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Food Supply Chain Demand Forecasting Based on Empirical Modal Decomposition and Graph Neural Network

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Abstract. *Traditional independent food enterprises have been gradually substituted through various supply chains, so that current business contest has gradually evolved from the company aspect to the supply chain aspect. Efficient and accurate supply chain demand prediction has become an important condition for each food enterprise to improve its competitiveness. Intending to the issue of insufficient feature extraction in the current forecasting model, which results in undesirable forecasting accuracy, the influencing factors of the supply chain demand of food enterprises are firstly comprehensively analyzed, and these factors are preprocessed. Optimization of Empirical Modal Decomposition (EMD) by superimposed Gaussian white noise (OEMD) is used to reduce the complexity of the model input variables by using OEMD to decompose the influencing factors into several modal components. The spatial features of the decomposed variables are then extracted using Graph Convolutional Network (GCN), and the output values of GCN are inputted into the temporal feature extraction module based on gated recurrent neural network (GRU), which is used to mine the patterns of variable changes over time. Finally, temporal features and time features are spliced and fused to enhance the important features using the attention mechanism, and the forecasting outcome are output through the fully connected network. The experimental outcome implies that the determined coefficient of the constructed model is improved by 4.7%-15.9%, and the predicted food supply chain order demand fits well with the actual demand, and the prediction effect is better.*
Keywords: Supply chain demand forecasting; Empirical modal decomposition; Graph convolutional network; Gated recurrent neural network; Attention mechanism.

1. Introduction.

With the further growth of informationization and industrialization in the world, the traditional independent food companies are progressively substituted through various supply chains, which makes the current business contest gradually evolve from the company aspect to the supply chain aspect [1]. In the process of food offer chain, there are material flow, commodity flow and information flow. The ultimate goal of everything is to adjust the quantity of commodities step by step under the maintenance of the final demand of users to achieve the optimal overall efficiency of the whole supply chain [2, 3]. But, in the real manufacture process, the requirement is usually indefinite, which makes the execution of offer chain management extremely tough. How to combine the nature of the offer chain service enterprises to analyze the rules, and apply all of them in the model analysis, which turns into the chief point to improve the precision of the offer chain requirement prediction model [4]. Improved forecasting accuracy can assist organizations to construct value from the "third source of benefit" by diminishing inventory and goods-in-transit expense and increasing the whole benefit to the food offer chain.

1.1. **Related work.** Da Veiga et al. [5] constructed a prediction model based on the ARIMA method, which effectively captures the linear relationship between the historical food supply chain order data, but it is difficult to be applied to the data with high volatility. Priyadarshi et al. [6] predicted the cost of the food supply chain based on a regression model by considering the influencing factors in multiple supply chains, but the model prediction results are highly deviated. The sequence of demand influencing factors in the food supply chain is affected by various potential factors such as seasons, economic crises, and irregular events. Abolghasemi et al. [7] constructed a demand forecasting model relied on Variational Mode Decomposition (VMD) and SVM, but the prediction accuracy was not high. Kantasa-Ard et al. [8] decomposed the influencing factors by Empirical Modal Decomposition (EMD) and used decision tree to forecast the supply chain demand, but there was a problem of modal overlapping by using EMD.

As the artificial intelligence rapidly growing, Feizabadi [9] pointed out in his study that prediction research has gradually shifted from shallow machine learning to deep learning, and artificial neural networks, as a representative module of DL, have achieved many successes in the field of prediction. Zhang [10] used BP neural networks to predict food supply chain orders with higher prediction accuracy compared to logistic and autoregressive models. Shajalal et al. [11] suggested supply chain order prediction based on Convolutional Neural Network (CNN) by constructing time series using users' historical order data as demand indicators, but the prediction effect is not satisfactory. Lutoslawski et al. [12] built a prediction model in horizontal and vertical time series, and utilized Recurrent Neural Network (RNN) to achieve effective prediction of the number of food orders. Ni et al. [13] constructed a supply chain inventory cost forecasting model relied on the LSTM network, and verified the validity of the LSTM for the long time-series prediction problem with long time-dependence by using examples. GRU is a variant of LSTM, which changes the three gates of LSTM to two, greatly diminishing the amount of parameters and thus accelerating the speed of convergence [14]. Noh et al. [15] collect the user historical search data from an online platform, and establish an order prediction model for food supply chain based on GRU.

As the actual food supply chain demand forecasting problem involves a more complex graph network structure, and Graph Neural Network (GNN) can deal with complex graph data has attracted extensive attention from scholars. Kosasih and Brintrup [16] in the food supply chain demand forecasting relied on the Graph Convolutional Network (GCN), to build a prediction approach that contains spatial-temporal correlation, which effectively improves the prediction accuracy. Wei et al. [17] combine GCN and RNN to construct a prediction model, which effectively obtains the spatio-temporal characteristics of the food supply chain while regularizing the graph data. Duan et al. [18] introduce the Attention Mechanism (AM) based on the spatio-temporal factors of the inventory cost of the food supply chain, which further improves the prediction performance relied on the graph structure. Gu et al. [19] proposed a combined model combining attentional temporal GCN and LSTM for food supply chain demand forecasting, which can capture global temporal dynamics and spatial correlation at the same time. Liang et al. [20] proposed the use of Attentional Mechanisms (AMs) to capture the spatial characteristics of dynamically changing influence variables for the prediction of the number of orders of food products and encoded them using GCN based on the Encoder-Decoder framework.

1.2. **Contribution.** From the current research status, the existing food supply chain demand forecasting methods have insufficient spatio-temporal feature extraction, resulting in unsatisfactory forecasting performance. For this reason, this paper constructs a food supply chain demand forecasting model relied on EMD and GNN. The chief work of the paper is summarized in the following four aspects.

(1) Firstly, from internal and external factors, this paper comprehensively analyzes the past operating conditions of food enterprises, marketing activities, food transaction prices and other influential factors of demand forecasting, and normalizes these factors. Pearson correlation coefficient method is used to eliminate redundant factors.
(2) To address the modal aliasing issue of EMD, the modal components obtained from multiple EMDs are averaged overall to efficiently suppress the generation of modal aliasing. The OEMD is utilized to decompose the final influencing factors into several modal components to reduce the complexity of the model input variables.
(3) The spatial features of the decomposed variables are extracted using GCN, and the output values of GCN are inputted into the GRU-based temporal feature extraction module, which is used to mine the patterns of variable changes over time. Splicing and fusion of temporal and temporal features, enhancement of important features using attention mechanism, and output of prediction results through fully connected network.
(4) The experimental outcome indicates that the MAE and RMSE of the constructed model are 0.2368 and 0.1896, respectively, and the forecasting accuracy is higher than that of the other models, which can provide a predictive model with application value for the food enterprises to understand the change of customers' demand.

2. Theoretical analysis.

2.1. **Empirical modal decomposition.** There are many factors influencing food supply chain demand, which need to be decomposed to reduce the complexity of input variables. The usually adopted decomposition techniques are wavelet decomposition, VMD and EMD [21]. Since EMD can be applied to decompose all kinds of variables, it has a significant advantage in dealing with nonsmooth and nonlinear data [22]. In addition, EMD does not adopt any already outlined operation as a base, and there is no problem of pre-selecting wavelet basis functions as in the case of wavelet transform, nor does it need a predefined number of modal components as in the case of VMD. It avoids the influence of unreasonable parameter settings on the time series decomposition results. Meanwhile, EMD has good time-frequency resolution and adaptability, which is suitable for food supply chain demand forecasting. EMD can transform the original sequence of variables into a series of intrinsic modal functions (IMFs) after decomposition as below.

1. Recognize all maxima and minima in the time series $x(t)$, obtain the extreme value envelope using the moving average method, and calculate the difference $h_1(t)$, i.e., $h_1(t) = x(t) - m_1(t)$, between $x(t)$ and the mean $m_1(t)$ of the envelope.
2. Determine whether the difference $h_1(t)$ is an IMF. If not, the original sequence in the new loop will be made $h_1(t)$, and step (1) will be repeated until $h_1(t)$ is an IMF; if so, $h_1(t)$ will be used as the 1st IMF component, $c_1(t) = h_1(t)$, and the difference between $x(t)$ and the IMF will be recorded as the residual component $r_1(t)$, i.e., $r_1(t) = x(t) - c_1(t)$.

3. Repeat step (1) and step (2) with $r_1(t)$ as the new original sequence and continue sieving to obtain the remaining IMF components until the residual component $r_n(t)$ is small or a monotonic function $x(t)$ can be expressed as follows.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

2.2. **Graphical convolutional network.** Food supply chain demand data is represented as a graph structure in the spatial dimension, as graphs do not have spatial limitations and there are no nodes and sequences that can be referenced. Therefore, traditional neural networks cannot work directly on graph data. To overcome the above difficulties, Graph Neural Network (GNN) came into existence. Graph Neural Network (GNN) is divided into Graph Attention Network (GAT) and GCN. Compared to GAT, GCN updates node representations by accumulating the feature information of neighboring nodes [23], and the computational process is relatively easy to implement, as shown in Figure 1.

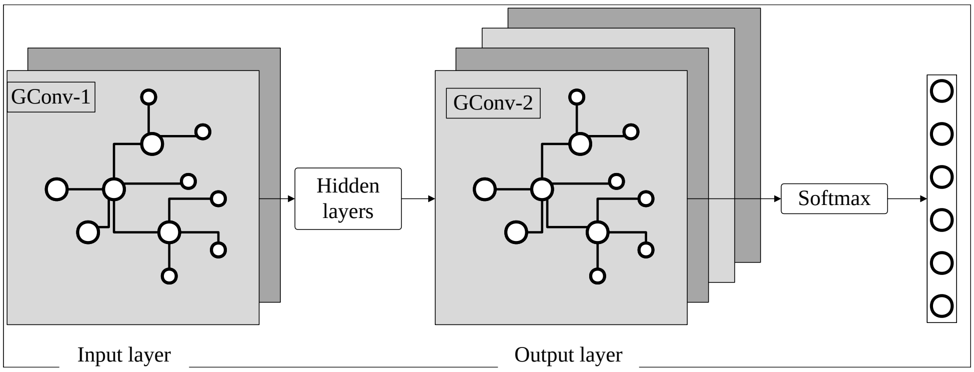

Figure 1. GCN architecture

GCN starts by assuming that the maximum number of features $\lambda_{max} = 2$ of the matrix $\tilde{L}$ (which introduces a scaling effect that can be automatically adapted by network learning), then $\tilde{L} = 2L/\lambda_{max} - I_N = L - I_N = I_N - D^{-1/2}AD^{-1/2} - I_N = -D^{-1/2}AD^{-1/2}$. The graph convolution function is as below.

$$x \star_G g_\theta = (\theta_0 - \theta_1(D^{-1/2}AD^{-1/2}))x \tag{2}$$

Extending Equation (2) to a signal with C input channels $X \in R^{N\times C}$ and F filters is characterized by the following mapping.

$$Z = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}X\Theta) \tag{3}$$

where $\Theta \in R^{C\times F}$ is the filter parameter matrix and $Z \in R^{N\times F}$ is the output matrix of the primary convolution. GCN proposes a simple and effective layer propagation method, which can be realized by stacking the map convolution layers to expand the range of the sensing field [24]. The convolutional kernel of GCN is smaller and has fewer parameters, which diminishes the computational complicatedness and simplifies the computation progress to the extreme. When actually building a GCN model, multiple graph convolution layers are usually superimposed, with every level defined as below.

$$H^{l+1} = f(H^l, A) = \sigma(\hat{A}H^lW^l) \tag{4}$$

where H^l is the node-to-feature representation vector of layer l and W^l is the corresponding parameter that defines $\hat{A} = \tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}$.

3. Analysis and pre-processing of demand influencing factors in food supply chain.

3.1. Analysis of factors influencing demand in the food supply chain. Food offer chain demand forecasting received a variety of factors coupled with the impact of the role of various factors are interlinked and mutual constraints, this paper will be respectively from the internal factors and external factors from two perspectives of a comprehensive analysis of the enterprise food supply chain demand impacting elements, and preprocessing of the influencing elements to enhance the model's predictive ability and generalization capability.

To realize the accurate prediction of enterprise food supply chain demand, it is necessary to comprehensively analyze the factors affecting the supply chain demand of coal port enterprises. Therefore, this paper analyzes the internal and external factors from two perspectives. First, internal factors are analyzed as follows.

$$X_i = \{c, b, s\} \tag{5}$$

where X_i is the internal factors affecting demand in the food offer chain, c is the past operations of the company, b is the lead time for replenishment of food products, and s is the implementation of marketing activities. The above factors are further refined and expressed as follows.

$$\begin{cases} c = \{c_1, c_2, c_3\} \\ b = \{b_1, b_2, b_3\} \\ s = \{s_1, s_2, s_3\} \end{cases} \tag{6}$$

where c_1 is the pressure on food inventories faced by the enterprise under the accumulation of historical operations, c_2 is the pressure on capital faced by the enterprise, and c_3 is the pressure on the market faced by the enterprise. b_1 is the time of approval of the purchase request, b_2 is the time of execution of the purchase process, and b_3 is the time of acceptance of the purchased food into the warehouse. s_1 is the price adjustment of the marketing campaign, s_2 is the total increase in food sales driven by the marketing campaign, and s_3 is the total number of new customer segments developed by the marketing campaign.

Secondly, external factors are analyzed and expressed as follows.

$$X_o = \{J, Q, E\} \tag{7}$$

where J is the operation of competing firms, Q is the transaction price of food, and E is the total amount of food circulating in the market.

Through the above approach, the food supply chain demand influencing factors are comprehensively analyzed to obtain the final influencing factors as X_j, which provides the basis for demand forecasting and guarantees the accuracy of the forecasting results.

3.2. Food supply chain demand data preprocessing. Due to the large differences between different factors, the direct use of factors will lead to unsatisfactory prediction, so it is necessary to standardize and normalize the influencing factors according to a certain proportion, so that they fluctuate within a certain range. Common normalization operations are linear (Min-Max) and zero mean (Z-score) normalization [25], because the distribution of demand in the food supply chain is not sufficiently normal, so this paper adopts the linear normalization operation, as shown in Equation (8).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{8}$$

where X_{norm} is the converted new data, X is the initial data, X_{max} is the maximum value of the corresponding eigenvalue, and X_{min} is the minimum value of the corresponding eigenvalue.

To eliminate the redundant variables affecting the factors, this paper utilizes the Pearson correlation coefficient approach [26] to remove the irrelevant factors, Pearson correlation coefficient is a kind of linear correlation coefficient, denoted as r, that is adopted to indicate the degree of linear correlation among the variables, the value of r ranges between -1 and 1, and the larger the absolute value indicates that the correlation is stronger.

$$|r_{x,y}| = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \cdot \sqrt{n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2}} \tag{9}$$

where x, y are the factors influencing the demand in the food supply chain, $0.8 < r_{x,y} \leq 1$ is very strong correlation, $0.6 < r_{x,y} \leq 0.8$ is strong correlation, $0.4 < r_{x,y} \leq 0.6$ is moderate correlation, $0.2 < r_{x,y} \leq 0.4$ is weak correlation, $0 < r_{x,y} \leq 0.2$ is very weak correlation or no correlation. This paper removes very weakly correlated or uncorrelated influences to obtain the final preprocessed food supply chain demand influences as $\{x_1, x_2, \ldots, x_m\}$.

4. **Food supply chain demand forecasting based on empirical modal decomposition and graph neural networks.**

4.1. **Demand influence factor decomposition of food supply chain based on optimized EMD.**

After preprocessing the influences, to diminish the complicatedness of the input variables, the influences were first decomposed into a number of linear data using EMD. The output of the GCN is then fed into a GCN-based spatial characteristic capture module to capture spatial features, and the output of the GCN is fed into a GRU-based temporal characteristic capture module to explore the patterns of data changes over time. Finally, the AM is adopted to fuse the temporal features with the temporal features and output the prediction results of the food supply chain demand through the fully connected network, and the model structure is shown in Figure 2.

Modal aliasing is a major problem in the EMD algorithm, in this paper, we optimize the EMD by superimposing Gaussian white noise (OEMD), and perform overall averaging of the related IMFs gained from numerous EMDs to offset the added white noise, for the goal of efficiently inhibiting the generation of modal aliasing. The steps in detail are as below.

1. Set up $r(t) = x(t)$, $x = 0$, $k = 0$ and terminate the threshold condition $SD < \delta$. Calculate the local maxima and minima obtained by $r(t)$. Calculate the local averages from the upper and lower envelopes $e_{max}(t)$ and $e_{min}(t)$ to get the average envelope $m(t)$.

$$m(t) = \frac{e_{max}(t) + e_{min}(t)}{2} \tag{10}$$

2. Introduce a zero-mean, unit-variance white noise sequence $w_i (i = 1, 2, \ldots, I)$, and generate the to-be-identified component $p_i(t) = m(t) + w_i$. Calculate the termination

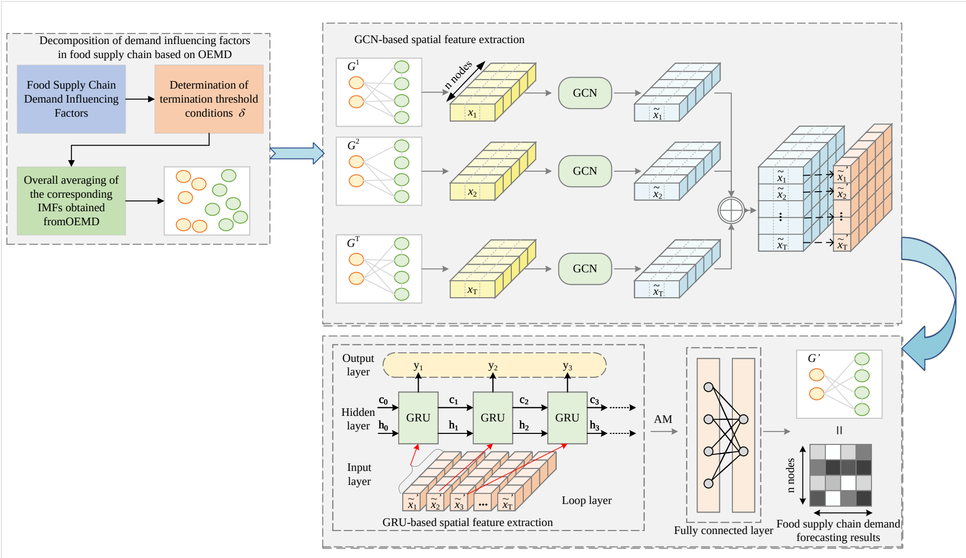

Figure 2. Demand forecasting model for food supply chain based on EMD and GCN

iteration condition SD, if $SD < \delta$, then $IMF_k(t) = p_i(t)$, and go to the next step, otherwise $r(t) = p_i(t)$, and loop through step (1) and step (2).

3. Calculate $r(t) = p_i(t) - IMF_k(t)$, determine whether $r(t)$ is monotonic or not, if it is not monotonic, go back to step (2), and perform $k = k + 1$ until $r(t)$ is a monotonic function. The final decomposition of the variable form is shown below.

$$x(t) = \sum_{K=1}^{m} IMF_k(t) + r(t) - w_i \tag{11}$$

where $IMF_k(t)$ is the decomposed subsequence and $r(t)$ is the residual.

4.2. **Spatial feature extraction based on GCN.** After using OEMD to obtain the modal components of the influencing factors of food supply chain demand, GCN is introduced to capture the spatial characteristics of each modal component, and the modal components can be presented in the form of nodes through the topological structure to realize the regular transformation of irregular graph data. In the process of processing data, GCN needs the adjacency matrix A, which expresses the connection among nodes, and the matrix X, which reflects the characteristics of nodes, and the internal hidden layer changes as follows.

$$H_l = f(H_{l-1}, A) \tag{12}$$

where H_l is the activation value of level l, H_0 is the eigenmatrix of each modal component, and f is the propagation rule. The specific rules for the propagation of the data are as follows.

$$H_l = \sigma(AH_{l-1}W_{l-1}) \tag{13}$$

where W_{l-1} is the weight matrix in each level; σ is the nonlinear activation function formula. The GCN module is constructed relied on the propagation and transformation rules of the integral layer of the scroll, and multiple convolution layers are superimposed to obtain the spatial information between the modal components of the influencing factors. The transformation formula is as follows.

$$H_l = \sigma(D^{\frac{1}{2}} \hat{A} D^{-\frac{1}{2}} H_{l-1} W_{l-1}) \tag{14}$$

where $\hat{A}$ is the original adjacency matrix $\hat{A}+I$, $I \in R_{n\times n}$ is the unit matrix, and D is the degree matrix of the adjacency matrix $\hat{A}$, whose transformation formula is $D_{ii} = \sum_j \hat{A}_{ij}$.

4.3. **GRU-based temporal feature extraction.** The features of each node have been updated through the spatial feature extraction in Section 4.2, next, the output of the GCN will be adopted as the input of the GRU to further study the relation of the feature vectors of each node over different time slices through the GRU network. There are several gating units in the GRU, in which the reset gate r_t and update gate u_t are used to obtain the before and after characteristics of the time series, c_t is used to store the information data at time t, X_t is the input state of the data, h_t is the output state at time t, and σ and tanh are both activation functions.

For each node in the GCN, the GRU mines the features of the modal components of the OEMD decomposition, and realizes the updating and resetting of the information under the joint action of the activation function and the weight matrix, the specific transformation is as follows.

$$u_t = \sigma(W_u * [X_t, h_{t-1}] + b_u) \tag{15}$$

$$r_t = \sigma(W_r * [X_t, h_{t-1}] + b_r) \tag{16}$$

where W_u and W_r are the weights of the update gate and reset gate in the GRU, σ is the activation function sigmoid, b_u and b_r are the offsets of the update gate and reset gate in the GRU.

At the same time, c_t acts in conjunction with the reset gate according to Equation (17) to store the output information of the preorder gated loop unit.

$$c_t = \tanh(W_c[X_t, (r_t * h_{t-1})] + b_c) \tag{17}$$

where W_c is the weight information of the storage module; b_c is the storage module offset. The temporal characteristics of the food supply chain demand are obtained through the transformation of Equation (18), which are sequentially passed to the subsequent gated cycle units.

$$h_t = u_t * h_{t-1} + (1 - u_t) * c_t \tag{18}$$

The GRU module can efficiently obtain the precession and cycle characteristics of the food supply chain demand, and has excellent memory function.

4.4. **Spatio-temporal feature fusion and prediction result output.** After obtaining the temporal and spatial features of the influencing factors separately, their spatio-temporal features $f = concat(H_l, h_t)$ are obtained by splicing and fusion. To better obtain the importance indicators of different influencing factors, an AM is introduced into the model, and on the premise of obtaining spatial and temporal characteristics, based on the scoring function, the comprehensive score of spatial characteristics under different time nodes is calculated, so as to obtain the pattern of demand changes under the global perspective, and ultimately realize a more accurate and effective prediction, as shown below.

$$s_i = w_2(w_1 F + b_1) + b_2 \tag{19}$$

$$k_i = \frac{\exp(e_i)}{\sum_{k=1}^{n} \exp(e_k)} \tag{20}$$

$$C_t = \sum_{i=1}^{n} k_i h_i \tag{21}$$

where s_i is the scoring function, F is the spatio-temporal feature set $\{f_1, f_2, \ldots, f_m\}$, w_1, b_1 and w_2, b_2 are the weights and biases of the first and second levels, individually, and the input value is the feature f at each time, and the output scores can be obtained by two hidden layers; k_i is the weight ratio of each spatio-temporal feature; and C_t is the global spatio-temporal feature information under the weight division.

C_t is fed into the fully connected network and the Softmax operation is adopted to generate the final forecast of the food supply chain demand as follows.

$$\hat{y}_i = \mathrm{softmax}(W_i C_t + b_i) \tag{22}$$

where W_i is the weight and b_i is the bias. In the training and testing of the model, it is necessary to set the loss function to judge the performance of the model. In this article, the L_2 regularized loss function is used to evaluate the performance. During the training process, we iterate continuously to minimize the loss function to determine the parameters needed in the model, as shown below.

$$Loss = \|y_i - \hat{y}_i\| + \lambda L_2 \tag{23}$$

where y_i and $\hat{y}_i$ denote the actual food supply chain demand and the forecasted demand, respectively.

5. **Experiment and result analysis.**

5.1. **Analysis of projected results.**

To estimate the performance of the constructed prediction model in supply chain demand forecasting, example simulation is carried out. 9,635 historical order data of six types of foodstuffs, including eggs, rice, pork, apple, greens and potato, in a food enterprise in a "first-tier city" from 2015-2019 are selected as the dataset, and the distribution of the samples of different types of foodstuffs is implied in Figure 3. The ratio of training and testing samples is 3:1, and the orders of the first 10 days are adopted to forecast the orders of the next day. All experiments were performed using the deep learning framework Pytorch and the programming language Python 3.8 on Mac OS Catalina 10.15.7 with the Intel®Core™i5-5350 CPU @1.8GHz. In the training phase, the batch size is 1024, the amount of iteration rounds is 500, the studying rate is 0.01, and the number of neurons is 20. The learning parameters were initialized with uniform distribution, sigmoid and tanh functions were used as activation functions, and the model was trained by Adam optimizer.

In this paper, supply chain order demand forecasting is performed on a weekly basis for 36 weeks starting from the 1st week of March 2018 for a food company, noting that the model in the literature [17] is GCN-RNN, the model in the literature [18] is GNN-AM, the model in the literature [20] is GLSTM, and the proposed model in this paper is EMD-GCN. The results of different models for supply chain order demand prediction are shown in Figure 4. In the 13th week, the actual order demand is 5683 pieces, and the prediction results of GCN-RNN, GNN-AM, GLSTM and EMD-GCN are 9735 pieces, 7245 pieces, 6891 pieces, 6103 pieces respectively, and the prediction outcome of EMD-GCN have a better fit with the actual order demand, and the prediction effect is better.

The Root Mean Square Error (RMSE) of the prediction of the order demand of six types of foodstuffs using EMD-GCN is implied in Table 1. From the table, it can be seen that the RMSE of EMD-GCN for the prediction of the order demand of the six types of foodstuffs is relatively small, and the maximum value is only 0.2117. EMD-GCN has the

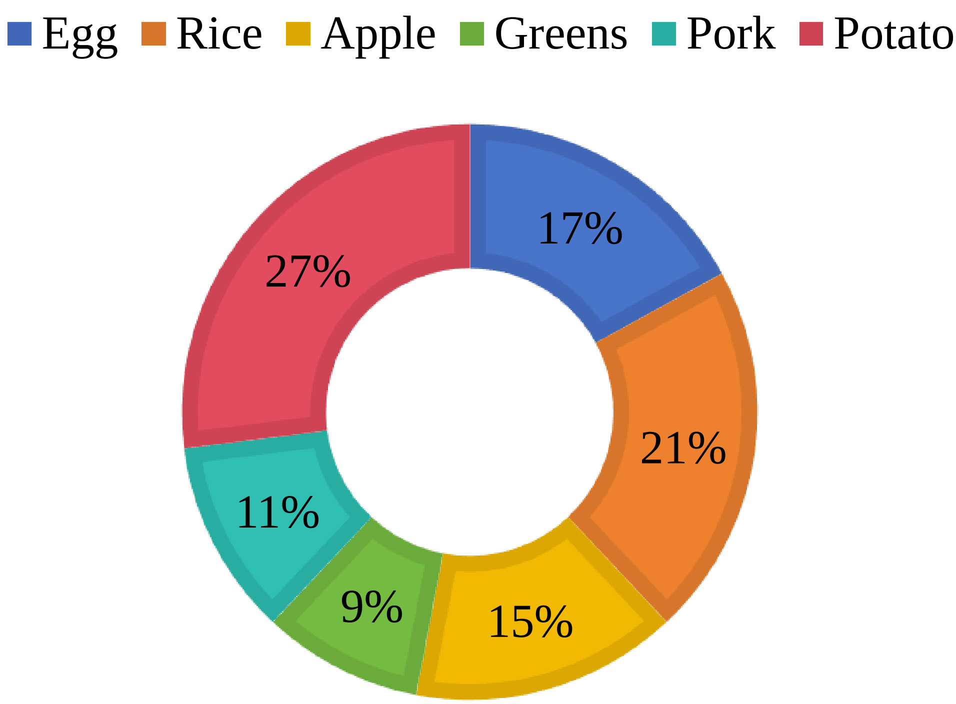

Figure 3. Percentage of 6 food items in the dataset

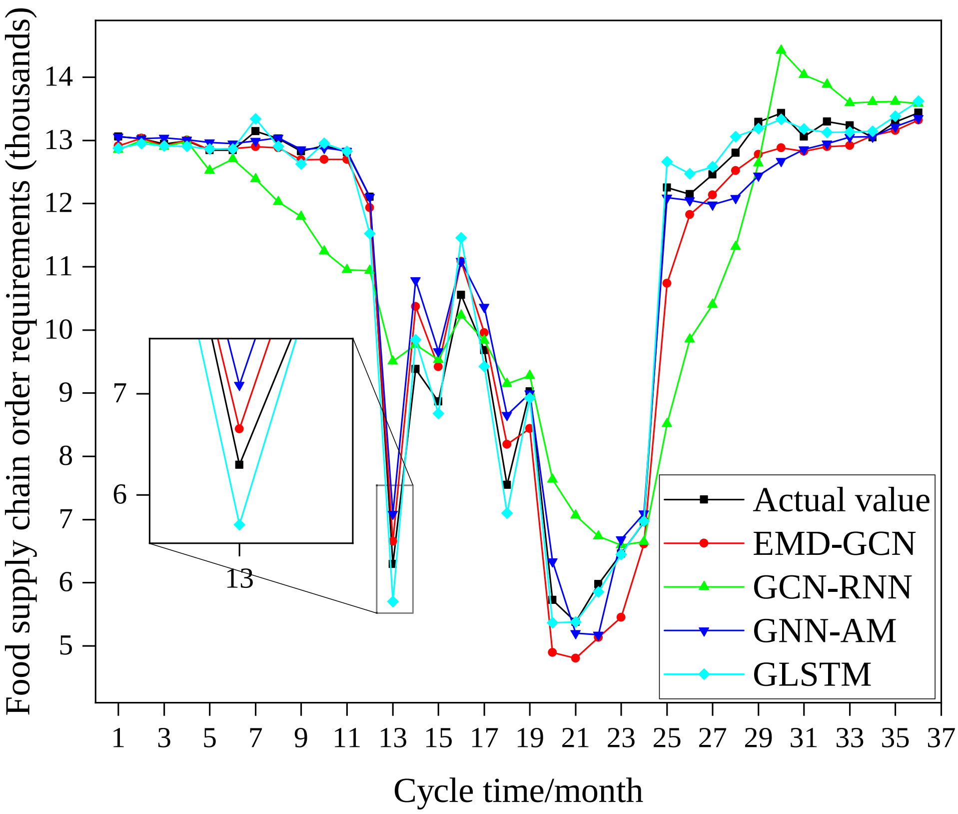

Figure 4. Comparison of prediction results of different models

highest accuracy in predicting the price of green vegetables, with an average RMSE of 0.1071, and the order prediction accuracy of apples and eggs is also high, but the order prediction accuracy of pork is the lowest, which may be due to the frequent price change of pork, which interferes with the order prediction of EMD-GCN to a certain extent.

Table 1. RMSE in EMD-GCN forecasting of order demand in food supply chain

Food category	Minimum value	Maximum value	Average value
Egg	0.1432	0.1496	0.1462
Rice	0.1526	0.1643	0.1591
Apple	0.1365	0.1372	0.1370
Greens	0.1056	0.1195	0.1071
Pork	0.2084	0.2152	0.2117
Potato	0.1731	0.1795	0.1753

5.2. **Predicted performance comparison.** To further validate the EMD-GCN model's performance in food order demand forecasting, GCN-RNN, GNN-AM, GLSTM, and EMD-GCN models were compared using the commonly used evaluation metrics of forecasting models, such as Mean Absolute Error (MAE), RMSE, Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and Variance of Releaseable Variance (VAR) [27]. comparative experiments. The MAE comparisons of different models predicting the demand for six types of food orders are shown in Table 2. There is a big gap in the order prediction process of the same type of food among the four models, indicating that the order prediction accuracy of different models is greatly different, among which the MAE of EMD-GCN and C is the smallest, and the MAE of 6 types of food orders is less than 0.27, and EMD-GCN is better than the GLSTM model. The MAE of GCN-RNN and GNN-AM are both greater than 0.5, indicating that after decomposition of the influencing factors of the food supply chain by EMD, it is more conducive for GCN to achieve accurate prediction of the number of food orders.

Table 2. MAE of different models for forecasting demand for food orders

Food Type	MAE			
	GCN-RNN	GNN-AM	GLSTM	EMD-GCN
Egg	0.7396	0.5396	0.2357	0.2152
Rice	0.7373	0.5482	0.2482	0.2251
Apple	0.7164	0.5163	0.2198	0.2043
Greens	0.7096	0.5072	0.2476	0.2298
Pork	0.7584	0.5689	0.2635	0.2465
Potato	0.7163	0.5132	0.2281	0.1924

Comparison of the prediction performance of different models is shown in Figure 5, where smaller values of MAE, RMSE, and MAPE indicate higher prediction accuracy. The MAE, RMSE, and MAPE of EMD-GCN are 0.2368, 0.1896, and 0.2067, respectively, which are lower than those of the other three models. R^2 is an important index to evaluate the model prediction fitting effect, and the closer the value is to 1, the better the forecasting effect is. The R^2 of EMD-GCN is 0.9861, which is improved by 4.7%, 11.8%, and 15.9% compared with GCN-RNN, GNN-AM, and GLSTM, respectively. The VAR measures how close the dispersion of all predicted values and the difference between the samples is to the dispersion of the samples themselves [28]. The maximum VAR value is 1, and the closer it is to 1, the better it is, with larger values indicating a similar dispersion distribution of predictions and sample values, and lower values being worse. EMD-GCN has a VAR of 0.9294, which is the closest to 1, and is at least 3.8% better compared to the other three models.

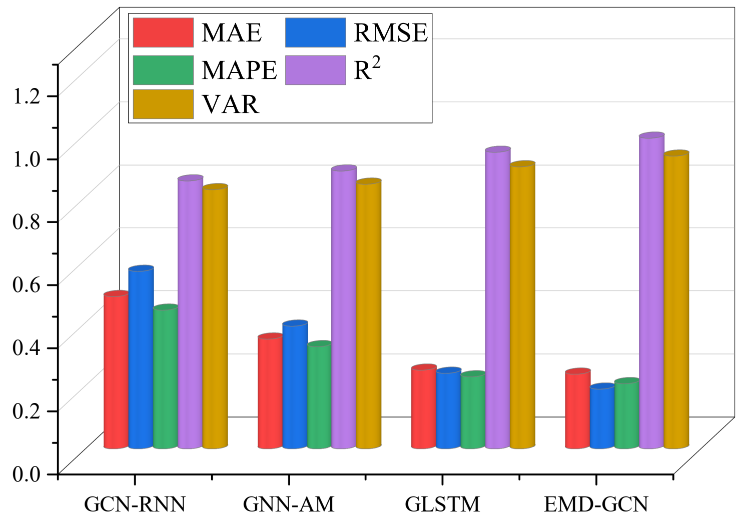

Figure 5. Comparison of the prediction performance of different models

Although GCN-RNN and GNN-AM consider the spatio-temporal features of the influencing variables, they do not remove the redundant indicators or decompose the variables, which leads to a high complexity of the input variables. GLSTM uses GCN-LSTM to predict the number of food orders, which is better than GCN-RNN and GNN-AM, but it is not optimized for EMD, and the operation of LSTM is more complex than GRU, which leads to less effective prediction than EMD-GCN.

6. **Conclusion.** The current food supply chain demand forecasting model has insufficient feature extraction, which leads to poor forecasting accuracy. To this end, this paper proposes a food supply chain demand forecasting model based on EMD and GNN. The influencing factors of supply chain demand of food companies are firstly comprehensively analyzed and standardized in terms of internal and external factors respectively. The EMD is optimized by superimposing Gaussian white noise (OEMD), and the final influencing factors are decomposed into several modal components using OEMD to reduce the complexity of model input variables. Then the spatial and temporal characteristics of the variables are captured using GCN and GRU individually, the spatio-temporal features are fused by splicing, and AM is introduced to enhance the key features, and the prediction results of the food supply chain demand are outputted through the fully connected network. The experimental outcome indicates that the suggested model has high prediction

accuracy, considers both temporal and spatial features, and has a great improvement in prediction efficiency over previous prediction models.

Although this research work has achieved some research results, only a single dataset was used for comparative experiments, which does not illustrate the model's ability to generalize to other datasets, so in future research, experimental evaluations will be carried out using a variety of datasets in order to verify the model's generalization and robustness.

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