new collection of node vectors. Where M denotes the number of input nodes and N denotes the number of features per node, which represents the high-dimensional feature vector of a node. Figure 1 illustrates the way in which attention coefficients are calculated and information is aggregated between nodes in a GAN.

A weight matrix $H \in \mathbb{R}^{N\times N}$ is adopted for mapping the relationship between input features and output features. The attention mechanism a is then used to compute the attention coefficient β_{ij}, defined as $f_{ij} = a(H\vec{w}_i, H\vec{w}_j).$, f_{ij} denotes the influence of node i on node j.

Using the *relu* nonlinear activation function, the attention coefficients of vertex i with its neighbour node j are computed as follows:

$$f_{ij} = \text{Relu}\left(\vec{a}^T \left[H\vec{w}_i \| H\vec{w}_j\right]\right), \tag{1}$$

where $\|$ denotes concatenation and T denotes matrix transposition. Then the neighbours of the current central node are normalised using the *softmax* function:

$$\beta_{ij} = \text{softmax}(f_{ij}) = \frac{\exp(f_{ij})}{\sum_{l \in N_i} \exp(f_{il})}. \tag{2}$$

Finally, the output features $\vec{w}_i' = \delta\left(\sum_{j \in N_i} \beta_{ij} \vec{w}_{ij}\right)$ are weighted and summed to get the updated node features.

(1) By means of the Hilbert transform, the different modal components $\rho_l(s)$ can be transformed into the corresponding analytical signals, so that their spectra can be calculated.

2.2. **Variational modal decomposition.** Variational Modal Decomposition (VMD) algorithm [26] is an enhanced EMD algorithm, which combines the processing of adaptive noise to decompose a nonlinear or unsteady signal into a set of EMD, which improves the signal-to-noise ratio and the accuracy of the decomposition, and it has the advantages of better time-frequency localisation characteristics and adaptive noise processing, no modal aliasing and so on. The specific implementation steps are as follows.

$$r(s) = \left[\ \vartheta(s) + \tfrac{j}{\pi s}\ \right] \rho_l(s) \tag{3}$$

(2) By predetermining a centre frequency $e^{-jh_l s}$, it is possible to modulate signals of different modes into a specific fundamental frequency band.

$$f(s) = \left[\left(\vartheta(s) + \frac{j}{\pi s}\right) \rho_l(s)\right] e^{-jh_l s} \tag{4}$$

(3) The gradient squares of the different demodulated signals are determined by taking the L^2-paradigm number and the bandwidth of each modal signal is estimated by solving the possible constrained variational problem.

$$\min_{\{\rho_l\},\{h_l\}} \{\ \sum_l ||\partial_s[\left(\vartheta(s) + \frac{j}{\pi s}\right) \rho_l(s)]e^{-jh_l s}||\ {}^2_2\} \tag{5}$$

where $\sum_l \rho_l = w$, $\{\rho_l\}$ are the L IMFs obtained from the decomposition and ϑ denotes the centre frequency corresponding to each mode.

(4) Introduce quadratic penalty factor β and Lagrange multiplier operator $\lambda(s)$ to compute the unconstrained variational problem.

$$\begin{aligned} L(\{\rho_l\}, \{h_l\}, \lambda) = \beta \sum_l ||\partial_l \left[\left(\vartheta(s) + \frac{j}{\pi s}\right) \rho_l\,(s)\right] e^{-jh_l s}||_2^2 \\ + ||w(s) - \sum_l \rho_l\,(s)\,||_2^2 + \prec \lambda(s), w(s) - \sum_l \rho_l(s) \succ \end{aligned} \tag{6}$$

(5) Solving Equation (6) yields the "saddle point" of the unconstrained variational problem, which is the final solution of Equation (5).

3. **Optimization of variational modal decomposition algorithms.** On the ground of singular transform [27], an enhanced VMD (EVMD) algorithm is suggested. EVMD is relied on the outcome of spectral segmentation, and the number of effective components is achieved by calculating the negative entropy index in the time domain of the sub-modalities, so as to differentiate the pairs of singular values corresponding to the effective frequency components, and then the effective singular values are extracted to

be reconstructed and the amplitudes in the reconstructed results are restored, so as to achieve adaptive decomposition of the original signals, and to improve the smoothness of the sequences.

(1) Selection of reconstruction components. Firstly, the frequencies in the divided i-th band are ranked $(i = 1, 2, ..., n)$ in order of magnitude from largest to smallest to obtain the frequency ranking matrix $S_i = [f_1^i, f_2^i, ..., f_j^i]$, where j is the bandwidth of the i-th band. Secondly, a set of sinusoidal signals $xs^i(r)$ with amplitude 1, frequency magnitude f^i and phase $\Phi(f^i)$ is constructed, where r is the modal component, $1 \leq l \leq j$.

$$xs_l^i(r) = \sin\left(f_l^i \times 2\pi r + \Phi(f_l^i)\right) \tag{7}$$

$$xs^i(r) = \left[xs_1^i(r); xs_2^i(r); \ldots; xs_j^i(r)\right] \tag{8}$$

After that, the first $w(w = 1, 2, ..., l)$ signals of the sinusoidal signal group $xs^i(r)$ are taken to be superimposed in turn, respectively, and the result obtained after superposition is denoted as $xt_w^i(r)$. The time-domain negentropy of the superimposed signals is computed by using Equation (9), and is denoted as R_w^i.

$$R_w^i = \prec \frac{(xt_w^i(r))^2}{\prec (xt_w^i(r))^2 \succ} \ln\left[\frac{(xt_w^i(r))^2}{\prec (xt_w^i(r))^2 \succ}\right] \succ \tag{9}$$

where $\prec \cdot \succ$ denotes the mean value calculation.

Finally, the number of effective frequencies in the frequency band b_i $(b_i = \arg\max(R^i))$ is calculated using the time-domain negentropy sequence R^i for each submodule. The first b_i frequencies $f_{s_1}^i, f_{s_2}^i, ..., f_{s_b}^i$ in the frequency ranking matrix S_i are the components of the i-th sub-module that need to be reconstructed.

(2) Magnitude enhancement. The amplitude enhancement was performed on the modal components to be reconstructed in each frequency band. The amplitude-enhanced frequency band signals $xE_i(r), \quad i \in [1, m]$ were constructed according to Equation (10).

$$xE_i(r) = x(r) + \sum_{l=1}^{b_i} y_{\max} \times \sin\left(f_l^i \times 2\pi r + \Phi\left(f_l^i\right)\right) \tag{10}$$

where $y_{\max}$ denotes the maximum value of the amplitude in the frequency band.

(3) The amplitude-enhanced signal $xE_i(r)$ is modally decomposed, and the first $2b_m$ singular values of $xE_i(r)$ are selected according to the amplitude filtering characteristics to reconstruct the component signal, which is denoted as $xE_i'(r)$. To ensure the stability of the signal sequence, it is necessary to recover the amplitude information in the reconstructed result. Then the final modal decomposition result $xd_i(r)$ is as follows.

$$xd_i(r) = xE_i'(r) - \sum_{l=1}^{b_i} y_{\max} \times \sin\left(f_l^i \times 2\pi r + \Phi\left(f_l^i\right)\right) \tag{11}$$

(4) The final decomposition results of all modes are obtained through cyclic iteration, and then each decomposed component is subjected to envelope demodulation processing to extract the characteristic information of the indicators affecting the green supply chain, which lays the foundation for the subsequent demand forecasting.

4. **Green supply chain demand forecasting based on adaptive decomposition and graph neural networks.**

4.1. **Preprocessing and adaptive decomposition of factors influencing green supply chain demand forecasting.** This article suggests a green supply chain demand forecasting method based on adaptive decomposition and GNN (GSCDF). As shown in Figure 2, the method firstly normalises the factor indicators affecting the inventory cost of green supply chain, and decomposes the influencing factors into Intrinsic Mode Functions (IMFs) with different frequency ranges by using the EVMD method, so as to reduce the difficulty of forecasting. Then the dynamic attention mechanism and bidirectional mechanism are introduced into the graph attention network, which can improve the prediction accuracy by fully integrating the feature information of the influencing factor indicator nodes and their neighbours to extract the spatial features. Finally, the prediction results are outputted through GNN.

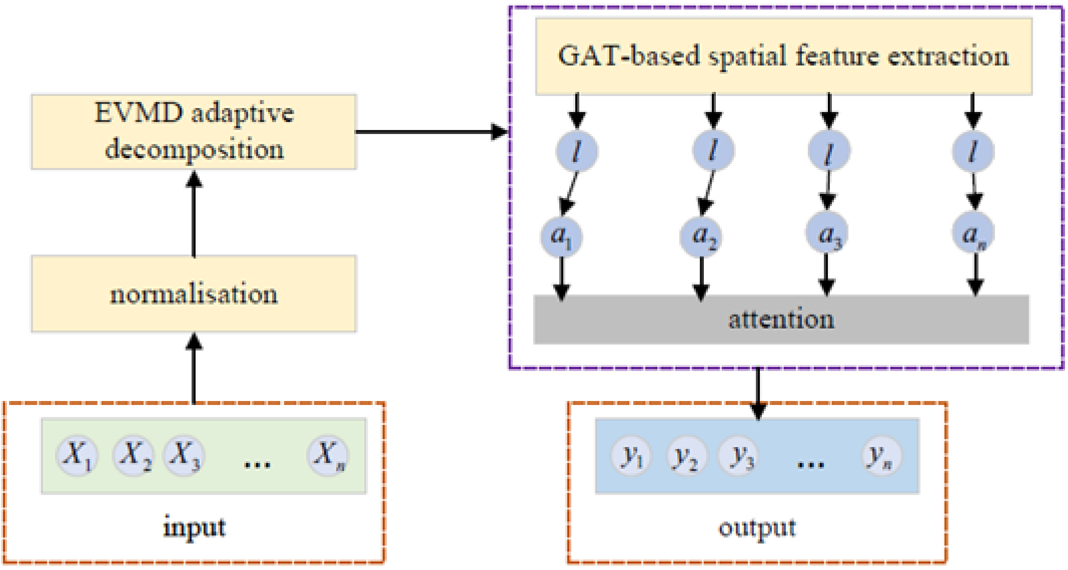

Figure 2. The flowchart of the proposed GSCDF method

To achieve an accurate prediction, it is necessary to analyse the indicator factors affecting the demand of green supply chain [28], which can be derived from the indicators of its influencing factors: operation status, marketing activities carried out, the approval time of the procurement application, the execution time of the procurement process, the time of the procurement of the product acceptance into the warehouse, the total number of user groups, and the transaction price, etc., which is denoted as $\{X_i \mid i = 1, 2, ..., n\}$, and the cost of inventory of the green supply chain, which is denoted as X_0.

For the purpose of eliminating the effect of magnitude on the prediction model, normalisation is adopted to make the model converge faster while reducing the computational complexity. Normalisation compresses all the data to between $[0, 1]$.

$$X_i^* = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{12}$$

where X_i^* represents the data obtained after normalisation of the original data, X_i represents the original data to be normalised, $X_{\min}$ represents the minimum value in the data and $X_{\max}$ represents the maximum value in the data.

As there are many influencing factors, it is difficult to separate them after their interactions are superimposed. In this paper, the above EVMD method is adopted to decompose the influencing factors into sub-modal IMF series and trend terms of different scales, and the statistical method of T-test is used to filter the high-frequency series. Then the new series are summed up to get the new series. The steps are as follows.

(1) Initialise the set size M, $l = 1$.

(2) Calculate standard deviation $\varepsilon_X = std[X(s)]$ of the signal to be decomposed, construct the auxiliary noises $e_1(s), e_l(s) \sim N(0,1)$, and add the auxiliary noises to $X(s)$ in pairs.

$$\begin{cases} z^{l+}(s) = X(s) + b \cdot \varepsilon_X \cdot e_l(s), \\ z^{l-}(s) = X(s) - b \cdot \varepsilon_X \cdot e_l(s), \end{cases} \tag{13}$$

where b is the auxiliary noise amplitude.

Using EVMD to decompose $z^{l+}(s)$ and $z^{l-}(s)$, two sets of intrinsic modal functions are obtained: $\{E_i^{l+}(s)\}_{i=1}^{M}$ and $\{E_i^{l-}(s)\}_{i=1}^{M}$, where $E_i^{l+}(s)$ is the i-th IMF obtained from the decomposition of $z^{l+}(s)$. A complementary IMF is obtained by averaging as follows:

$$E_i^l(s) = \frac{E_i^{l+}(s) + E_i^{l-}(s)}{2}. \tag{14}$$

If $l < M$, then set $l = l + 1$, return to step (2), else perform step (5).

By performing median operations on the modal functions of each order in the N sets of complementary IMF, the final result $\{E_i(s)\}_{i=1}^{M}$ is obtained:

$$E_i(s) = \text{median}\{E_i^1(s), E_i^2(s), \dots, E_i^M(s)\}. \tag{15}$$

4.2. **Spatial feature extraction of influential factors based on graph attention networks.** After EVMD decomposition of the influencing factors, the historical interaction information can be used to obtain the inventory cost-influence factor pair $\langle X_0, X_i \rangle$. Similarly, based on product attributes, the influence indicator-green product characteristics pair $\langle X_i, G \rangle$ and the user characteristics pair $\langle X_0, G \rangle$ are generated. The matrix R is constructed accordingly. The final adjacency matrix B of the generated graph is

$$B = \begin{bmatrix} 0 & R \\ R^T & 0 \end{bmatrix}, \tag{16}$$

where R denotes the interaction matrix between inventory cost and influencing factors, and R^T is its transpose.

Feature vectors of inventory cost nodes and impact factors are represented by high-dimensional vectors. Let h_M denote the inventory cost and impact factor feature vectors, and l_M denote the embedded high-dimensional vector:

$$h = [h_1, h_2, ..., h_M]. \tag{17}$$

Then, GAN computes the attention coefficient $e_{i,j}$ of the current node and its neighbors as

$$e_{i,j} = \varphi(V\vec{h}_i, V\vec{h}_j). \tag{18}$$

where $\varphi(\cdot)$ denotes that defining a $\vec{b} \in \mathbb{R}^{2M}$ and then splice the mapped vectors to make an inner product with $\vec{b}$, V denotes the feature vector of inventory cost, and finally activate it with *relu* as shown in Equation (19).

$$e_{i,j} = relu\big(\vec{b}^T [V\vec{h}_i \| V\vec{h}_j]\big) \tag{19}$$

To facilitate the weighting of the aggregated information, the resulting $e_{i,j}$ is Softmax normalised so that all weights sum to 1.

$$\beta_{i,j} = Softmax_j(e_{i,j}) = \frac{\exp\left(relu(\vec{b}^T[V\vec{h}_i \| V\vec{h}_j])\right)}{\sum_{l \in N_i} \exp\left(relu(\vec{b}^T[V\vec{h}_i \| V\vec{h}_l])\right)} \tag{20}$$

Secondly, the neighbourhood information is aggregated with its own information according to certain weights to form a new representation of the node's features, which contain the spatial information of the influencing factors.

$$\vec{h}_i^s = \delta\left(\frac{1}{L}\sum_{l=1}^{L}\sum_{j \in N_i} \beta_{i,j}^l V^l \vec{h}_j\right) \tag{21}$$

where δ is the activation function.

The final supply chain inventory cost influencing factor characterisation is expressed as Equation (22).

$$e_{X_i} = relu\left(\sum_{h=1}^{H}\sum_{G=1}^{M} \beta_{X_i}^{m(h)}\left(V_h^{(h)} e_{X_i}^{m(h)}\right)\right) \tag{22}$$

where $\beta_{X_i}^{m(h)}$ and $e_{X_i}^{m(h)}$ denote the extent to which the influencing factors affect the inventory cost, and m denotes the number of total feature combinations.

4.3. **Green supply chain demand forecasting based on adaptive decomposition and GNN.** The historical interaction information between the inventory cost and the influencing factors is a reliable source of model training data, based on the existing data information to build a suitable graph neural network model, as indicated in Equation (23).

$$m_{X_i \to X_0}^{(l)} = \frac{1}{\|X_i\|\|N_i\|}\left(V_1^{(l)} e_{X_i}^{(l-1)} + V_2^{(l)} e_{F_i}^{(l-1)} + V_3^{(l)}\left((e_i^{(l-1)} \oplus e_{F_i}^{(l-1)}) \odot e_{il}^{(l-1)}\right)\right) \tag{23}$$

where e_{X_i} and e_{F_i} denote the influencing factors and green products; V_1, V_2, V_3 denote the coefficient matrices of the science system; e_i denotes the embedded representation of the green products; l denotes the current number of layers; $\oplus$ and $\odot$ denote the addition and multiplication of the corresponding positional elements of the matrix, respectively.

By stacking the multilayer networks, the magnitude of correlation between the current node and its non-direct neighbours can be characterised. The green product feature vector after passing through the L-layer graph neural network is indicated in Equation (24).

$$e_i^{(L)} = relu\left(m_{i \leftarrow i}^{(L)} + \sum_{i \in N_{X_i}} m_{i \leftarrow X_i}^{(L)}\right) \tag{24}$$

where $e_i^{(L)}$ denotes the final green product feature vector obtained, L denotes the number of layers of the GNN, $\sum_{i \in N_{X_i}} m_{i \leftarrow X_i}^{(L)}$ denotes the L-th layer neighbour convergence of the influencing factors to the product, and $m_{i \leftarrow i}^{(L)}$ denotes the self-convergence process from the green product to the product itself.

After the above calculations, the dot product of the embedded representation of the inventory cost and the embedded representation of the different types of green products is used to indicate the correlation of the inventory cost for each type of product. The output of the prediction results is implied in Equation (25).

$$X_0 = y(X_i, l, f) = e_{X_i}^T e_i \tag{25}$$

where $y(\cdot)$ denotes the proposed model, i denotes the set of input green products, f denotes the set of input product features, e_{X_i} denotes the vector representation of the final output of influencing factors, and e_i denotes the vector representation of green products.

5. **Performance test and analysis.**

5.1. **Comparison of inventory cost prediction results for green supply chain with different models.**

To estimate the performance of the proposed method, the inventory cost data of a green product manufacturer and the data related to the influencing factors from 2010 to 2020 are selected to establish the GSCDF forecasting method designed in this paper, the MSCIC method proposed by the literature [14], the ADDNP method proposed by the literature [22] and the SCDAM method proposed by the literature [24]. The forecasting results of these methods are compared and analysed. All experiments were done on a personal computer with Python V3.8 platform for programming and Tensorflow 2.1 framework to build the algorithmic model. The specific parameters of the model are implied in Table 1.

Table 1. Model parameter setting

Network layer	**Parameter settings**
EVMD	$\beta = 1000$, VMD=uniformly distributed
GNN	Layer=2, Kernel_nums=20, Kernel_size=40, Strides=25
Learning_rate	0.001
Dropout	0.05
Activation function	relu

This experiment investigates the inventory cost data of green supply chain. The order data of a green product manufacturing company is taken, and the sales volume data from January 2010 to December 2014 is selected as the training sample, and the sales volume data from January to December 2020 is selected as the test sample. The input sample size is set to 48, and the prediction length of each dataset is divided into two groups of 4 and 12.

Table 2. Predictions of models with different evaluation indicators

Predicted length	**Norm**	**MSCIC**	**ADDNP**	**SCDAM**	**GSCDF**
4	MAE	0.294	0.218	0.154	0.113
	MSE	0.192	0.175	0.093	0.071
	RMSE	0.429	0.394	0.305	0.287
12	MAE	0.417	0.382	0.216	0.191
	MSE	0.392	0.341	0.197	0.152
	RMSE	0.671	0.589	0.317	0.282

To estimate the prediction performance, the mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) were adopted to analyse the prediction results. The GSCDF model has more stable long-term prediction performance, and the values of MAE, MSE, and RMSE are 0.113, 0.071, and 0.287 respectively when the prediction length of the dataset is 4. Comparing the present method with the best-performing comparative method, SCDAM, it can be found that the MAE decreases from 0.154 to 0.113, and the error is reduced. Compared with the optimal comparative method SCDAM, it can be found that the MAE is reduced from 0.154 to 0.113, with an error

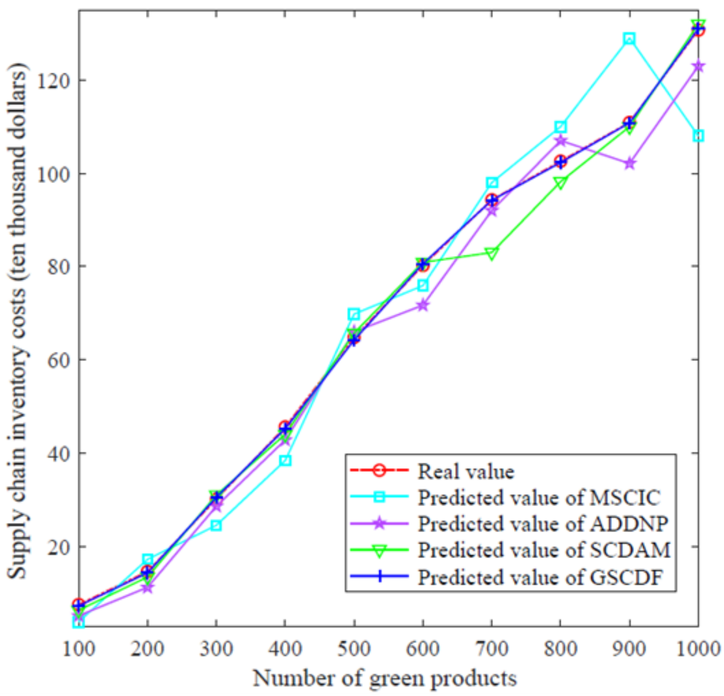

Figure 3. Comparative graph of contrasting models in green product supply chain demand

reduction of 26.62%; the MSE is reduced from 0.093 to 0.071, with an error reduction of 23.66%; and the RMSE is reduced from 0.305 to 0.287, with an error reduction of 5.9%. By decomposing the indicators of influencing factors, the complexity of data is reduced, and attention is paid to spatial and influencing factor characteristics. The prediction errors of this model and the SCDAM model are much smaller than those of the MSCIC and ADDNP models and slightly better than those of the SCDAM model, which fully demonstrates the superiority of the GSCDF model.

Figure 3 is a line graph comparing the contrasting models for different green product supply chain demands. The horizontal coordinate is the sequence of green products, the vertical coordinate is the inventory cost. It can be seen that the deviation of GSCDF model is very small and the prediction curve is close to the real value, while the SCDAM model can predict the trend of the real value better and the prediction deviation is small, and most of the experimental results of the MSCIC model are far away from the error tolerance interval. The ADDNP model only extracts the characteristics of the indexes affecting the demand of the green supply chain by using the GAN method, and doesn't decompose the data of these indexes, which leads to a great deviation from the real value of the prediction results. results deviated greatly from the true values. To summarize, the long time series prediction results of the GSCDF method proposed in this chapter for green supply chain demand forecasting are better than those of MSCIC, ADDNP and SCDAM.

5.2. **Comparison and analysis of the advantages and disadvantages of different models based on accuracy evaluation indexes.** In addition to visualizing the predictive ability of the comparison models through MAE, MSE, and RMSE, the prediction effect evaluation indexes AUC, Accuracy, Recall, Precision, and F1 values of each type of method can also be further analyzed in depth to obtain more information. The prediction effect evaluation indexes of each model are summarized as shown in Table 3 and Figure 4.

Table 3. Results of the assessment of the prediction accuracy of the models

Method	AUC	Accuracy	Recall	Precision	F1
MSCIC	0.781	0.764	0.762	0.779	0.770
ADDNP	0.829	0.837	0.814	0.835	0.824
SCDAM	0.894	0.861	0.904	0.907	0.905
GSCDF	0.927	0.912	0.931	0.918	0.924

As can be seen from Table 3 and Figure 4, the accuracy of all four models is greater than 0.7, and the ratio of the number of correctly predicted samples to the total number of samples described by the accuracy indicates that the total prediction accuracy of the four models is quite high. The accuracy of GSCDF is the highest at 0.912, followed by SCDAM with an accuracy of 0.894, which is above 0.85 and has a strong prediction ability; the accuracy of ADDNP model is 0.837, which is close to 0.85, and the prediction ability of MSCIC is the lowest among the four models, with an accuracy of 0.764.

Looking at the accuracy alone is easy to make the model prediction fall into a misunderstanding. F1 is the reconciled average of precision rate and recall rate, which makes the evaluation more comprehensive, and will not fall into the predicament of predicting too many negative samples as positive samples to improve the recall rate, nor fall into the misunderstanding of predicting insufficient positive samples, and can guarantee the precision rate and recall rate at the same time, which is more accurate. From the above table, we can see that the strongest ability to correctly predict is GSCDF, with a composite score of 0.924, the composite scores of ADDNP and SCDAM models are between 0.8 and 0.9, and the composite score of MSCIC is the lowest, at 0.770, which indicates that the prediction performance of MSCIC is the poorest among these four models.

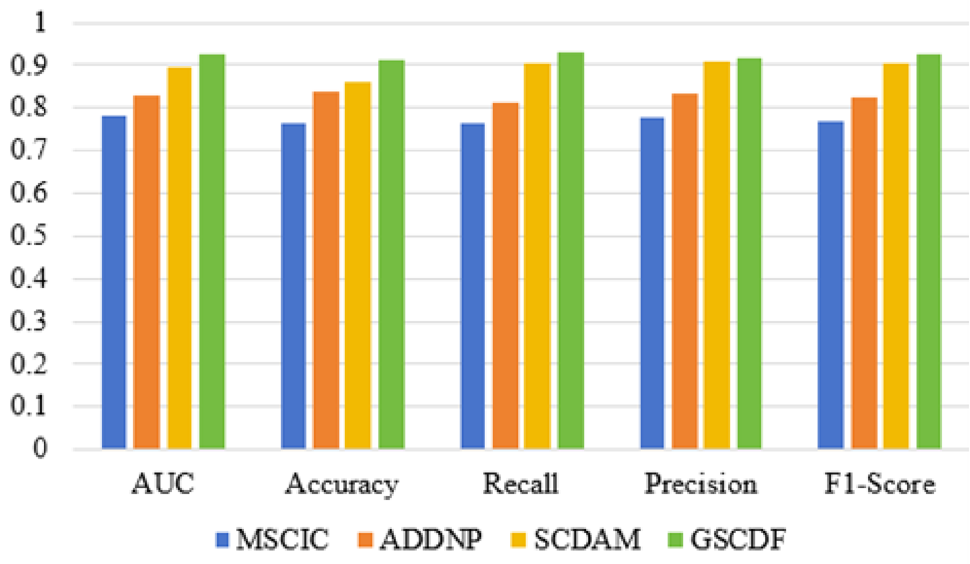

Figure 4. Comparison of prediction accuracy of different models

6. **Conclusion.** Aiming at the issue of low accuracy in the existing green supply chain demand forecasting methods, this paper proposes a green supply chain demand forecasting method based on adaptive decomposition and GNN. Firstly, the variational modal decomposition algorithm is enhanced to adaptively decompose the original signal into a number of submodal components, each of which has a certain smoothness and regularity,

which can reflect the periodic characteristics of the original signal. Then, the factors affecting the green supply chain are decomposed into IMF with different frequency ranges using the EVMD method, and the dynamic attention mechanism and bi-directional mechanism are introduced into the GAN, which can improve the prediction accuracy by fully integrating the feature information to extract the spatial features. Finally, the prediction results are output through GNN. The results indicate that the designed method has low MAE, MSE and RMSE, and can efficiently realize green supply chain demand prediction.

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