Inventory Demand Prediction Based on Gated Recurrent Neural Network and Fuzzy Time Series

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Keywords: Inventory Demand, Gated Recurrent Neural Network, Fuzzy Time Series.

Abstract: Current situation of auto parts inventory management based on VMI management mode, parts suppliers do not fully consider the influence factors of the parts themselves and the vague external influence factors such as environment, region and economy. To improve the forecasting accuracy of auto parts inventory demand, this paper proposed a combined forecasting model based on advantage matrix combined with gated recurrent neural network and fuzzy time series model (CRU_FTS_AM). Firstly, the gated recurrent neural network (GRU) is used to learn the multi-dimensional features of auto parts. Then, fuzzy time series model (FTS) is used to learn fuzzy and uncertain external factors that affects parts inventory demand. Finally, obtains the optimal weight coefficient of a single model by introducing the advantage matrix, and forecasts parts inventory demand through the weighted combined model. Compared with four models used in previous studies on three real data sets, the experimental results show that the proposed model improves RMSE by about 18%.

1 INTRODUCTION

The existing inventory management mode is mostly VMI management mode, which breaks the disadvantages of separate inventory management in the traditional supply chain, and allows upstream organizations to plan the inventory strategy and ordering strategy of downstream organizations. The supplier mainly analyzes the inventory and demand data of downstream distributors, and then exercises the decision-making power of inventory management. It fully mobilizes the flexibility of the supply chain and avoids the "bullwhip effect" caused by the continuous amplification of market demand.

The setting of traditional inventory is often based on the historical demand data of parts, the same supply strategy is adopted for all dealers, and set high safety inventory, resulting in a serious inventory backlog of parts in the peak season of vehicle sales. This not only increases inventory costs, but also causes unnecessary losses due to parts past their expiration dates. Reasonable inventory settings help to improve customer satisfaction and reduce capital costs, and inventory settings rely on the prediction of inventory demand.

The demand of auto parts inventory will also be affected by environmental, regional, economic and other external factors, when a new product has just been released or a certain type of vehicle sales surge, the demand for related parts will increase, and the demand for the same parts by dealers in different regions is also different. Therefore, the study of auto parts inventory needs to consider the influence of both internal and external factors of auto parts.

The research on inventory demand forecasting is as follows. Kumar et al. (A. Kumar, 2015] aiming at the problem that traditional safety inventory setting relies on random summation method with excessively high data requirements, proposed to use multiplication method to estimate variance without specifying data relations in advance. Beutel et al. (A. L. Beutel, 2012) proposed two ways to set safety inventory, the first method is to use regression model to predict inventory demand and use error to set safety inventory, another method is to optimize the target inventory function with linear programming under different service level constraints. Dennis et al. (P. Dennis, 2017) derived the correct method for determining safety inventory when the mean and variance of demand are uncertain. Juan et al. (R. Juan, 2018) proposed the kernel density estimation method and the autoregressive conditional heteroscedasticity model GARCH(1,1) to calculate the safety inventory. Liao et al. (W. Z. Liao, 2020) proposed a spare parts inventory forecasting method based on long and

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short term memory in order to predict spare parts inventory. This method can accurately predict the spare parts inventory with large amount of data and short replacement cycle. Chen et al. (Y. Chen, 2010) used auto-regressive moving average (ARMA) model to forecast the demand for auto parts. Li et al. (F. Li, 2023) proposed a point forecasting model based on long short-term memory network and a quantile forecasting model based on quantile Long short-term memory, which captured the uncertainty of sales and improved the accuracy of inventory forecasting. Huo et al. (X. Huo, 2022) proposed an inventory forecasting method G-FTS based on gaussian mixture model and fuzzy time series (FTS). Singh et al. (P. Singh, 2012) combined particle swarm optimization with fuzzy time series model for inventory forecasting. Erol et al. (E. Erol, 2012) applied intelligent algorithms such as genetic algorithm and artificial neural network to fuzzy time series to forecast inventory demand. Zhang et al. (M. Zhang, 2022) used histogram algorithm and gradient one-sided sampling algorithm to reduce the number of features, and used LightGBM model based on bayesian optimization for coal inventory prediction. Boukhtouta et al. (A. Boukhtouta, 2018) used the support vector machine (SVM) method to predict spare parts inventory requirements of the canadian armed forces. Hasmin et al. (E. Hasmin, 2020) used the double exponential smoothing method to predict frozen food inventory demand. Cheng et al. (F. Cheng, 2017) proposed a combined model of grey correlation analysis and time series neural network. Grey correlation analysis method is used to select the influencing factors, and then inventory forecasting is carried out by time series neural network. Wang et al. (J. Wang, 2008) proposed a combination model of support vector machine and markov chain for supply chain inventory forecasting.

As can be seen from the existing related research. (1) The forecasting model based on mathematical theory and hypothesis has a simple structure, which is difficult to describe the complex changing trend of inventory demand, and cannot fully obtain its inherent characteristics. (2) The model is relatively single, regarding the different characteristics of inventory demand forecasting using the same kind of prediction method. (3) Mainly consider the impact of single features, lacks the consideration of multi-dimensional features. Therefore, based on the characteristics of auto parts inventory demand, this paper introduces the advantage matrix combination gating recurrent neural network and fuzzy time series model, which can reflect the superposition influence of various laws more comprehensively and improve the accuracy of inventory demand prediction.

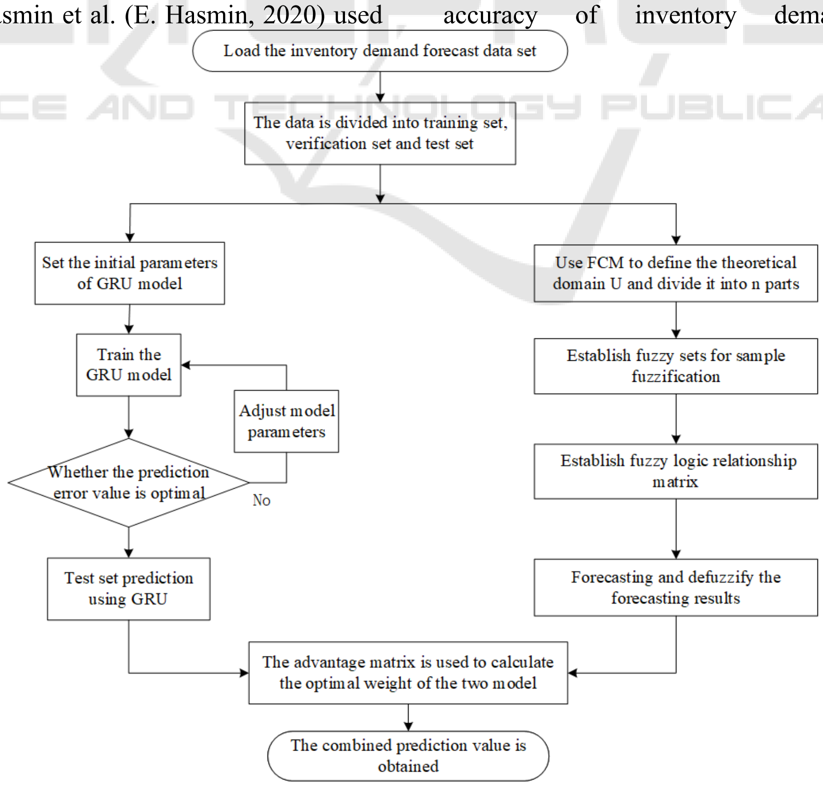

Figure 1: Frame diagram of GRU_FTS_AM combination model.

2 PROPOSED MODEL

Based on VMI inventory management model, a combination model of gated neural network and fuzzy time series model based on advantage matrix is proposed to forecast auto parts inventory demand in multi-value chain. While fully considering inventory influencing factors, the influence of interference and parameter changes on forecasting effect is reduced, and the robustness of forecasting model is enhanced. The frame diagram of the proposed model is shown as figure 1.

2.1 Gated Recurrent Neural Networks

Due to the large time interval for auto parts suppliers to supply parts, the size of inventory demand data is mostly small sample data and there are many factors affecting inventory demand, so GRU model is used to forecast. GRU, a variant of LSTM(K. Greff, 2016), was proposed by cho et al. (K. Cho, 2014) in 2014. It can not only solve the problem of gradient disappearance in recurrent neural networks, but also has higher computational efficiency, simpler structure and better prediction effect for small data sets. GRU has two gates, one is the update gate, which mainly controls how much state information is saved at the previous time. The second is the reset door, which mainly controls how much information needs to be forgotten. The operation process of GRU is shown in equations (1) - (4).

$$z_t = sigmoid(W_z \cdot [h_{t-1} \cdot x_t] + b_z) \quad (1)$$

$$r_t = sigmoid(W_r \cdot [h_{t-1} \cdot x_t] + b_z) \quad (2)$$

$$\tilde{h}_t = tanh(W_{\tilde{h}_t} \cdot [r_t * h_{t-1} \cdot x_t] + b_z) \quad (3)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (4)$$

z_t is the update gate, r_t is the reset gate, h_{t-1} is the activation status at time $t-1$, x_t is the input value at time t . W_z , W_r , $W_{\tilde{h}_t}$, represents the parameters in the training process, $\tilde{h}_t$ is the state at time t, "·" represents the multiplication of matrix sample points, "*" represents the multiplication of matrices, $sigmoid$ and $tanh$ are activation function.

2.2 Fuzzy Time Series

There are many factors that affect the inventory demand, among which the inaccurate and ambiguous phenomena such as environment, region and economy cannot be described by accurate data. To overcome these defects, fuzzy time series model is used to forecast inventory demand. Fuzzy sets can effectively reflect the continuous transition state between objects, and have natural advantages in dealing with fuzzy small sample data. Fuzzy time series model can reduce the influence of interference and parameter change on prediction effect, enhance the robustness of prediction model, and make effective prediction while learning the uncertainty of data set. The general prediction steps of fuzzy time series are as follows. (1) Determine and divide the theoretical domain. (2) Fuzzify the actual data. (3) Establish fuzzy relationship. (4) Defuzzifying the predicted value.

1) Determine and divide the theoretical domain
Divide the theoretical domain U=[D_{min} - D_1 , D_{max} + D_2], D_{max} and D_{min} are the maximum and minimum values of the historical time series dataset $\{ x_1, x_2 ,..., x_T \}$, respectively. FCM (K. Li, 2009) algorithm is used to calculate membership degree and find cluster center $\{c_1, c_2,..., c_n\}$, then divide the domain of discourse, where $D_1 = \frac{c_2 - c_1}{2}$, $D_2 = \frac{c_n - c_{n-1}}{2}$. Finally, the domain of theoretical is divided into n subintervals $\{u_1, u_2, ... u_n\}$.

2) Fuzzify the actual data
Data fuzzification, based on the subintervals $\{ u_1, u_2 ,... u_n \}$. The fuzzy sets defined on the theoretical domain is shown as follows.

$$A_k = \frac{f_{A_k}(u_1)}{u_1} + \frac{f_{A_k}(u_2)}{u_2} + \cdots + \frac{f_{A_k}(u_n)}{u_n} \quad (5)$$

Where, $k = 1,2, \ldots, n$. f_{A_k} is the membership function of the fuzzy set A_k, $f_{A_k}(u_i)$ represents the membership value belonging to the fuzzy set, $f_{A_k}(u_i) \in [0,1]$.

3) Establish fuzzy relationship
Form fuzzy relation based on the calculated fuzzy sets, and then establish a fuzzy matrix. Let the first-order fuzzy relation A_k be obtained by A_{k-1}, and their fuzzy relation be expressed as $R(k, k-1)$, therefore $A_k = A_{k-1} \cdot R(k, k-1)$, Let $R(k, k-1)$ be $r_{k,\ k-1}$, the calculation formula of fuzzy relation matrix R is as follows.

$$R=\begin{bmatrix} r_{11} & \cdots & r_{1n} \\ r_{12} & \cdots & r_{n1} \\ \cdots & \cdots & \cdots \\ r_{1n} & \cdots & r_{nn} \end{bmatrix} \quad (6)$$

4) Defuzzifying the predicted value
The predicted value is obtained by defuzzification. If the membership degree value of the fuzzy prediction has only one maximum value, the center of the cluster is selected as the predicted value of the defuzzification. If the membership degree value of the fuzzy prediction has two or more maximum values, the arithmetic mean value of the corresponding cluster center is selected as the defuzzification prediction value, set $f_{A_k}(u_i)= f_{ki}$, as shown in equation (7).

$$F(i+1) = \sum_{k=1}^{n} c_k (f_{ki} / \sum_{k=1}^{n} f_{ki}) \quad (7)$$

Where, $F(i+1)$ is the predicted value, c_k is the center value of the interval, also the midpoint of A_k.

2.3 Advantage Matrix

The commonly used methods of combination prediction model include least square method, voting method, weighted average method, etc. (L. W. Ling, 2019) .In this paper, Advantage matrix (Y. L. Bai, 2020) is used to determine the weight coefficients of a single prediction model. Assuming that there are two prediction models m_1 and m_2, a single model is trained separately to obtain the predicted value, and then a comparison matrix of model prediction error is established according to the calculated RMSE of prediction, as shown in equation (8).

$$\begin{bmatrix} RMSE_{m_1}^{1} & RMSE_{m_2}^{1} \\ RMSE_{m_1}^{2} & RMSE_{m_2}^{2} \\ \cdots & \cdots \\ RMSE_{m_1}^{n} & RMSE_{m_2}^{n} \end{bmatrix} \quad (8)$$

According to the error comparison matrix, advantage matrix can be obtained, if $RMSE_{m_1}^{1}$ less than $RMSE_{m_2}^{1}$, $RMSE_{m_1}^{1}$ is 1, otherwise it is 0. If the two errors are equal, it is 0.5. The advantage matrix is shown in equation (9).

$$\begin{bmatrix} 1 & 0 \\ 1 & 0 \\ \cdots & \cdots \\ 0 & 1 \end{bmatrix} \quad (9)$$

Then calculate the weight coefficients of m_1 and m_2, where n is the number of rows of the matrix, n_1 is the sum of the first column of the advantage matri x, and n_2 is the sum of the second column of the adv antage matrix. The calculation formula is as follows.

$$w_{m_1} = \frac{n_1}{n_1 + n_2} \quad (10)$$

$$w_{m_2} = \frac{n_2}{n_1 + n_2} \quad (11)$$

Let y_t (t=1,2,3,…,n) represents the predicted value at time t, then the weighted combined predicted valu e of the two models based on the dominance matrix i s as follows.

$$\bar{y}_t = \sum_{t=1}^{n} w_{m_1} * y_{t_1} + w_{m_2} * y_{t_2} \quad (12)$$

The GRU_FTS_AM algorithm is as follows.

```
Model  GRU_FTS_AM
Input  Parts stock demand forecast datasets X={x_1, x_2, ..., x_T};
Output Parts stock demand forecast value ŷ^t_m3;
Load X;
Initialize GRU;
Execute GRU use equations(1)-(4);
Save ŷ^t_m1;
Preprocess X;
Using FCM algorithm to divide the domain;
Fuzzify the data use equation(5);
Establish the fuzzy relationships use equation(6);
Defuzzify the forecasting results use equation(7);
Save ŷ^t_m2;
Calculate ŷ^t_m3 use equations(8)-(12);
Return ŷ^t_m3;
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3 EXPERIMENT

This paper takes the multi-value chain data of A automobile manufacturing as the experimental data set, takes the parts suppliers as the research object, and uses three real data sets of "transmission components", "radiator assembly" and "license mounting plate" supplied by them for example analysis and model comparison. Due to the large time interval of parts supply, the fitting is processed in months, the time range is from January 2017 to December 2021, and the training set and test set are divided according to 8:2. The influencing factors of auto parts inventory demand mainly come from the part itself. Based on the real data of parts and the existing research literature, the three influencing factors of historical sales data of part, vehicle ownership of part and life of part are selected. "License mounting plate" part of the data set are as shown in table 1.

Table 1: "License mounting Plate" part dataset.

Date	Historical sales data	Total vehicle ownership	Life span
January 2017	3275.00	167.4	3.7
February 2017	3740.00	169.8	4.2
March 2017	3560.00	172.3	3.8
…	…	…	…
December 2021	4001.00	281.2	3.4

In this paper, root mean square error, mean absolute error and coefficient of determination are used as the evaluation indicators of the model. The formulas are as follows:

(1) Root Mean Square Error:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_t - \hat{Y}_t)^2} \quad (13)$$

(2) Mean Absolute Error:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_t - \hat{Y}_t| \quad (14)$$

(3) R-squard:

$$R^2 = 1 - \frac{\sum_{i=1}(Y_t - \hat{Y}_t)^2}{\sum_{i=1}(Y_t - Y)^2} \quad (15)$$

Where, Y_t is the real inventory demand, $\hat{Y}_t$ is the forecast inventory demand. RMSE and MAE calculate the prediction error, the smaller the value, the smaller the error from the true value. R^2 calculate the correlation coefficient, the larger the value, the more representative the real data.

After experiments, the optimal parameters of the GRU model are shown in the table 2. The historical sales data of auto part is used as the input of FTS model, and fuzzy C-means clustering algorithm with cluster center 16 is used to divide the theoretical domain.

Table 2: The parameters of the GRU.

Parameter	Optimal Value
Hidden layer	1
Units	8
Time steps	4
Batch size	4
Epochs	50

In order to verify the rationality of GRU_FTS_AM model, it was compared with GRU, FTS (X. Huo, 2022), SVM (Boukhtouta, 2018) and ARMA(Y. Chen, 2010) prediction models. Based on the 12 months starting from 2021 of the "Transmission components" dataset, the weight coefficient of GRU and FTS is 0.589 and 0.411, respectively, calculated by the advantage matrix. Based on the 12 months starting from 2021 of the "Radiator Assembly" dataset, the weight coefficient of GRU and FTS is 0.624 and 0.376, respectively, calculated by the advantage matrix. Based on the 12 months starting from 2021 of the "License mounting plate" dataset, the weight coefficient of GRU and FTS is 0.547 and 0.453, respectively, calculated by the advantage matrix. The experimental results are shown in the figure 2.

As can be seen from the figure 2, the red line is the prediction result of GRU_FTS_AM. Where the prediction error of GRU and FTS models is large, GRU_FTS_AM can achieve better prediction results. In order to further understand the prediction accuracy of each model, the three evaluation indicators proposed above are used for evaluation.

Table 3: Error comparison between different models.

Model	"Transmission component"			"Radiator assembly"			"License mounting plate"		
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
ARMA	247	154	0.752	186	122	0.741	416	224	0.786
SVM	208	128	0.851	138	83	0.881	312	189	0.861
GRU	187	113	0.874	132	81	0.887	284	168	0.887
FTS	212	132	0.846	146	91	0.869	302	187	0.873
GRU_FTS_AM	**171**	**106**	**0.915**	**126**	**75**	**0.904**	**267**	**152**	**0.907**

It can be seen from the evaluation results in the table 3 that the GRU_FTS_AM model is better than the other four prediction models in the three evaluation indicators of RMSE, MAE and R^2. The experiment proves that GRU_FTS_AM model can effectively and fully consider the influencing factors of parts inventory demand, and improve the forecasting accuracy of parts inventory demand.

4 CONCLUSION

Based on the VMI inventory management mode, this paper takes the auto parts suppliers as the research object, fully considers the influencing factors of inventory demand, and proposes the GRU_FTS_AM combination forecasting model.

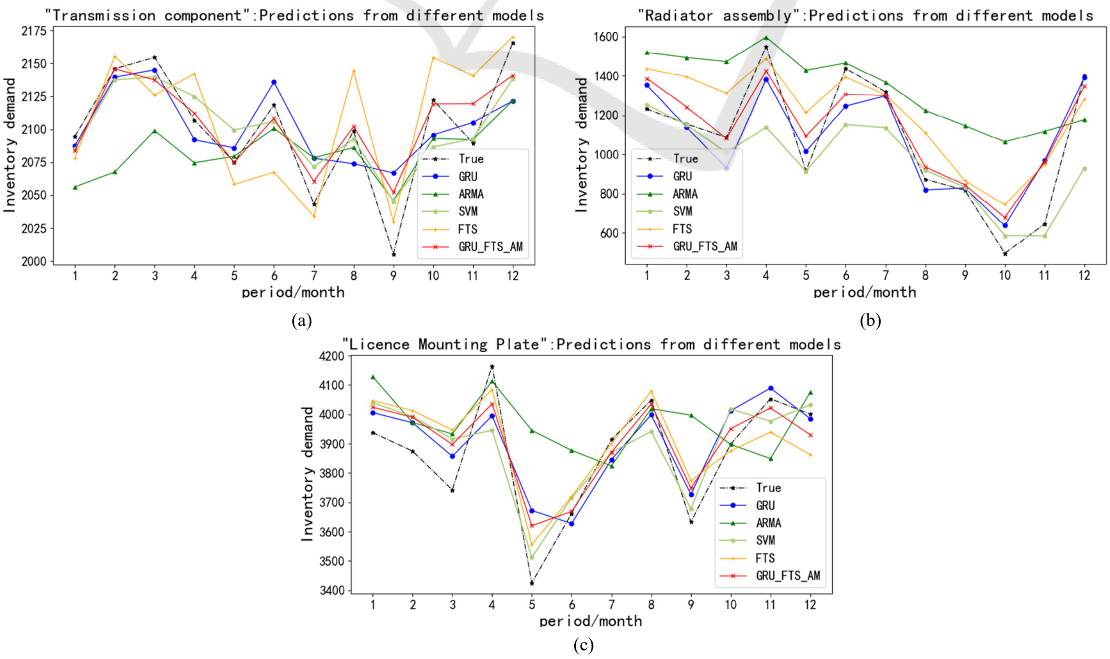

Figure 2: Values predicted by different models.

The model uses GRU to learn the internal features of auto parts and FTS to learn the fuzzy external features of parts inventory, which not only improves efficiency but also has a simple structure. Finally, the validity of the GRU_FTS_AM model was verified through three data sets. Compared with the four existing single prediction models, the prediction accuracy of GRU_FTS_AM model is significantly improved in each evaluation index.

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