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Research on Material Demand Forecasting Algorithm Based on Multi-Dimensional Feature Fusion

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ABSTRACT

Material demand forecasting has a profound impact on the supply chain and is an important prerequisite for manufacturing enterprises to produce. In order to accurately predict the material demand of enterprises, this paper proposes a material demand forecasting algorithm based on multi-dimensional feature fusion (DFMF). Secondly, in order to obtain the spatial features, the vector representation of the relevant materials of a material is obtained through the attention mechanism. Then, the authors aggregate the relevant material representation and material vector representation of materials to obtain the final material vector representation through aggregation function. Then the final material vector representation under different time scales is used as input, and the prediction value of material demand is obtained by using BP neural network. Finally, experiments show that the model can effectively obtain multi-dimensional features of materials for prediction, and the prediction results have high accuracy.

KEYWORDS

Cycle Features, Forecasting Algorithm, Historical Information, Multi-Dimensional Feature Fusion, Neural Network,

INTRODUCTION

Demand forecasting is an important basis for enterprises to formulate strategic planning, production arrangement, sales plan, and logistics management plan (Moscoso-López et al., 2016). For a business to efficiently manage its production, inventories, supply chain, finances, and market position, demand forecasting is a crucial tool. Businesses can make decisions that improve operational performance and boost profitability by precisely estimating demand. Manufacturers of standard products are expected to produce a certain amount of products ready for market or, at least, to keep a sufficient amount of raw materials and spare parts in order to minimize delivery time. Accurate material demand prediction can not only reduce inventory, but also ensure the normal production of enterprises, and

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effectively prevent production accidents, procurement accidents, and other material shortages caused by suppliers (Waller & Fawcett, 2013).

In recent years, many scholars have conducted extensive research on demand forecasting. FeiFei Ming et al. (2020) predicted the material distribution time in the production logistics system of the assembly workshop by establishing backpropagation (BP) neural network. Dong Jiang et al. (2019) used BP neural network to forecast engine material requirements and achieved good results. Zhou Yangfan et al. () studied the application of deep learning in logistics inventory prediction; the error reverse transmission function can be used in the prediction model.

To analyze the relationship between various impact factors and flow changes, and then use error correction to realize system changes (GuoXiang et al., 2021). Stockouts, poor quality, excess inventory, higher costs, and regulatory changes are some of the problems that might delay production. Enterprises can pinpoint the underlying causes of production issues and take appropriate action to address them by examining the relationship between these impact factors and flow fluctuations. Gupta and Kumar (2013) analyzed historical data, used ARIMA prediction model for fitting and prediction, and verified the applicability of the model. YuTong et al. (2014) first predicted the number of disaster victims with the grey theory, and then predicted the material demand of emergency logistics for flood disasters with the safety inventory method. Calculating the excess inventory, a business keeps on hand as insurance against unforeseen supply chain disruptions or demand fluctuations has been designated as safety inventory. Reducing the dimensionality of a dataset while preserving as much of the original data as feasible is what principal component analysis entails. YuanYuan et al. (2016) used Poisson distribution to establish the time model of material demand, then BP neural network to construct the sample matrix of material prediction, and finally genetic algorithm and neural network to obtain the optimal solution of the demand prediction function. Based on historical data and other pertinent variables, demand prediction function is a mathematical function that aids in forecasting future demand for a good or service. Demand forecasting is crucial for manufacturing, since it helps with inventory control and production scheduling. YanXia et al. (2013) adopted a three-layer neural network algorithm to predict material demand, but this method is not comprehensive enough to select influencing factors. An input layer, a hidden layer, and an output layer are all parts of the algorithm's three-layer neural network architecture; it is an effective method for forecasting material demand in a manufacturing organization by examining past data and spotting patterns in material consumption. Ling et al. (2020) proposed a prediction model based on evolutionary deep learning feature extraction, and compared the prediction methods such as BP and DBN, finding that the model has higher prediction accuracy. Dragan et al. (2021) determined the eigenvalue through principal component analysis when studying the case of Adriatic seaports, and then input it into the multivariate time series prediction model for prediction.

To sum up, there have been many researches on material demand forecasting at home and abroad, and some scholars have begun to apply artificial intelligence technology in material demand forecasting, achieving good results, but there is still a problem of poor accuracy of material demand forecasting. Time series analysis, regression analysis, machine learning models, econometric models, and judgmental forecasting are some of the typical models used in demand forecasting. The choice of these models relies on the nature of the business, the data that are available, and the needed level of accuracy.

This paper presents a material demand prediction algorithm called multidimensional feature fusion (DFMF) to assist manufacturing organizations in optimizing their supply chain, inventory management, and production planning processes by accurately predicting future demand for materials required for industrial activities. The proposed algorithm also incorporates various features from different dimensions to enhance the prediction accuracy. It leverages timporal features by mining the cyclic patterns of users' material information over different time scales. This helps in capturing the time-based variations and trends in material demand. To extract material-related information, the algorithm utilizes the gated recurrent unit (GRU) to generate material online vectors. Finally, the material demand is predicted using a BP neural network. The BP neural network learns from the extracted features and makes predictions based on the patterns observed in the training data.

RELATED WORK

In this paper, the features of materials are mined from the aspects of temporal features and space features for material demand prediction. In the process of acquiring timporal features, the historical sequence information of materials is used for mining. Taking into account the innate advantages of the recurrent neural network (RNN) in dealing with time series problems (Dragan et al., 2021; Sbrana et al., 2020), and the improvement of the RNN by the GRU network simplifies the network structure and solves the problem of not being able to learn long-term dependence (Jo et al., 2021). The GRU network is used to mine emporal features. The authors present a new function interpolation technique, which harnesses triply periodic minimal surfaces to generate optimized architected materials at the structural scale. The method ensures a smooth and meaningful transition within lower material microstructures, resulting in reduced stress concentration and facilitating successful three-dimensional printing manufacturing (Zhang et al., 2022).

Each unit in the GRU will obtain the status of two gate controls, reset gate r_t and update gate z_t, according to the state h_{t-1} transmitted from the previous unit and the input x_t of the current unit:

$$r_t = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right]\right) \tag{1}$$

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right]\right) \tag{2}$$

Then GRU will calculate the candidate hidden state to assist the later hidden state calculation. The calculation of the candidate hidden state in time step *t* is as follows:

$$h_t^* = \tanh\left(W * \left[r_t * h_{t-1}, x_t\right]\right) \tag{3}$$

The calculation of the hidden state *ht* of the last time step *t* uses the update gate z_t of the current time step to combine the hidden state *ht-1* of the previous time step with the candidate hidden state h_t^* of the current time step:

$$h_t = \left(1 - z_t\right) * h_{t-1} + z_t * h_t^* \tag{4}$$

In the process of acquiring spatial features of materials, attention mechanism is used to obtain the overall representation of related materials. The attention mechanism is essentially similar to that of the human brain, whose core goal is to give more attention to the more critical information in the global information (Aslam et al., 2021). The attention mechanism can be used to select the more critical material information in the relevant material as the whole representation of the relevant material.

In the attention mechanism, given a task related query vector Query, it calculates the attention value by calculating the similarity between Query and Key and assigning value to it. First, calculate the attention distribution á:

$$\alpha_i = softmax\left(s\left(x_i, Q\right)\right) \tag{5}$$

where, x_i is the input information, $s\left(x_i, Q\right)$ is the attention scoring mechanism, and Q is the query vector. In this model, the additive model is used as the scoring mechanism:

$$s\left(x_i, q\right) = v^T tanh\left(Wx_i + Q\right) \tag{6}$$

Finally, the weighted average of the input information is calculated according to the attention distribution α:

$$att\left(Q, X\right) = \sum_{j=1}^{N} \alpha_i x_i \tag{7}$$

ALGORITHM

In this study, the authors designed a material demand prediction algorithm based on DFMF. In this model, the researcher consider two features of material demand forecasting: Time and spatial feature. In the process of material purchase, enterprises will purchase some materials periodically over time, and different material purchases will have different periodic feature, which is referred to as time feature, in this paper. The following are only a few examples of the periodic features that may be connected with material purchases in a manufacturing company: Delivery schedule, lead time, seasonality, price variations, minimum order size, and payment terms. In order to obtain the time feature, the historical information of materials is divided by different time scales, and the vectors in the same time scale are aggregated to obtain the sequence of periodic vectors divided by different time scales. Different periodic vector sequences are used as input of the GRU network to obtain vector representation of material history information. The output of the GRU network is a vector representation of the material information of the data, which highlights its key temporal and geographical characteristics. The model can successfully capture the intricate temporal patterns and correlations in the data by splitting them up into separate periodic vector sequences and processing them through a GRU network, which results in more precise demand estimates. Enterprises will use a variety of materials in the process of equipment production and manufacturing. Many manufacturing organizations use a variety of materials, including raw materials, components and parts, chemicals and substances, packaging materials, energy sources, and tools and equipment. In the process of procurement, materials constituting the same equipment will affect each other. This feature is described in this paper as a spatial feature. In order to obtain spatial features, the material vector representation related to the material to be predicted is obtained through the attention mechanism, and the final vector representation is obtained by polymerization with the material vector to be predicted. Finally, the vectors divided into different time scales are used as the input of BP neural network to get the final prediction result. Figure 1 shows its model framework.

Timporal Feature

In this model, the authors take into account the relevant feature of material demand prediction, and count the material data every day before the material prediction. The input X_i of the model is mainly composed of the following features, such as the existing quantity of materials, safety stock, allocated production capacity, outgoing quantity, incoming quantity, production cycle, number of suppliers, and market price. The interaction of supply and demand determines the market price, with buyers and sellers negotiating prices based on their own requirements and preferences. Economic conditions, geopolitical events, and technical advancements are just a few of the variables that might affect supply and demand that are taken into account when determining market price.

These features are respectively represented, so the historical information of material i can be expressed as:

$$X_i = \left\{x_{ia}, x_{ib}, x_{ic}, x_{id}, x_{ie}, x_{if}, x_{ig}, x_{ih}\right\} \tag{8}$$

After making statistics on the daily material data, it is possible to get the historical information sequence $\left\{X_{i1}, X_{i2}, X_{i3}, \ldots, X_{it} \ldots, X_{in}\right\}$ of the material, where *n* is the data length. The historical information sequence is normalized as follows:

$$X^*_{it} = \frac{X_{it} - X_{i\,min}}{X_{i\,max} - X_{i\,min}} \tag{9}$$

where $X_{i\ max}, X_{i\ min}$ is the maximum and minimum value in the historical information sequence of the material. Each item in *H* is normalized to obtain historical information sequence:

$$I = \left\{X^*_{i1}, X^*_{i2}, \ldots, X^*_{in}\right\} \tag{10}$$

In this paper, the researchers formulate different time scales T^K to divide the historical information sequence *I* of material *i*. The project sequence can be divided into different historical information set sequences I^{T^K} according to the time scale T^K. I^{T^K} is a sequence composed of multiple sets. Each set in the set sequence I^{T^K} is composed of material historical information in the same time scale:

$$I^{T^K} = \left\{I_1^{T^K}, I_2^{T^K}, \ldots, I_j^{T^K}, \ldots, I_U^{T^K}\right\} \tag{11}$$

where *U* is the number of sets divided by time scale, $I_j^{T^K}$ is the *jth* historical information set in the set sequence. After obtaining the physical historical information set sequence I^{T^K} divided by the time scale *TK*, the historical information in each set in the sequence is aggregated through the additive aggregation function. A technique for integrating numerous variables or factors into a single score is the additive aggregation function. Each variable is given a weight, which is then multiplied by its corresponding value and added to produce the final score. The aggregation function formula is as follows:

$$agg_{sum} = \sigma\left(\omega\left(X^*_{ip} + \ldots + X^*_{iq}\right)\right) + b \tag{12}$$

where ω and b are weight and bias, X^*_{ip}, X^*_{ip} is the elements of the historical information set $I_j^{T^K}$. $V_{ij}^{T^K}$ represents the vector representation after aggregation of the *jth* item set in item set sequence I^{T^K} of material *I*. At the same time, the sequence of the material after time scale division and aggregation is also obtained, which is called periodic sequence $V_i^{T^K}$:

$$V_i^{T^K} = \left\{V_{i1}^{T^K}, V_{i2}^{T^K}, \ldots, V_{it}^{T^K}, \ldots, V_{iM}^{T^K}\right\} \tag{13}$$

The historical sequence of material i is divided and aggregated with the same time scale, and the set vectors in this sequence have periodic features, that is, the periodic features of material i. The historical sequence of material i is divided and aggregated with the same time scale, and the set vectors in this sequence have periodic features, that is, the periodic features of material i. In addition, different materials have different cycle features. The division of historical information series of materials with a single time scale will ignore other cycle features of materials. Therefore, different time scales are used to divide historical series. Once the historical demand series has been divided into several time scales, these various components can be used as inputs to demand forecasting models like the GRU network, in order to capture the intricate temporal patterns in the demand series and increase forecasting accuracy. After dividing and aggregating the historical sequence at different time scales, different periodic sequences can be obtained.

After dividing and aggregating the historical sequence at different time scales, different periodic sequence $V_i^{T^K}$ can be obtained (Figure 2).

After obtaining the periodic sequences divided by different time scales, the GRU network is used to process different periodic sequences, and different periodic sequences are input into the GRU network as input information. In order to solve some of the problems with more conventional RNNs,

Figure 1. Diagram of the DFMF model

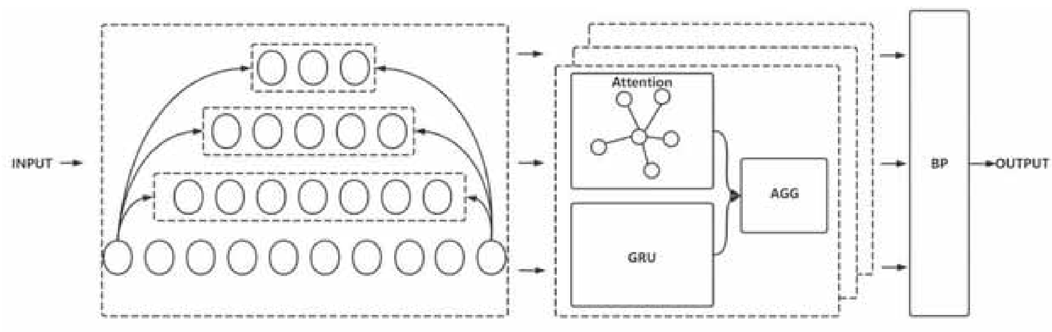
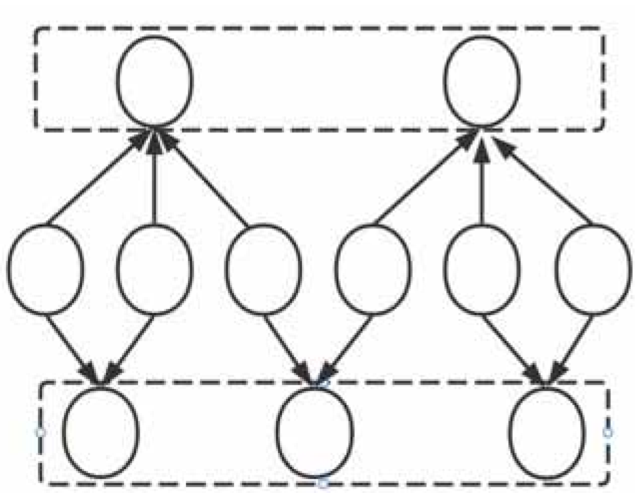


Figure 2. Diagram of a periodic sequence



such as the vanishing gradient problem, the GRU is a form of RNN. The GRU makes use of specialized gating mechanisms to selectively recall or forget data from earlier time steps. It is necessary to obtain the input of each unit to obtain the reset gate r_t and update gate z_t status of the two door controls. The terms "two door controls" and "GRU networks" usually belong to the reset gate and update gate, which are used in the network architecture to selectively incorporate or discard information from previous time steps and to update the hidden state based on new input information, in each case. It is possible to obtain the reset gate r_t and update gate z_t through the input of each unit:

$$r_t = \sigma\left(W_r \cdot \left[h_{t-1}, V_{it}^{T^K}\right]\right) \tag{14}$$

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, V_{it}^{T^K}\right]\right) \tag{15}$$

The candidate hiding state of each time step is calculated as follows:

$$h_t^* = \tan\left(W \cdot \left[r_t * h_{t-1}, V_{it}^{T^K}\right]\right) \tag{16}$$

The hidden state h_t of each time step is calculated as follows:

$$h_t = \left(1 - z_t\right) * h_{t-1} + z_t * h_t^* \tag{17}$$

The items in the periodic sequence have to be input into the GRU network in turn. Finally, the output h_M of the last cell is obtained, which is the vector representation W_i of material *i*.

Spatial Feature

The vector representation W_i of material *i* is obtained from the previous section, and the set of material vector representations *R* related to material *i* can also be obtained:

$$\mathrm{R} = \left\{W_1, W_2, \ldots\ldots, W_\mathrm{R}\right\} \tag{18}$$

where W_r is the vector representation of material *r*. In this section, the authors use the attention mechanism to obtain $W_{relevant}$. It is the overall representation of relevant materials from the relevant material representation set R. L vectors have to be randomly selected from the relevant material vector representation set, and the attention mechanism has to be used to obtain the relevant material vector representation $W_{relevant}$.

The *L* materials related to material *i* have to be taken as the Key and Value in the attention mechanism. Material *i* is Query:

$$V_r = K_r = W_1, W_2, \ldots, W_L \tag{19}$$

$$Q_r = W_i \tag{20}$$

V_r, Q_r and K_r are the *Value*, *Query,* and *Key* corresponding to the input of *L* material vectors related to material *i*. Then, the similarity matrix C_r of Q_r and K_r are calculated:

$$C_r = Q_r^T K_r \tag{21}$$

After obtaining the similarity matrix, a_r is derived through the softmax function. a_r is the output vector of the related material after the attention mechanism. It is the overall representation of the related material $W_{i\text{-}relevant}$:

$$W_{i-relevant} = a_r = V_r softmax_{\beta}\left(\frac{C_r}{\sqrt{d}}\right) \tag{22}$$

where d is the vector dimension and $\sqrt{d}$ is applied to the similarity matrix to avoid too large value of dot product in C_r. The softmax function calculates the weight of each entity vector in V_r. The weight is calculated as follows, where X_m is the *mth* column of the similarity matrix C_r and β is the parameter vector:

$$softmax_{\beta}\left(X_m\right) = \frac{\exp\left(\beta^T X_m\right)}{\sum \exp\left(\beta^T X_n\right)} \tag{23}$$

After the overall representation of related materials related to material *i* is obtained, the representation of material *i* and its related material representation are aggregated by concating aggregation function. In order to capture the information for both the material *i* and its associated materials to the demand prediction model, the features of each linked material are concatenated or merged together into a single vector. The aggregation function is as follows:

$$agg_{concat} = \sigma\left(\omega \cdot concat\left(W_i, W_{i-relevant}\right) + b\right) \tag{24}$$

where ω and b are weight and bias. The aggregation function is used to obtain the representation $W_{i-concat}$ of the aggregated material information of material *i*. The aggregated vector represents the information of material *i* and its related materials. Since entering different periodic sequences will result in different material representations, $W_{i-concat}^{T^K}$ represents the vector representation of material *i* obtained from different periodic sequences and its related materials after aggregation.

Finally, $W_{i-concat}^{T^K}$ is taken as the input of BP neural network to obtain the demand forecast quantity Y_i of material *i*:

$$Y_i = F\left(W_{i-concat}^{T^K}\right) \tag{25}$$

EXPERIMENTS

In this paper, the authors conduct experiments on the DFMF model. The authors' ultimate purpose is to provide material demand forecasting for industrial manufacturing enterprises. This purpose is also fully considered when selecting the influencing factors that affect material demand forecasting:

Time frames, spatial characteristics, material types, and outside influences. These influencing elements increases forecasting accuracy and aids manufacturing organizations in better managing their inventories and production procedures. The authors will use the real data of a hydrogen production equipment manufacturing enterprise to work on the original data, use the model to forecast the future material demand data, and study the influence of independent variables on the model structure.

The data in this paper come from the 36-month real data of a manufacturing enterprise, from January 2019 to December 2021. Considering the amount of data obtained in this paper, the authors use 60% of the sample data as the training set, 20% as the verification set, and 20% as the test set. The test set may be a portion of the initial dataset that is kept back until the model has been trained and verified. At that time, it is used to gauge the way the model performs on fresh, unexplored data. The author selected the historical data of 50 kinds of materials in the equipment of the enterprise as the original data.

Comparison Method and Parameter Setting

The authors compared the model they propose in this paper with the following methods:

- **ARIMA (Hamilton et al., 2020):** This method is based on its own past data for regression, and the prediction error is a linear combination of past respective errors. The data are replaced with stable data, and the combination method is used to fit the past data and predict the future data.
- **Group-BiLSTM (Livieris et al., 2020):** This method preprocesses the original data and constructs delay samples. Then, the samples are input into the two-way short- and long-term memory network to analyze the delay samples to obtain the forecast value of material demand.
- **CNN-LSTM (Kai et al., 2022):** This method combines the convolutional neural network (CNN) model and the short-term memory network model. A convolutional LSTM (CLSTM) network is created when a CNN model and a short-term memory (STM) network model are merged. This pairing enhance performance in tasks involving both spatial and temporal variables. In this model, variables are first convolved through a one-dimensional convolution layer, and then maximum pooling is adopted in the pooling layer. Then, the variable dimension is reduced to 1 through the full connection layer, and then the variable is input into the STM network model to obtain the predicted material demand.

BP network and GRU network are the networks used in the model proposed in this paper, so they are compared with the experimental results of GRU-BP network. While GRU networks are recurrent networks that employ gates to govern the flow of information through the network and capture long-term dependencies in the data, BP networks are feedforward networks that update the weights depending on backpropagated error.

In the experiment, time scales T^1, T^2, and T^3 are set to be 15 days, 30 days, and 60 days respectively. According to the actual situation of the enterprise, material procurement can be divided into short period, medium period, and long period, which can correspond to different time scales in the model. Table 1 shows other parameter settings in the experiment, where M is the selected quantity of related materials, E is the maximum number of iterations, and d is the dimension of the vector, λ Is the regularization weight, *lr* is the learning rate, and *batch* is the batch size.

Evaluating Indicator

In order to verify the reliability of the model in this paper, root mean square error (RMSE) and square percentage error are selected as evaluation indicators in the experiment:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}\left(observed_t - predicted_t\right)^2}{N}} \tag{26}$$

Table 1. Parameter settings

Parameter	Setting
E	100
λ	10-4
lr	3×10-4
$batch$	16
d	9
M	8

$$MAPE = \sum_{t=1}^{N} \left| \frac{observed_t - predicted_t}{observed_t} \right| \times \frac{100\%}{N} \tag{27}$$

where N is the number of samples in the test set, and $predicted_t$ is the predicted value of the material demand at time t, $observed_t$ is the real value of the material demand at time t.

Experiment Result

To compare the experimental results, the authors compared the model proposed in this paper with other five methods on dataset. Table 2 shows the experimental results.

The experimental results evivdence that the experimental results of this study are generally better than those of other methods. comparing comparison with AMIMA, Group BiLSTM, and CNN-LSTM methods highlights that the method the authors proposed in this paper to integrate the time and spatial feature of materials can effectively improve the accuracy of prediction. These models can reflect the intricate interactions may result in more precise and trustworthy forecasts, which in turn may assist companies in making wiser choices regarding inventory management, production scheduling, and resource allocation. By comparing the GRU-BP method under multiple time scales, the authors concluded that the proposed fusion of material spatial feature can effectively improve the accuracy of prediction. A manufacturing organization can benefit significantly from increasing the accuracy of material demand prediction by the suggested fusion of material spatial data, which can result in better efficiency, cost savings, customer satisfaction, and resource allocation. Since different time scales are used to acquire periodic sequences, the authors conducted comparative experiments with different periodic sequences as input. Table 3 shows the experimental results.

By comparing the methods under single time scale with the methods under multiple time scales, the authors found that the methods under multiple time scales are generally better than the methods

Table 2. Experiment result in different methods

	RMSE	MAPE
AMIMA	359.13	0.081
Group-BiLSTM	360.97	0.077
CNN-LSTM	361.96	0.079
BP	361.34	0.076
GRU-BP	362.67	0.074
DFMF	363.34	0.071

under single time scale. Utilizing various time periods allows to recognize and record all pertinent trends and variations in the data, which can result in more precise projections and better decision-making. It can also assist in conducting a deeper analysis of the data and locating underlying patterns or changes that might manifest themselves at various scales. Thus, the method proposed in this paper to fuse the time feature of materials can effectively improve the accuracy of prediction. Since it is necessary to obtain the overall representation of relevant materials through the attention mechanism in the spatial feature acquisition module, it is possible to explore the impact of the number of relevant materials *M* on the experimental performance. Figures 3 and 4 show the prediction effect of this model compared with different *M* numbers.

The line shows that, when *M* is small, the performance is poor the number of related materials is small, and the features of related materials cannot be well excavated. With the increase of *M*, the performance will decline, which may be due to over fitting.

Table 3. Experiments result in different time scale

	RMSE	MAPE
DFMF-T^{1}	360.43	0.077
DFMF-T^{2}	360.76	0.078
DFMF-T^{3}	361.90	0.077
DFMF-$T^{1,2}$	362.34	0.077
DFMF-$T^{1,3}$	362.96	0.075
DFMF-$T^{2,3}$	362.98	0.076
DFMF	363.34	0.071

Figure 3. RMSE line of models under different M

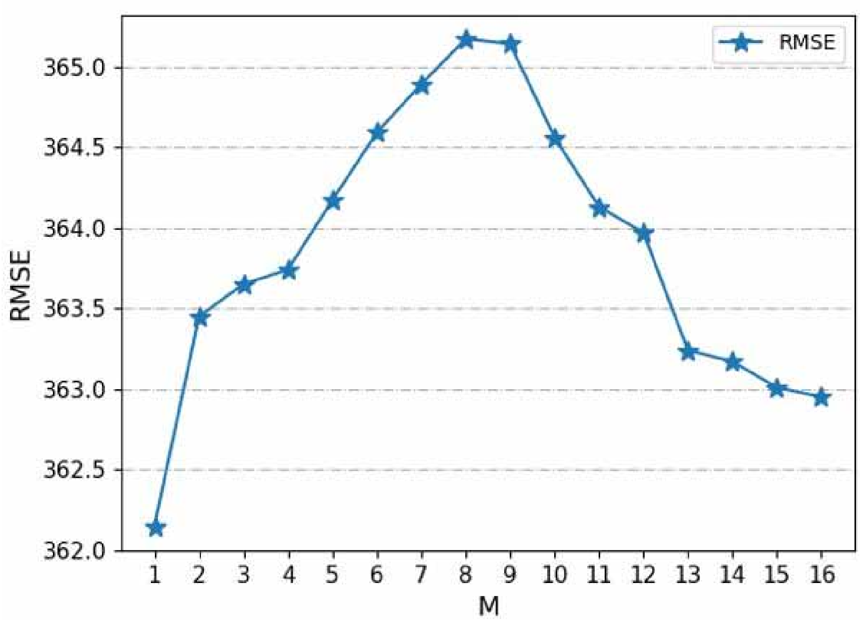
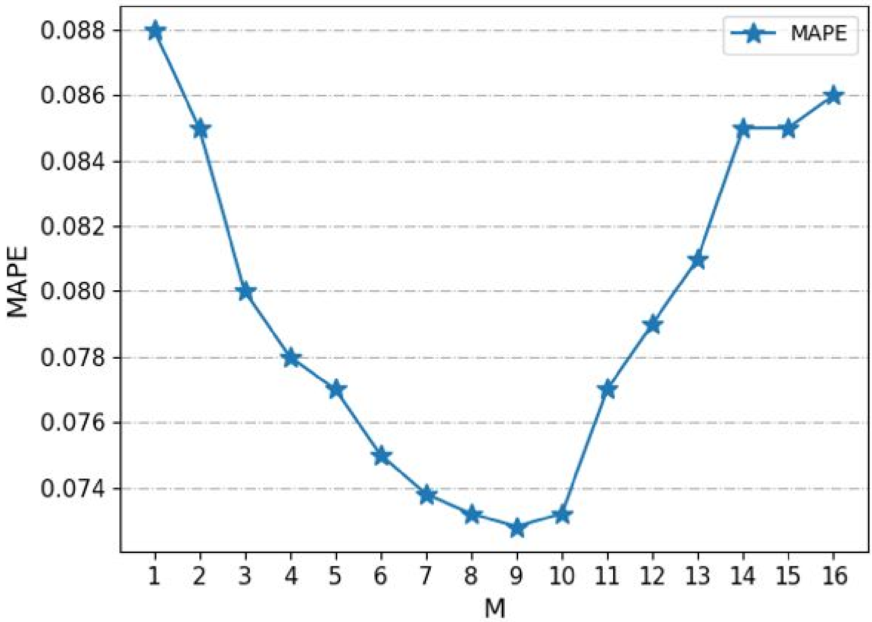


Figure 4. MAPE line of models under different M



CONCLUSION

In this study, the authors investigated the material demand forecasting algorithm based on DFMF. The main contributions are as follows: 1) Mining material features from two aspects of timporal features and space features for material demand forecasting; 2) The authors proposed the DFMF network model; 3) the experimental results show that the proposed method can meet the requirements of material demand forecasting and improve the accuracy of material demand forecasting.

Considering the development of the research content and field of this paper, in the subsequent research, the authors can consider adding more associated features, such as adding other features such as process and sales forecast, and selecting features for each feature to obtain the best feature set.

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