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ARTICLE

A Study on an Extensive Hierarchical Model for Demand Forecasting of Automobile Components

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ABSTRACT

Demand forecasting and big data analytics in supply chain management are gaining interest. This is attributed to the wide range of big data analytics in supply chain management, in addition to demand forecasting, and behavioral analysis. In this article, we studied the application of big data analytics forecasting in supply chain demand forecasting in the automotive parts industry to propose classifications of these applications, identify gaps, and provide ideas for future research. Algorithms will then be classified and then applied in supply chain management such as neural networks, k-nearest neighbors, time series forecasting, clustering, regression analysis, support vector regression and support vector machines.An extensive hierarchical model for short-term auto parts demand assess-ment was employed to avoid the shortcomings of the earlier models and to close the gap that regarded mainly a single time series. The concept of extensive relevance assessment was proposed, and subsequently methods to reflect the relevance of automotive demand factors were discussed. Using a wide range of skills, the factors and co-factors are expressed in the form of a correlation characteristic matrix to ensure the degree of influence of each factor on the demand for automotive components. Then, it is compared with the existing data and predicted the short-term historical data. The result proved the predictive error is less than 6%, which supports the validity of the prediction method. This research offers the basis for the macroeconomic regulation of the government and the production of auto parts manufacturers.

1. Introduction

Today, companies are using an ever-increasing number of decisive methods to stay competitive and sustain or increase their profit margins. As a result, predictive models have been extensively used to forecast demand in order to understand and meet the customers' needs and interests. For this reason, people are increasingly paying attention to using predictions obtained from customer data and trading records to analyze consumer behavior and preferences to manage the product supply chain (SC) accordingly.

Supply chain management (SCM) focuses on the stream of goods, on the provision of services, and on the

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flow of information from the point of origin to customers through a series of interdependent events and entities. In a typical SCM problem, ability, request and price are assumed to be known parameters. In reality, this is not the case, as changes in customer demand, supply and transportation, organizational risks, and delivery time and factors will bring uncertainty. Demand uncertainty has the greatest impact on supply chain performance, and has a large impact on production and inventory planning. In this perspective, demand forecasting is a pivotal method for resolving supply chain uncertainty.

The main characteristic of demand analysis for automotive parts is that there are numerous factors that affect the pressure changes in demand, and these factors are very complex. The linkage between primary and secondary variables varies widely, and it is difficult to perform an accurate quantitative analysis. At the same time, demand analysis involves a large amount of data. At the same time, it also has high demands on the speed of analysis algorithms and the costs of arithmetic operations, Naaman R, Goldfarb L [1]. The Influence of Gain and Loss on Arithmetic Performance.

During the research process, we found that when forecasting demand, our domestic auto parts makers generally use straightforward analytical tools and adopt retrospective methods.

In addition, they analyze quantitative and qualitative analysis separately. Usually, the diversity of demand often makes the forecast conclusions from the modeling method inadequate. Therefore, we need to establish an effective automotive parts demand forecasting model. The key to the implementation of scientific forecasting depends on the fact that qualitative methods and quantitative methods are interrelated, which requires quantitative methods as a basis and qualitative analysis of qualitative objectives; Andow J. [2], Qualitative tools and experimental philosophy.

Therefore, this article provides a continuous dynamic time series forecasting model that is based on qualitative analysis.

The model consists of two parts. The first is a quantitative forecasting model based on a continuous-time dynamic model, in which we use the continuous-time dynamic model to fit new sequences, understand historical demand data, and make quantitative forecasts for product demand. The second is based on the generalized level analysis and evaluation model of product demand influencing factors. The analysis of demand influencing factors of the automotive market provides relevant index models of influencing factors. This article combines these two models, establishes the resulting prediction model through the quantitative model of qualitative analysis, and provides better objective predictability results on this basis.

This article focuses on "demand forecasting" in the automotive parts industry. In today's expanding and erratic global supply chain, the characteristics of demand data make the use of big data analytics (and machine learning) a necessary requirement for demand forecasting. The digitization of the supply chain and the company's integrated blockchain technology allow for better tracking of the supply chain, further emphasizing the role of big data analytics.

Supply chain data are highly dimensional data generated at many points in the supply chain. Its purpose is to cause various objectives (products, supplier capabilities, orders, shipments, customers, retailers) due to the large number of suppliers, products and customers.

Their number and speed are high. They result in numerous transactions across supply chain networks. In the sense of this complexity, it has moved away from the traditional (statistical) method of demand forecasting, which relies on identifying average statistical trends in historical data (characterized by the attributes of mean and variance), while moving toward intelligent forecasting changes drawn from the data. Historical data and intelligent adjustment to forecast demand changes in the supply chain.

This ability is achieved by applying big data analytics technology, which extracts forecasting rules by discovering potential relationships between demand data in supply chain networks.

Processing these technologies are computationally intensive and require sophisticated machine programming algorithms. With SCM endeavors to meet the requirements of customers while reducing the overall procurement cost, the implementation of machine learning/data analytics algorithms can support accurate (data-driven) demand forecasts and make supply chain activities consistent with these forecasts, thereby improving efficiency and satisfaction. Given these opportunities, this article connects the two models from each party, develops a final prediction model via a quantitative model that is based on a qualitative analysis, and gives a more objective forecast result based on that.

2. Literature Review

Today's businesses are putting more and more effort into precision marketing to remain competitive and maintain or increase their profit margins. Therefore, to better understand customer expectations and needs, such forecasting models have been heavily applied. Supply chain management in the automotive parts industry centers on the flow of assets, services, and information from sources to customers via a chain of interconnected entities and activities. In these types of supply chain management challenges, it is hypothesized that cost, demand and capacity are known parameters.

In fact, this is not the reality, as there are complexities related to fluctuations in customer demand, transportation of supplies, organizational contingencies, and delays. Demand contingencies, in particular, have the most significant impact on supply chain performance with broad effects on production planning, stock planning and transportation.

In this regard, demand forecasting is a pivotal tool for dealing with the uncertainties of automotive parts demand. Diverse statistical analysis methods have been utilized for demand forecasting in supply chain management, notably regression analysis and time series analysis. With improvements in information technology and enhanced computational efficiency, big data analysis has become a means to achieve more accurate forecasts that better capture customer needs, improve supply chain efficiency, support supply chain risk assessment, and reduce reaction time and facilitate supply chain performance evaluation. Continuous-time methods in the dynamics of demand forecasting have been proven to be useful in leading to substantial advances in contemporary growth theory and business cycle theory. Continuous-time modeling has mainly technical advantages, as continuous-time systems prove to be more manageable from the perspective of mathematical convenience.

Despite the use of various statistical analysis tools for demand forecasting in supply chain management, there is a vital limitation in time-based depictions of continuous dynamic systems that is related to fitting the model to the data and estimating the structural parameters of dynamic models. An influential subset of these required parameters is essential for designing and evaluating economic policies. Several methods have been adopted in the literature to address continuous-time systems with discrete-time systems. Similarly, inference in continuous-time models has expanded considerably in recent years.

The objective of this article is to employ the necessity of utilizing a hierarchical model to overcome the discrepancies between continuous-time and discrete-time depictions in automotive component demand forecasting by combining them with the primary factors. We characterize the link between the two by correlating the degrees of the impact factors that show a representation of the growth of the economy. The contribution of this paper is the presentation of the hierarchical model, in addition to exploring and investigating the principal factors and their applications in the models.

2.1 A Continuous Time Model of the Dynamical System

Due to the micromanagement of the automotive components industry in the country, it is difficult to build a forecasting model for short-term automotive components sales trending by the classical forecasting methods. Based on a large amount of historical data, all forecasting models such as ARIMA, ANN, Holt-winter, etc. are established to find the causal relationship that affects future trends, so the forecasting can be done by setting up related inference type models [3].

The core of automotive component forecasting is to study the dynamic system time shift rule, and infer the future variations of the system based on the prevailing state data. And the model of dynamic system may be represented by higher order equations.

When we are using the continuous time to observe the dynamic behavior of component sales, we refer to it as the continuous time model of dynamic system applied by Zhao Shipeng [4]. Under the characteristics of short-term shifts of automotive component sales, differential equations of:

$$\frac{d^n x_1}{dt^n} + \sum_{i=1}^{n} a_i \frac{d^{n-1} x_1}{dt^{n-1}} = b_0 + \sum_{i=1}^{h-1} b_i x_i + 1 \quad [1]$$

Noted as $D(n, h)$, where

$X_i (i = 1, 2, \ \ , h-1)$ is an accumulated time series of primary time series, the next three following mathematical models will be considered.

First dynamic linear model, single sequence Dynamic model (1,1) model:

$$\frac{dx_1^{(1)}}{dt} + ax_1^{(1)} = \mu \quad [2]$$

Where a, are constant.

second, 1st order linear dynamic model with three sequences (DM (1, 2) model:

$$\frac{dx_1^{(1)}}{dt} + ax_1^{(1)} = bx_2^{(1)} \quad [3]$$

Where $x_2^{(1)}$ is once accumulated of $\{x_2^{(0)}\}$ series, a and b are constant.

Third dynamic linear model with three sequences dynamic model (1,3) model:

$$\frac{dx_1^{(1)}}{dt} + ax_1^{(1)} = bx_2^{(1)} + cx_3^{(1)} \quad [4]$$

Where $x_3^{(1)}$ is once accumulated sequence of $\{x_3^{(0)}\}$,a, b and c are constant.

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2.2 Data Processing

Once the data from the previous Generative Operation process is obtained before setting up the fluctuating economic sequence model, while an inverse Accumulated Generative Operation is usually used to restore the predicted value created from the previous model. Economic sequence $x^{(0)}$ is a nonnegative sequence (i.e., each component, $x^{(0)}(k)\ge 0$) ,Thus $x^{(1)}$ is monotonically increasing. Liu Zhu emphasizes that after the sequence of cumulative generation operations $x^{(1)}$ has superior characteristics to the properties than the initial sequence $X^{(0)}$ i.e., it has higher regularity, and the varying sequence produces a new monotonous sequence, which undermines the probability of the sequence of measured values Liu, Through the accumulated generation process, the time series $\left\{x^{(0)}(t)\right\}, x^{(0)}(t)\ge 0, t=1,2,\dots,n$ get monotone increasing $x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(t)$ The initial time series is non-negative and the variation of its data magnitudes is erratic, but the resulting time series is not only non-negative, but also monotonous, i.e., the change of data variance has a certain smoothness. Compared to the initial sequence, the sequence continued by an improved identification. Due to the fact that the smooth continuous function can derivate from any point, the sequence $\left\{x^{(0)}(t)\right\}$ Consists of discrete single points, so typically it has no derivative, so we cannot search for the uniformity of the sequence. $\left\{x^{(0)}(t)\right\}$ with derivative. We study the characteristics of smooth continuous function, but sequence $\left\{x^{(0)}(t)\right\}$ consists of discrete single points, so typically it has no derivation, so we cannot search for the consistency of the sequence $\left\{x^{(0)}(t)\right\}$ with derivation. We investigate the features of smooth continuous functions from the subsequent perspectives considered as smooth.

Definition1: assume that $X(t)$ is continuous function defined on [a, b], insert interior points on.

Hypothesis 1: if a sequence has roughly similar characteristics with smooth and continuous function, the sequence is considered to be smooth.

Definition1: $a=t_1, t_2<\ldots<t_n<t_{n+1}=b$

Assume that (t) is continuous function defined on [a, b], insert interior points on [a, b] Now on [a, b] there is a division $\Delta t_k=\left[t_k, t_{k+1}\right], k=1,2,\ldots,n$. We use Δt_k to express the length of $\Delta t_k=\left[t_k, t_{k+1}\right], k=1,2,\ldots,n$ Take any point on $\left[t_k, t_{k+1}\right]$, we get $x(k)$ thus we have series

$$X=(x(1),x(2),\ldots,x(n)),\quad X_0=(x(t_1),x(t_2),\ldots,x(t_n))$$

is recorded as lower boundary point sequence. Let $\Delta t \ \frac{\max}{1\le k\le n}\{\Delta t_k\}$ assume that d is a distance function in n-dimensional space, X^* is the 1≤k≤n representative sequence for specified function. No matter how time zone [a, b] is divided and how interior point in small time interval is selected, when Δt → 0 there are:

(1) For any interior point sequence

$X_{i,} X_{j,} d(X^*, X_i)=d(X^*, X_j)$;

(2) $d(X^*, X)=d(X^*, X_0)$

Then we call x(t) smooth continuous function.

Theorem 1: assume a sequence, $X=(x(1),(2),\ldots,x(n), x(n+1))$, Z is a mean sequence generated from $X, Z=(z(1),z(2),\ldots,z(n))$ among which $z(k):=0.5x(k+1)$, $k=1,2,\ldots,n.X^*$ is a representative sequence for a derivative function, and d is a distance func-tion in n-dimensional space. We still call it X after deleting $x(n+1)$ from X, if the following conditions are satisfied, we call X smooth sequence.

In that case we can say that $x(t)$ is the smooth Continuous function. K is sufficiently large,

(1) $x(k)<\sum_{i=1}^{k-1} x(i)$

(2) $\frac{\max}{1\le k\le n}\left|x^*(k)-x(k)\right|\ge \frac{\max}{1\le k\le n}\left\|x^*(k)-z(k)\right|$

(1), (2) are called sequence smoothness conditions.

Theorem 2: assume that $X^{(0)}$ is nonnegative sequence,

$X^{(0)}=(x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(1))$, $x^{(0)}(k)\ge 0$ and $x^{(0)}(k)\in\left[a,b\right]k=1,2,\ldots n.X^{(r)}=(x^{(r)}(1),x^{(r)}(2),\ldots,x^{(r)}(n))$ is accumulated generating time sequence of $X^{(0)}$ when *r* is sufficiently large, for any $\varepsilon>0$, there exist, $N, N<k\le n$, $\frac{x^{(r)}(k)}{\sum_{i=1}^{k-1} x^{(r)}(i)}$, i.e., for the bounded non-negative sequence, after many accumulated generating operations, the resulting sequence is adequately smooth, and the smooth rate is $\rho(k)\to 0(k\to\infty)$

Theorem 3: assume that $X^{(0)}$ is a nonnegative sequence, $X^{(0)}=(x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}x(n))$ $x^{(0)}(k)\ge 0$ and $x^{(0)}(k)\in\left[a,b\right]$, $k=1,2,\ldots,n$. $X^{(1)}=(x^{(1)}(1),x^{1}(2),\ldots,x^{(1)}(n))$ is once accumulated generating sequence of $X^{(0)}, Z^{(1)}=(z^{(1)}(1),z^{(1)},(2),\ldots, z^{(1)}(n))$.

where $z^{(1)}(k)=0.5x^{(1)}(k)+0.5x^{(1)}(k-1)$ is adjacent mean generated sequence of $X^{(1)}$,then for any $\varepsilon_1\le\varepsilon_2\in\left[0,1\right]$, there is a positive integer N, and for any $k, N<k\le n$ there are

$$\rho(k)=\frac{x^{(0)}(k)}{\sum_{i=1}^{k-1} x^{(0)}(i)}<\varepsilon_1, \frac{x^{(0)}(k)}{z^{(1)}(k)}<\varepsilon_2 \quad [5]$$

As both the accumulated generation operation and the average one can improve the consistency of the sequence, we can use two types of methods by combination, even if we implement an average generation after the accumulation and generation process [5].

3. Assessment Model of the Driving Factors

3.1 Feasibilities Affecting the Environment of Automotive Components

The following are relevant factors impacting the future tendencies of the automotive parts business and industry: political factors, economic factors, social factors, and technological factors. With the aid of the research and analysis of past, present and future of China's automobile components industry, we find that: political factors are the guarantee for the healthy development of the automobile industry; economic factors are the basis for the automobile parts industry to take off; technical factors are the prerequisite for the prosperity of the automobile parts industry; social factors are the creation of automobile consumption the key to the market [6,7]. Based on the relevance of the factors affecting automobile parts demand [8], we established a hierarchical model for assessing auto parts demand factors, as follows:

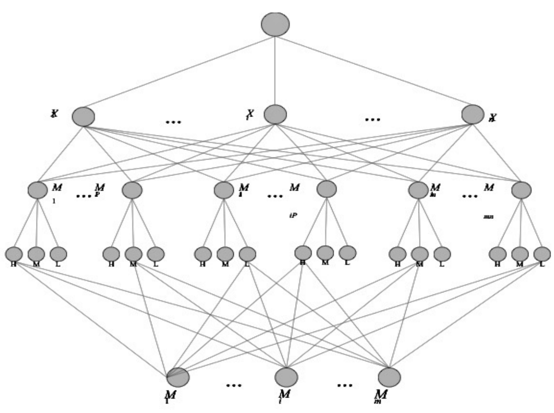

Figure 1. Hierarchical assessment model of driving factors

Car parts demand prediction time series for, $x_n(j), i=1, 2,...,n; j=1,2,...,m$ here is the actual time series, we obtained

$$R_r = \begin{bmatrix} & M_1 & M_2 & \cdots & M_n \\ c_1 & x_{r1}(1) & x_{r2}(1) & \cdots & x_{rn}(1) \\ c_1 & x_{r1}(2) & x_{r2}(2) & \cdots & x_{rn}(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_m & x_{r1}(m) & x_{r2}(m) & \cdots & x_{rn}(m) \end{bmatrix} \quad [6]$$

$$R_f = \begin{bmatrix} & M_1 & M_2 & \cdots & M_n \\ c_1 & x_{f1}(1) & x_{f2}(1) & \cdots & x_{fn}(1) \\ c_1 & x_{f1}(2) & x_{f2}(2) & \cdots & x_{fn}(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_m & x_{f1}(m) & x_{f2}(m) & \cdots & x_{fn}(m) \end{bmatrix} \quad [7]$$

3.2 Characteristics of One-layer Correlation Right

If R_W is the weight matrix influencing the factors of each predictive model and w_i (i=1,2, …, n) is the weights of *i-th* factors of each predictive object. We obtain

$$R_w = \begin{bmatrix} & M_1 & M_2 & \dots & M_n \\ w_i & w_i & w_i & \cdots & w_n \end{bmatrix} \quad [8]$$

3.3 Characteristics of the Two-layer Correlation Line

The request for car parts includes various levels of influencing factors, so its related weight needs to be divided into various layers. Consider two layers as a sample, the remaining can be done in the similar way, this includes:

$$R_w = \begin{bmatrix} & M_1 & M_2 & \cdots & M_n \\ w_i & w_1 & w_2 & \cdots & w_n \\ & c_{11}c_{12}\dots c_{1k} & c_{21}c_{22}\dots c_{2k} & \cdots & c_{n1}c_{n2}\dots c_{nk} \\ w_{ik} & w_{11}w_{12}\dots w_{1k} & w_{21}w_{22}\dots w_{2k} & \cdots & w_{n1}w_{n2}\dots w_{nk} \end{bmatrix} \quad [9]$$

Where c_{ik} stands for the k-th secondary influential factor which belongs to the i-th main influential factor of the hierarchy model of the automobile parts demand, we use w_{ik} (*i*= 1,2…, n; *k*=1,2…*p*) to express their corresponding right.

3.4 Correlation Degree Eigenmatrix

By correlation processing of the respective membership degree of the automotive parts demand forecasting method, we obtain the corresponding correlation coefficient to create the eigenmatrix of the correlation coefficient, like the following. R_ζ, as followed

4. A Dynamic Continuous Time Model and Evolutionary Extension Correlation Evaluation Based Predictive Learning Algorithm

4.1 Correlation Transformation Algorithm

Obviously, the membership degree of each influence feature is quite scattered. This is not conducive to the

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comparison of overall factors. Therefore, we need to rely on results. Usually, we use a centralized weighted treatment. Here, we have a new approach to figure out the weight, that is, we add the eigenvalues of drivers at different time points, plus we normalize the eigenvalues of every driver.

$$R_\xi = \begin{bmatrix} - & M_1 & M_2 & \cdots & M_m \\ c_1 & \xi_{11} & \xi_{21} & \cdots & \xi_{m1} \\ c_1 & \xi_{12} & \xi_{22} & \cdots & \xi_{m2} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ c_n & \xi_{1n} & \xi_{2n} & \cdots & \xi_{mn} \end{bmatrix} \quad [10]$$

Next, after obtaining the correlation coefficient of each driver, take car part sales as the center, calculate the time interval between each time point and car parts sales, and finally average the time interval of every time point in the identical time [9].

The relationship between automobile parts demand and various factors. Proceed as follows:

Step1: we determine the mathematical average of each driver, i.e.:

$$\begin{aligned} &M_1 \frac{1}{m}(\xi_{11}+\xi_{12}+\dots+\xi_{1m}) = \frac{1}{m}\sum_{j=1}^{m}\xi_{1j} \\ &M_2 \frac{1}{m}(\xi_{21}+\xi_{22}+\dots+\xi_{2m}) = \frac{1}{m}\sum_{j=1}^{m}\xi_{2j} \\ &M_n \frac{1}{m}(\xi_{n1}+\xi_{n2}+\dots+\xi_{nm}) = \frac{1}{m}\sum_{j=1}^{m}\xi_{nj} \end{aligned} \quad [11]$$

Step2: Develop a normalization treatment in accordance with the typical degree of every factor.

$$R_\xi = \begin{bmatrix} & M_1 & M_2 & \cdots & M_n \\ c_1 & \frac{\xi_{11}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{1j}} & \frac{\xi_{21}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{2j}} & \cdots & \frac{\xi_{21}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{mj}} \\ c_2 & \frac{\xi_{12}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{1j}} & \frac{\xi_{22}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{2j}} & \cdots & \frac{\xi_{m2}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{mj}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ c_n & \frac{\xi_{1n}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{1j}} & \frac{\xi_{2n}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{2j}} & \cdots & \frac{\xi_{mn}}{\frac{1}{n}\sum_{j=1}^{n}\xi_{mj}} \end{bmatrix} \quad [12]$$

Step3: $M_k, 1 \le k \le m$, evaluate the interval between $M_i, i = 1,2,\dots,k-1,k+1,\dots,m$ and $M_k, 1 \le k \le m$ $d_{ik}(M_i, M_k), i = 1,2,\dots,k-1,\dots m; 1 \le k \le m$

$\hat{a} = (B^T B)^{-1} B^T Y$;

$$whereB = \begin{bmatrix} -1/2(x_1^{(1)}(2)+x_1^{(1)}(1)) & 1 \\ -1/2(x_1^{(1)}(3)+x_1^{(1)}(2)) & 1 \\ \dots & \dots \\ \dots & \dots \\ -1/2(x_1^{(1)}(n)+x_1^{(1)}(n-1)) & 1 \end{bmatrix} \quad [13]$$

$$\hat{a} = (a, \mu)^T \quad [14]$$

$$Y = (x_1^{(0)}(2), x_1^{(0)}(3), \dots\dots, x_1^{(0)}(n))^T \quad [15]$$

Step4: obtaining a, μ, the response to the second model is

$$x_1^{(1)}(t) = (x_1^{(1)}(0) - \frac{\mu}{a})e^{-at} + \frac{\mu}{a} \quad [16]$$

Step5: Implement inverse accumulated operation

$$x_1^{(0)}(t) = (x_1^{(1)}(t+1) - x_1^{(1)}(t)) \quad [17]$$

We may then extract the expected result.

4.2 Forecast Value of the K-moment System in the Future

Step 1: we handle the observed random event sequence with the accumulated operation and the mean value handling.

Step 2: If it is a linear dynamical system with a one-factor succession, set up the prediction model using formula (2), or if it is a linear dynamical system with a two-factor sequence, set up the prediction model using formula (3), in case it concerns a linear dynamical system with a three-factor sequence, set up the prediction model applying formula (4);

Step 3: Complete the model by using 3.3;

Step 4: Obtain the solutions by the cumulative inverse process, and afterwards the results are expected values of the unstable phase.

4.3 Short-term Demand Analysis and Forecasting of Automotive Components

Step1: We will do a qualitative analysis with the factors that influence the demand for auto parts in Algorithm 3.1, which will lead us to the correlation coefficients factor that influences the demand.

Step 2: the primitive correlation $\{x^{(0)}(t)\}$ will also be processed using Algorithm 3.2; this will lead us to the weights of each factor that influences demand.

Step 3: The analysis should lead us to make, within the framework of the algorithm, a short-term forecast of the demand for car parts.

4.4 Analysis Procedure

We analyze the proposed model in this article by selecting the data of auto parts demand. The results can support the government to make a comprehensive control of the auto parts industry and the auto parts manufacturing companies to make a preventive action plan. The statistics of car parts sales in the local area and the influencing factors of auto parts demand are available:

During the analysis, we found that different factors enlighten the demand such as, workers' income, workers' annual savings balance, annual per capita income, gross domestic product, GDP per capita, investment in social fixed assets, a quarter of industry GDP, retail sales of social consumers.

In this article, we specifically selected the above factors for analysis to prove their relationship with the demand for spare parts.

In Table 1, the data were processed according to algorithms 4.1 and 4.2, which will give us Tables 2, 3 and 4.

Table 2 gives us the correlation coefficients of the demand factors in different time periods, Table 3 will evaluate the intervals between car parts sales and the factors.

Table4 shows the correlation coefficients of the impact factors according to the car parts sales. Finally, Table 5 shows us the values of correlation based on car part sales.

Let's highlight Table 5 with Figure 2, which plots the degrees of correlation amongst the drivers with respect to auto parts sales, by which we can observe that y04>y 08>y01>y02>y05>y07>y06>y03, so fixed asset capital investment has the highest correlation level with auto parts sales, the second closet is the incentive. The third industry GDP holds the minimal influence.

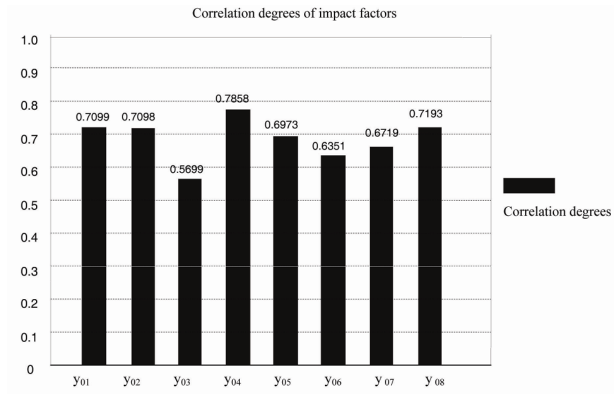

Figure 2. Extent of interrelationship between the impact factors

In Table 6, a comparison between actual values from 2007 to 2019 and auto parts values was undertaken. Based on the method and model, the existing data were also utilized to compare them with the forecast of the sustained demand for auto parts for the period 2007-2019.

Table 1. Numerical Table of factors

year	Sum of car component sales	gross domestic	per capita	proportion of the	social fixed	retail sales of	premium (one	per capita	urban and rural
	(10 thousand)	product (GDP)	GDP	third industry	assets	social	hundred	annual income	residents'
		(one	(Yuan)	GDP (%)	investment	consumption	million Yuan)	(Yuan)	year-end savings
		hundred million			(one hundred	(one hundred			balance
		Yuan)			million Yuan)	million Yuan)			(one hundred
									million Yuan)
2007	205.42	99214.6	7858	39.02	32917.73	39105.7	1596	3711.83	54332
2008	249.96	109655.2	8622	40.46	37213.49	43055.4	2109.0	4058.54	73762.0
2009	289.67	120332.7	9398	41.47	43499.91	48135.9	3054.0	4518.90	86911.0
2010	358.36	135822.8	10542	41.23	55566.60	52516.3	3880.0	4993.22	103617.0
2011	423.65	159878.3	12336	40.38	70477.40	59501.0	4714.0	5644.62	119555.4
2012	572.90	184937.4	14185	40.51	88773.60	67176.6	4932.0	6366.56	141051.0
2013	721.60	216314.4	16500	40.94	109998.16	76410.0	5640.0	7174.73	161587.3
2014	879.15	265810.3	20169	41.89	137323.94	89210.0	7036.0	8475.04	172534.2
2015	938.05	314045.4	23708	41.82	172828.40	114830.1	9784.0	9794.87	217885.4
2016	1364.50	340506.9	25575	43.36	224598.77	132678.4	11137.0	10753.98	260771.7
2017	1806.19	401512.8	30015	43.24	251683.77	156998.4	14528.0	14811.72	303302.5
2018	1850.51	473104.1	35198	43.37	311485.13	183918.6	14339.3	15694.32	343635.9
2019	1930.64	519470.1	38459	44.65	374694.74	210307.0	15487.9	17145.76	399551.8

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Table 2. Treatment of the transformation of the correlation of the factors

year	total car Part sales $x_0(t)$	(GDP) $x_1(t)$	Per capita GDP $x_2(t)$	proportion of the third industry GDP $x_3(t)$	fixed assets investment $x_4(t)$	Retail sales of social consumption $x_5(t)$	premium $x_6(t)$	per capita income $x_7(t)$	savings year-end balance $x_8(t)$
2007	0.342181	0.509703	0.527762	0.949184	0.338243	0.541166	0.296203	0.566758	0.390314
2008	0.416374	0.563340	0.579074	0.984213	0.382384	0.595824	0.391411	0.619697	0.529897
2009	0.482521	0.618195	0.631192	1.008782	0.446979	0.666131	0.566794	0.689990	0.624357
2010	0.596942	0.697773	0.708025	1.002943	0.570969	0.726749	0.720092	0.762413	0.744371
2011	0.705700	0.821355	0.828514	0.982267	0.724184	0.823407	0.874875	0.861875	0.858871
2012	0.954315	0.950093	0.952698	0.985429	0.912184	0.929626	0.915334	0.972108	1.013292
2013	1.202014	1.111289	1.108178	0.995889	1.130275	1.057403	1.046732	1.095508	1.160822
2014	1.464454	1.365568	1.354597	1.019242	1.411059	1.234536	1.305816	1.294052	1.239464
2015	1.562568	1.613370	1.592284	1.017295	1.775881	1.589081	1.815820	1.495576	1.565261
2016	2.272932	1.749313	1.717676	1.054757	2.307842	1.836076	2.066924	1.642022	1.873350
2017	2.025820	1.5624913	1.5449290	1.0364716	1.7120793	1.6022214	1.9225304	1.742890	1.6169524
2018	2.075529	1.8410897	1.8117079	1.0395877	2.1188781	1.8769511	1.8975592	1.893263	1.8319759
2019	2.165402	2.0215234	1.9795579	1.0702696	2.5488616	2.1462536	2.0495566	1.9203561	2.1300679

Table 3. intervals between factors and car parts sales

year	$\Delta_{01}(t)$	$\Delta_{02}(t)$	$\Delta_{03}(t)$	$\Delta_{04}(t)$	$\Delta_{05}(t)$	$\Delta_{06}(t)$	$\Delta_{07}(t)$	$\Delta_{08}(t)$
2007	0.167522	0.185581	0.607003	0.003938	0.198985	0.045978	0.224578	0.048133
2008	0.146967	0.162700	0.567839	0.033990	0.179450	0.024963	0.203324	0.113523
2009	0.135673	0.148670	0.526260	0.035542	0.183610	0.084273	0.207468	0.141836
2010	0.100831	0.111083	0.406001	0.025973	0.129807	0.123150	0.165471	0.147429
2011	0.115655	0.122815	0.276567	0.018484	0.117707	0.169175	0.156176	0.153171
2012	0.004221	0.001617	0.031114	0.042130	0.024689	0.038981	0.017793	0.058977
2013	0.090725	0.093835	0.206125	0.071738	0.144610	0.155282	0.106506	0.041191
2014	0.098886	0.109857	0.445213	0.053396	0.229918	0.158638	0.170403	0.224991
2015	0.050802	0.029717	0.545272	0.213313	0.026514	0.253252	0.066992	0.002693
2016	0.523619	0.555255	1.218175	0.034911	0.436856	0.206008	0.630909	0.399581
2017	0.4633287	0.4808910	0.9893485	0.3137408	0.4235986	0.1032897		0.4088677
2018	0.2344397	0.2638214	1.0359416	0.0433488	0.1985782	0.1779701		0.2435534
2019	0.1438796	0.1858453	1.0951334	0.3834586	0.0191494	0.1158464		0.035335

Table 4. Coefficients correlation of factors

periods	$\xi_{01}(t)$	$\xi_{02}(t)$	$\xi_{03}(t)$	$\xi_{04}(t)$	$\xi_{05}(t)$	$\xi_{06}(t)$	$\xi_{07}(t)$	$\xi_{08}(t)$
2007	0.786373	0.768503	0.502187	0.996214	0.755755	0.932281	0.732554	0.929223
2008	0.807753	0.791286	0.518898	0.949659	0.774477	0.963180	0.751719	0.845137
2009	0.820001	0.805937	0.537901	0.947373	0.770414	0.880790	0.747903	0.813271
2010	0.860246	0.848000	0.601627	0.961648	0.826512	0.834026	0.788455	0.807259
2011	0.842650	0.834408	0.689552	0.973124	0.840271	0.784703	0.798032	0.801178
2012	0.995754	1.000000	0.953926	0.937789	0.963597	0.942346	0.974196	0.914140
2013	0.872670	0.868808	0.749136	0.897006	0.810278	0.798966	0.853424	0.939143
2014	0.786373	0.768503	0.502187	0.996214	0.755755	0.932281	0.732554	0.929223
2015	0.807753	0.791286	0.518898	0.949659	0.774477	0.963180	0.751719	0.845137
2016	0.820001	0.805937	0.537901	0.947373	0.770414	0.880790	0.747903	0.813271
2017	0.38001623	0.388703907	0.368026275	0.384428269	0.36347096	0.545756953	0.723199	0.39094783
2018	0.56663028	0.556027588	0.357197476	0.826606082	0.56277135	0.409574148	0.786101	0.53521372
2019	0.70326967	0.657734929	0.344326489	0.337832202	1	0.516861264	0.758231	1

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Table 5. Impact degrees of correlating factors

degrees	yr01	yr02	yr03	yr04	yr05	yr06	yr07	yr08
	0.7099	0.7098	0.5699	0.7858	0.6973	0.6351	0.6719	0.7193

Table 6. Comparison between periods 2007 to 2019 of car parts and actual values

period	actual value	predicted value	absolute error	relative error
2007	205.42	205.42	0.00	0.0000
2008	249.96	234.90	15.06	0.0602
2009	289.67	289.44	0.23	0.0008
2010	358.36	358.17	0.19	0.0005
2011	423.65	443.22	19.57	0.0462
2012	572.90	548.46	24.44	0.0427
2013	721.60	678.70	42.90	0.0595
2014	879.15	839.86	39.29	0.0447
2015	938.05	1039.28	101.23	0.1079
2016	1364.50	1286.07	78.43	0.0575
2017	1806.19	176124	44.95	0.0249
2018	1850.51	1792.68	57.83	0.0313
2019	1930.64	1889.12	41.52	0.0215

The results we found or predicted, based on the hierarchical model that was the approach in this research, show a fine and adjusted degree between the primitive series and the predictive series of the years 2007 to 2012. While some errors were found in the statistics of the year 2008, fairly the other years were controlled in the 6%, which means that the model we applied can precisely predict the short-term demand. The main reason for the rise in prediction errors in 2008 is due to the financial crisis which raised the instability of the demand for spare parts. Fortunately, the prediction errors return to normal in 2009.The results obtained show us a trustworthy demand system, at the same time the objective of monitoring spare parts by the relevant policies of the economy has been fulfilled.

5. Conclusions

The auto component industry has emerged as an important portion of China's automotive business. The forecasting model studied in this article solves short-term problems that traditional forecasting methods cannot cope with. It can also adapt to uncertain shifts in demand for auto parts with greater accuracy. By utilizing predictive models for forecasting the request for automotive components over the next three years, we realize that the request for components will continue to increase, and the rate of growth will expand in the future.

Simultaneously, the in-depth assessment model established in this article offers a feasible as well as effective method for forecasting and analyzing the demand for automotive parts for automotive companies and government agencies. The model analyzes the major factors that affect the demand for automotive components and ranks them according to their degree of impact. We note that out of the various influencing drivers, capital investment and bonuses have a large impact. In contrast, service industry GDP has little impact. These analyses will enable the government to exercise macro management over the request for automotive components and help manufacturers formulate production plans.

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