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RESEARCH ARTICLE

Research on Multi-Characteristic Enterprise Product Intelligent Pricing Method Based on GSADF-TOPSIS-BP Model

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ABSTRACT Enterprise product shows many characteristics, thus, pricing is an essential strategy of an enterprise, but the multi-characteristic enterprise product pricing method does not adapt to the dynamic and changeable market demand. As a method of artificial intelligence, the prediction ability of BP (Back ProPagation Network) has been questioned and challenged. Therefore, this article established a multi-characteristic intelligent pricing method research system for an enterprise products, through GSADF (Generalized Sup ADF Statistic) model, measured the price bubble of enterprise products; TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, established the multi-characteristic enterprise product price impact factor index system and sort the weight, clarify the weight of price impact factor; Further, built GSADF-TOPSIS-BP model as an intelligent pricing method model and make the final pricing based on the price bubble risk level and risk alert, the multi-characteristic enterprise product intelligent pricing method is determined. It reflects the intelligence and superiority compared with the traditional pricing method model, and provides new ideas and methods for multi-characteristic enterprise product pricing.

INDEX TERMS Multi-characteristic enterprise product, GSADF-TOPSIS-BP model, intelligent pricing method.

I. INTRODUCTION

With the popularization of entrepreneurship and surge of entrepreneurial enterprise, the innovation the ability of enterprise is facing new challenges and requirements. Enterprise innovation is reflected in product, system, and management, and product innovation refers to the creation of a new product or the original product function innovation to meet the market and consumer needs. Product innovation improves the degree of product differentiation, and thus the product price increases, to increase the profitability of the enterprise [1]. Based on the requirement of product innovation, the enterprise product shows multiple characteristics, can meet different needs of the consumers, the basic characteristic of the product make the product have use value, and other characteristic make the product have investment value. The multi-characteristic product brings some trouble to product pricing, which makes product pricing more difficult. Product pricing is a bridge connecting the behavior of both product transaction [2]. Reasonable pricing allows the suppliers to balance profit and sales, mis-pricing errors lead to poor sales or low profit [3]. With the dynamic change in product characteristics and the market environment, the intelligence and timeliness of product pricing need to be continuously improved, and is imperative to the proposal and application of intelligent pricing methods.

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Due to the needs of academic research and enterprise development, artificial neural network methods have gradually received attention, Wang et al. [4] predicted electric prices through an artificial neural networks. Wang et al. [5] made an intelligent prediction based on the BP model. Sun [6] built a dynamic pricing method of an intelligent prediction model based on the BP neural network and support vector mechanism. Kong [7] used reinforcement learning to make real-time pricing, and the LSTM network complete prediction. Lu [8] used the ANN model to pricing options based on the machine learning method. Chen [9] used the neural network method to study the pricing of weather derivatives. Yang and Wang [10] used the ELM model and Monte Carlo simulation the method to conduct an empirical study of air temperature derivatives pricing. Hou [11] believed random forest has the highest prediction accuracy, and the boosting and support vector regression is second, in contrasts, the BP model has the most significant error in the empirical study of option pricing.

Although intelligent pricing methods have been questioned, Google, Microsoft, and small-scale enterprises have widely used them. The rational use of an intelligent pricing method makes pricing reasonable, and improves operating efficiency and profit [12]. This method has been used in gasoline [13], electric [14], sports [15], and online retail [16]. Computer science and Internet technology are applied to product pricing, to realize intelligent product pricing, avoid the subjective qualitative analysis and effectively solve the problem of the poor effect of traditional pricing method.

Although the intelligent pricing method is constantly developed, improved, and widely used in many fields, its disadvantage and limitation cannot be ignored. The trend to complexity in machine learning contains the complexity of data, models, AI algorithms, and explanatory techniques [17]. The main reasons for the low pricing accuracy are the weak theoretical basis, abnormal datas, and insufficient pricing power. To solve this problem, this article proposes multi-characteristic intelligent pricing method for enterprise product, through the GSADF model measured the price bubble of multi-characteristic enterprise product, TOPSIS model analyzed the price impact factor index system and weight, GSADF-TOPSIS-BP model made intelligent pricing of multi-characteristic enterprise products, and determine the final product pricing based on the price bubble risk level and risk alert. This article combined the historical data of the enterprise, product, market, and prediction of future demand together for self-learning, and intelligent product pricing, thus providing a reference for enterprise product pricing. Different from previous studies, the multi-characteristic enterprise product intelligent pricing method solves the prediction accuracy problem of intelligent pricing method, it reflects the intelligence and superiority compared with traditional pricing method model, and provides new ideas and methods for multi-characteristic enterprise product pricing.

II. SAMPLE ANALYSIS AND SELECTION

In addition to the basic characteristic, the product also contains other characteristics. The enterprise product characteristic determines the product value and price, so that product has use and investment value and present financial characteristics. Zhang and Liu [18] divided commodity financialization into two stages: the first stage is the transition from ordinary commodities to capital goods. The price of ordinary commodities in this stage is mainly affected by supply and demand. However, due to the intervention of capital, the market demand changes from pure consumption demand to the coexistence of consumption and investment demand. This stage can be further divided into low-level and high-level stages. The price of commodities in the low-level stage, such as shallot and garlic, are mainly determined by supply and demand. There is no large-scale unify market and there are only a few market participants. High-level stage of commodities such as cotton, sugar, and tea et al., the price has been affected by investment, has formed a certain scale of the market, market trading more active and under the influence of the peripheral market, is difficult to control by a small amount of money market, the price often appears more moderate persistent rise, generally only for a periodic callback. The second stage is the transition from capital goods to financial products, representing goods such as padauk. The entity attribute of commodity still exists, but its consumption function is weak, and most transactions are motivated by investment. The price changes from being mainly influenced by supply and demand to expectations.

Therefore, based on the research theme and empirical needs of this article, it is more appropriate to select enterprise products in the high-level of the first stage. The selection of samples should reflect the multi-characteristic of enterprise product. The trading market has formed a certain scale, and the characteristic of each market segment is different.

A. SAMPLE ANALYSIS

Pu'er tea producing area, species, planting method, the different characteristic of processing technology and packing design, and the value is different, because of Pu'er tea producing area is wide, the processing technology is tedious, and the level is uneven, it is impossible to give a comprehensive description of its characteristic. But in the end product characteristic embodied in the product value, the product value and market segments for analysis. The basic characteristics are edible, medicinal, drinks and cultural value, and other characteristics have investment value. Edible, medicinal, drinks, and cultural value are use value, just the value is different, and the investment value is part of the product's unique value.

The value of Pu'er tea is embodied in the following five aspects: (1) Edible value. Pu'er tea is combined with other ingredients to produce distinctive dishes as raw materials. (2) Medicinal value. Pu'er tea has health and medicinal effects such as anti-oxidation, lowering blood pressure, and reducing weight. Hong Kong and Macao consumer call it "the best thing for keeping healthy", while consumers in

Southeast Asia, Japan, and western Europe call it "beauty tea", "slimming tea", and "longevity tea". (3) Tasting value. The aroma of Pu'er tea is its core tasting value, which can be perceived by taste, touch, vision, and smell. (4) Cultural value. Pu'er tea is China's traditional famous tea with profound historical, cultural connotations and deposits, representing "tea and horse culture" and "horse gang culture". Pu' er tea culture reflects inclusiveness, openness, and compatibility of Yunnan ethnic culture. (5) Investment value. The older Pu'er tea is preserved in an appropriate environment, the higher its market price will be. The market value is becoming more and more expensive with the characteristic of long-term investment in the collection. The popularity is not just a temporary speculation behavior, but because it meets the needs of modern society for collection and investment, which makes it stand out among many products, it become a new collection investment object, and attracts more and more collectors and investors.

Compared with the other three values, Pu'er tea's edible and medicinal value is weak, and its substitutes can be found in the market. Based on its value characteristics and benefits for consumers or investors, the Pu'er tea consumption market can be divided into a gift, auction, collection, and terminal markets. In the gift, auction, and collection market, consumers and investors mostly make purchase and investment decisions based on the investment value of the product, while the terminal market pays more attention to the consumption of the product and sells them as consumer goods, so it is the mainly based on the product use value, without too much consideration of product investment value. But the market segmentation overlap and fuzzy classification problems, such as gift market and product in the auction market traders are also possible for collection purposes, but it is overlap with the collection market. So in this article, based on market segmentation, according to the interests of the consumers in the Pu'er tea market demand will be divided into consumption and investment market. In the consumer market, consumer make a purchase decisions based on the use value of the product, while in the investment market, investors make an investment decisions based on their investment value. Sample product value and market segment are shown in Fig.1.

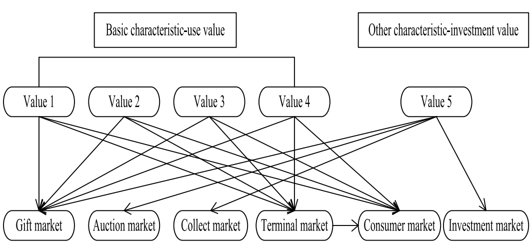

FIGURE 1. Sample product value and market segment.

B. SAMPLE SELECTION

This article selected DY 7542 raw tea and DY 7572 ripe tea made every year, DY 7542 raw tea, and DY 7572 ripe tea made in 2011 as a research samples. DY 7542 raw tea made every year is product 1, DY 7572 ripe tea made every year is product 2, DY 7542 raw tea made in 2011 is product 3, and DY 7572 ripe tea made in 2011 is product 4. Among them, products 1 and 2 are new products produced and promoted by DY enterprise, it takes some time to store, then have more drinking value, large appreciation space, storage value, and more investment value. Products 3 and 4 are suitable for drinking and low appreciation space and storage value, mainly as a daily consumer products. Therefore, this article selected products 1 and 2 as representing products of the investment market, and products 3 and 4 as representing products of the consumer market. The weekly price data of four products from June 12, 2012 to December 27, 2020, each product has 446 price data, a total of 1784 price data. The data source is from *China Pu'er Tea Network*.

III. MULTI-CHARACTERISTIC ENTERPRISE PRODUCT PRICE BUBBLE MEASUREMENT

Through the establishment of price bubble model, the existence of a price bubble is detected, and the length, frequency, and strength of price bubble are further analyzed.

A. MODEL CONSTRUCTION

Product price can be expressed as:

$$P_t = \sum_{i=0}^{\infty} \left(\frac{1}{1+r_f} \right)^i E_t \left(D_{t+i} + U_{t+1} \right) + B_t \tag{1}$$

where, P_t is the product price in period t; D_{t+i} is the product revenue in period t+i; r_f is the risk-free interest rate; U_t is an unknown factor; B_t is the speculative bubble in the product price. Theoretically, the speculative bubble B_t satisfies the submartingale property of explosion. If the product price explode, it is proved that there is a bubble.

B. DETECTION METHOD

According to Phillips et al. [19], [20], the price bubble obeys the following process:

$$P_t = \gamma T^{-\eta} + \rho P_{t\text{-}1} + \varepsilon_t \tag{2}$$

where, γ is constant, T is sample size, η>1/2, and ε_t obeys the independent identically distributed assumption. Under the null hypothesis (ρ=1), Pt follows a random walk process, under the alternative hypothesis (ρ>1), the commodity price series contains an explosive process (price bubble). The commodity price series is sequentially detected by double recursion method with variable window to detect the bubble existence and estimate the starting and ending times.

1) CONSTRUCT GSADF STATISTIC TO DETECT THE EXISTENCE OF PRICE BUBBLE IN PRODUCT PRICE SERIES

GSADF statistic is defined as:

$$GSADF(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} \{ADF_{r_1}^{r_2}\} \tag{3}$$

where, γ_0 represents the sequence of minimum sample window that guarantees effective estimation, $\gamma_0 \in(0,1]$; γ_1 represents the sample window sequence starting point; γ_2 represents the ending point; ADF_{r1}^{r2} represents standard ADF value calculated from the selected window sequence observations.

2) CONSTRUCT A BACKWARD SUP ADF STATISTIC (BSADF) SEQUENCE TO ESTIMATE THE STARTING AND ENDING POINT OF THE PRICE BUBBLE PROCESS

BSADF statistic is defined as:

$$BSADF(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2} \tag{4}$$

By constructing the BSADF statistics, estimated the bubble starting and ending times. Starting and ending time of the Kth price bubble are defined when multiple price bubbles occurs:

$$\hat{r}_{ke} = \inf_{r \in [r_{k-\hat{1}}, 1]} \{r : BSADF(r_0) > cv\} \tag{5}$$

$$r_{kf} = \inf_{r_2 \in [r_{ke} + \hat{L}_T, 1]} \{r_2 : BSADF\,(r_0) < cv\} \tag{6}$$

where, $L_T = \delta \log(T)/T$, δ varies with the sample data frequency (monthly, weekly, and daily). cv represents the critical value series, and its value is calculated by Monte Carlo simulation. Use a sample BSADF series compare with it, the starting and ending point of the sample series price bubble process can be identified.

C. MULTI-CHARACTERISTIC ENTERPRISE PRODUCT PRICE BUBBLE MEASUREMENT

The four products are run respectively. The detection time of product 1 is 44h13'59'', the detection time of product 2 is 60h11'27'', the detection time of product 3 is 49h17'13'', and the detection time of product 4 is 62h18'30''.

After Monte Carlo 2000 simulations, the GSADF value with the corresponding 95% confidence threshold[①] comparison, the detection results are shown in Fig. 2-4. The GSADF value of product 1, product 2, and product 4 price sequence is more significant than the critical value of 95% confidence, indicating that there has a price bubble phenomenon in price sequence. The GSADF value of the product 3 price sequence is less than the critical value of 95% confidence, indicating that there is no price bubble phenomenon in the price sequence. The result is shown in Table 1.

D. MULTI-CHARACTERISTIC ENTERPRISE PRODUCT PRICE BUBBLE LENGTH, FREQUENCY, AND STRENGTH MEASUREMENT

By comparing BSADF sequence and corresponding critical value sequence, estimate the starting and ending time of bubble events, reference to Li and Li [21] research, according to the bubble length (total days), bubble frequency (price bubble events) and bubble strength (maximum bubble days) three indicators, analysis, and compare the three products' market price bubble degree and difference, as shown in Table 2.

[①] GSADF method has three critical values: 90%, 95%, and 99%, with no unified requirement for the critical value choice. This article refers to other scholars' research, and selects 95% critical value.

E. PRICE COMPARISON ANALYSIS BETWEEN PRICE BUBBLE AND NO BUBBLE

This article established the following formula:

$$Ip_t = Ip_t^* + Ib_t \tag{7}$$

Among them, Ipt represents the price range during the bubble period, Ipt* represents the price range during no bubble period, Ibt represents the interval difference value. Therefore, this section will compare the price range of three products to analysis of the price bubble degree, as shown in Table 3-5.

TABLE 1. Price sequence bubble test result of four products.

Product	GSADF value	CV value	Is there a bubble
Product 1	13.70	2.26	yes
Product 2	12.53	2.26	yes
Product 3	2.60	3.54	no
Product 4	3.88	3.54	yes

IV. ANALYSIS OF PRICE IMPACT FACTOR OF ENTERPRISE PRODUCT

Through analysis the multi-characteristic enterprise product price bubble, the characteristic of the product price bubble are clarified. This part will further establish a multi-characteristic enterprise product price impact factor index system and analysis its weight, to lay a foundation for subsequent multi-characteristic enterprise products pricing.

A. ESTABLISHMENT OF MULTI-CHARACTERISTIC ENTERPRISE PRODUCT PRICE IMPACT FACTOR INDEX

With 5 level indicators, and 16 secondary indicators to establish multi-characteristic enterprise product research sample price impact factor index system, data sources from *World Tea Industry Development Report, China Agricultural Network,* et al. In this system, CSD represents the national tea supply and demand factor, YSF represents the tea supply factor in Yunnan province, PSD represents the supply and demand factor of Pu'er tea, ECO represents the economic development factor, and YIL represents the Internet development level factor in Yunnan province, as shown in Table 6.

B. SELECTION EVALUATION METHOD FOR PRICE IMPACT FACTOR OF MULTI-CHARACTERISTIC ENTERPRISE PRODUCT

MCDA (Multi-criteria Decision Analysis) is a kind of common decision-making method. It comprehensively evaluates object from a multi criteria dimensions, which improves the scientific evaluation and application performance. The theoretical basis of MCDA is utility theory, combined with the statistical methods, gradually developed into a discipline

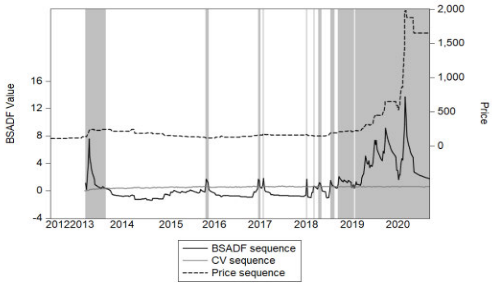

FIGURE 2. Product 1 price bubble.

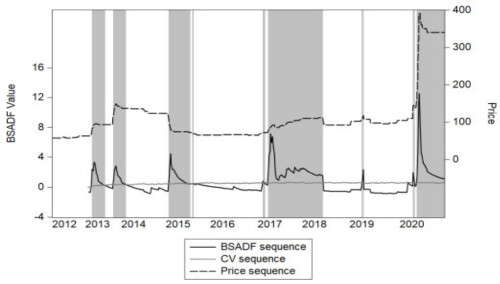

FIGURE 3. Product 2 price bubbl.

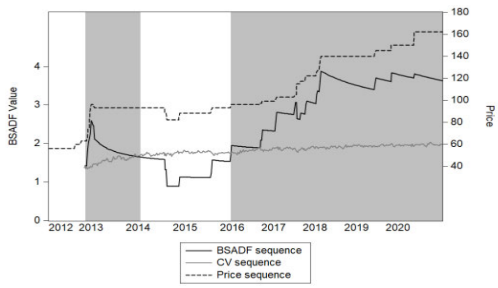

FIGURE 4. Product 4 price bubble. Note: 1. BSADF sequence and CV value sequence are marked in the left vertical axis, price sequence in the right vertical axis; 2. CV value sequence refers to the eigenvalue sequence with 95% confidence; 3. Commodity price bubbles are marked in the shadows.

and widely applied. It is mainly used to deal with decision-making problems in the fields of enterprise management, national defense requirement, social policy-making et al., to help decision-makers combine internal and external information in organizations and reduce decision-making risks. Currently, MCDA mainly includes AHP, TOPSIS, MARCOS, VIKOR, PROMETHEE et al. AHP method was proposed by Saaty in the early time of 1970s, this method is used for quantitative analysis of qualitative problems, which characteristic is simple, flexible and practical. The TOPSIS method was first proposed by Hwang C, Yoon K in 1981. It is an MCDA method based on positive and negative ideal solution distances [22]. This method needs to select the best and worst value corresponding to each evaluation index in all evaluation schemes and name them as "positive ideal solution" and "negative ideal solution". Finally, a positive and negative ideal solution scheme is formed. By evaluating the direct distance between the scheme and positive and negative ideal solution schemes, the relative closeness degree is calculated, and the final ranking is carried out.

The scheme with maximum relative closeness degree is an optimal scheme. The TOPSIS method has been vigorously developed because of its simplicity and high computational efficiency. MARCOS method was first proposed by Stević et al., and applied to the selection of medical suppliers, which proves its good performance in decision-making [23]. Different from TOPSIS, MARCOS considers positive and negative ideal solutions at the beginning of the formation of the initial matrix to further determine the utility associated with these two solutions and strengthen the relationship between them. A deterministic utility function is proposed to sort schemes. The utility function represents the distance between an alternative scheme and a positive and negative ideal solution, which enables the model to consider more alternative schemes while ensuring the results stability. VIKOR method is a more scientific "near ideal solution", which seeks the optimal solution based on considering the relative importance of the distance between the scheme and positive and negative ideal solutions. Compared with the TOPSIS method, the core idea of VIKOR is not to solve the solution with the closest distance, but to solve the compromise solution in the solution to be decided, and the optimized compromise solution is the best distance from an ideal point in the solution to be decided. PROMETHEE method determines the priority of the scheme through the value ranking relationship to solve the decision problem [24]. This relationship defines the preference structure of PROMETHEE method is based on the comparison between schemes. When the cooperation between experts is limited by their respective professional fields, it can handle the conflicts between the subjective judgments of experts [25]. In addition, the output result of the PROMETHEE method is relatively stable. It determines the relative advantage of schemes by comparing the differences between schemes and avoids the rounding error in the process of data normalization.

Compared with other MCDA methods, TOPSIS method has the following advantages: (1) After the same trend, normalization, and other standardized processing of the original data, it can solve the problem that dimensional differentiation between the multi-attribute indicators leads to the inability to compare the same level, thus eliminating the influence caused by the coexistence of dimensional multi-attribute indicators and the high/low optimal indicators. (2) TOPSIS method is usually applied to the MCDA problem in the existing alternatives. It has no special requirements or restrictions on the evaluated sample data and has strong universality. (3) The final output results of TOPSIS method is presented in the form of a global ranking, which meets the requirements of this article. Considering the types of problems studied in this article, theoretical background, and expected results, we final choose TOPSIS method. Weight model of price impact factor

TABLE 2. Test result of three indicators of three products price bubble.

Product	Bubble length	Bubble frequency	Bubble strength
Product 1	1050	10	616
Product 2	1113	9	441
Product 4	2114	2	1680

TABLE 3. Price range and difference of product 1 during different periods.

Year	Price range during the whole sample data period	Price range during the bubble period	Price range during no bubble period	Interval difference
2012	(109,114)	/	(109,114)	/
2013	(114,243)	(136,243)	(114,243)	(22,0)
2014	(179,240)	/	(179,240)	/
2015	(113,165)	(113,119)	(130,165)	(-17,-46)
2016	(113,145)	(113,113)	(118,145)	(-5,-32）
2017	(145,177)	(159,177)	(145,170)	(12,7）
2018	(145,210)	(145,210)	(148,190)	(-3,20)
2019	(210,575)	(210,575)	(210,210)	(0,365)
2020	(530,1980)	(530,1980)	/	/

TABLE 4. Price range and difference of product 2 during different periods.

Year	Price range during the whole sample data period	Price range during the bubble period	Price range during no bubble period	Interval difference
2012	(57,60)	/	(57,60)	/
2013	(60,149)	(83,149)	(60,93)	(23,56)
2014	(108,137)	(108,137)	(124,137)	(-16,0)
2015	(65,90)	(69,90)	(65,72)	(4,18)
2016	(64,69)	/	(64,69)	/
2017	(70,110)	(72,110)	(70,72)	(2,38)
2018	(92,112)	(110,112)	(92,102)	(18,10)
2019	(96,118)	(111,118)	(96,108)	(15,10)
2020	(105,390)	(145,390)	(105,140)	(40,250)

of multi-characteristic enterprise product: Construct original data matrix:

$$X = \{x_{ij}\}_{n\times m,}\ (m = 16, n = 9) \tag{8}$$

Transform the original data matrix into a standardized matrix:

$$Y_{ij} = \{y_{ij}\}_{n\times m} \tag{9}$$

The positive indicator is $y_{ij} = \frac{x_{ij}-a_j}{A_j-a_j}$, the negative indicator is $y_{ij} = \frac{A_j-x_{ij}}{A_j-a_j}$, and neutral indicator is $y_{ij} = \left\{\begin{matrix} \frac{x_{ij}-a_j}{x_0-a_j}, (x_{ij} < x_0) \\ \frac{A_j-x_{ij}}{A_j-x_0}, (x_{ij} \geq x_0) \end{matrix}\right\}$, $A_j = \{x_{ij}\}_i^{\max}$, $a_j = \{x_{ij}\}_i^{\min}$.

Normalization y_{ij}:

$$Z_{ij} = \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}} \tag{10}$$

TABLE 5. Price range and difference of product 4 during different periods.

Year	Price range during the whole sample data period	Price range during the bubble period	Price range during no bubble period	Interval difference
2012	(56,56)	/	(56,56)	/
2013	(56,96)	(63,96)	(56,63)	(7,33)
2014	(89,93)	(93,93)	(89,93)	(4,0)
2015	(82,90)	/	(82,90)	/
2016	(93,96)	(95,96)	(93,93)	(2,3)
2017	(96,117)	(96,117)	/	/
2018	(117,140)	(117,140)	/	/
2019	(140,150)	(140,150)	/	/
2020	(150,162)	(150,162)	/	/

Entropy value of j index:

$$e_j = -k \cdot \sum_{j=1}^{n}, [Z_{ij} \cdot l_n(Z_{ij})] \times \left(j = 1, 2, 3, \ldots, n; k = \frac{1}{l_n(n)}, \text{is } cons\ \tan t\right) \tag{11}$$

Coefficient of differentiation:

$$g_j = 1 - e_j \tag{12}$$

Entropy

$$c_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \tag{13}$$

Index weight

$$w_j = \frac{c_j}{\sum_{j=1}^{m} c_j} \tag{14}$$

C. WEIGHT ANALYSIS OF PRICE IMPACT FACTOR INDEX OF MULTI-CHARACTERISTIC ENTERPRISE PRODUCT

Calculate the weight result of price impact factor index of multi-characteristic enterprise product research sample, the weight analysis is the basis of subsequent BP training, it involves the selection of input layer index, and the result is shown in Table 7.

V. MULTI-CHARACTERISTIC ENTERPRISE PRODUCT PRICING MODEL TRAINING BASED ON GSADF-TOPSIS-BP MODEL

BP is multi-layer feed-forward network trained, is mainly used in function approximation, model identification and classification, time series prediction, and so on. The model consists of input, hidden, and output layer. BP advantages are highly nonlinear and has strong generalization ability, but its shortcomings are slow convergence speed, large iteration steps number, and poor global search ability et al. BP model as shown in Fig.5.

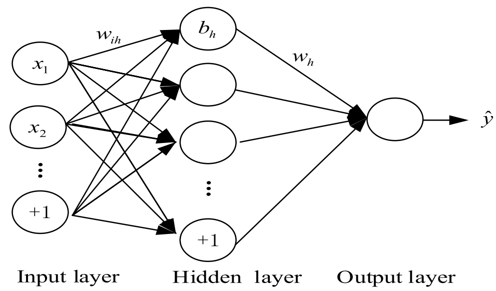

FIGURE 5. BP neural network model.

The sample in this part is four products which reflect the multi-characteristic enterprise product, and the GSADF-TOPSIS-BP model is trained based on the weekly price data of four products from 2012-2020 and the weekly data of 16 price impact factors from 2012 to 2020. BP model input layer neurons are price impact factor, and the number is 3-16. The number of input layer neurons is set from 3 because the first three factors are important price impact factors, and the sum of weight ratios reaches 0.3042. Output layer neurons are product price with a number of 1.

A. PRODUCT 1 PRICING MODEL TRAINING

Product 1 has 296 no bubble weekly price data, we used 236 data as training set and 60 data as validation set. When the input and hidden layer neurons number is 6 has the highest prediction accuracy, prediction result see Table 8. The network training result see Fig.6.

B. PRODUCT 2 PRICING MODEL TRAINING

Product 2 has 287 no bubble weekly price data, we used 227 data as training set and 60 data as validation set. When the input and hidden layer neurons number is 13 has the highest prediction accuracy, prediction result see Table 9. The network training result see Fig.7.

TABLE 6. Multi-characteristic enterprise product price impact factor index system of the research sample.

Target layer	Level indicator	Secondary indicator	Unit
Multi-characteristic enterprise product price impact factor index system	National tea supply and demand factor (CSD)	National tea garden area (CSD_1) National tea production (CSD_2) National tea drinkers (CSD_3) National tea sales volume (CSD_4)	Ten thousand mu Ten thousand tons One hundred million person Ten thousand tons
	Tea supply factor in Yunnan province (YSF)	Tea garden area in Yunnan province (YSF_1) Tea yield in Yunnan province (YSF_2) Number of tea manufacturers in Yunnan province (YSF_3)	Ten thousand mu Ten thousand tons Family
	Supply and demand factor of Pu'er tea (PSD)	Pu'er tea yield (PSD_1) Storage quantity of Pu'er tea (PSD_2) Pu'er tea sales volume (PSD_3)	Ten thousand tons Ten thousand tons Ten thousand tons
	Economic development factor (ECO)	GDP (ECO_1) Per capita disposable income (ECO_2) Inflation rate (ECO_3) Interest rate (ECO_4)	One hundred million RMB RMB % %
	Internet development level factor in Yunnan province (YIL)	Internet penetration rate in Yunnan province (YIL_1) Yunnan province tea e-commerce sales (YIL_2)	% One hundred million RMB

TABLE 7. Weight result of price impact factor index of multi-characteristic enterprise product research sample.

Level indicator	Weight	Secondary indicator	Weight	Level indicator	Weight	Secondary indicator	Weight
CSD	0.2195	CSD_1	0.0494	PSD	0.1793	PSD_2	0.0609
		CSD_2	0.0521			PSD_3	0.0578
		CSD_3	0.0626	YIL	0.1972	YIL_1	0.0590
		CSD_4	0.0554			YIL_2	0.1382
YSF	0.1851	YSF_1	0.0562	ECO	0.2181	ECO_1	0.0048
		YSF_2	0.0595			ECO_2	0.0545
		YSF_3	0.0694			ECO_3	0.0966
		PSD_1	0.0606			ECO_4	0.0622

C. PRODUCT 4 PRICING MODEL TRAINING

Product 4 has 144 no bubble weekly price data, we used 114 data as training set and 30 data as validation set. When the input layer is 3, and hidden layer neurons number is 7 has the highest prediction accuracy, prediction result see Table 10. The network training result see Fig.8.

Through the three detection standards, the prediction accuracy are shown in Table 11.

TABLE 8. Product 1 relative error of best training result during no bubble period.

Date	Relative error	Date	Relative error
2017.7.31-2017.8.6	0.034006250	2018.2.26-2018.3.4	0.034000000
2017.8.7-2017.8.13	0.034006250	2018.3.5-2018.3.11	0.051779141
2017.8.14-2017.8.20	0.034006250	2018.3.12-2018.3.18	0.063272727
2017.8.21-2017.8.27	0.034006250	2018.3.26-2018.4.1	0.040000000
2017.8.28-2017.9.3	0.034006250	2018.4.2-2018.4.8	0.002838710
2017.9.4-2017.9.10	0.034006250	2018.4.9-2018.4.15	0.002838710
2017.9.11-2017.9.17	0.034006250	2018.4.16-2018.4.22	0.002838710
2017.9.18-2017.9.24	0.034006250	2018.4.23-2018.4.29	0.003636364
2017.9.25-2017.10.1	0.034006250	2018.4.30-2018.5.6	0.016842105
2017.10.2-2017.10.8	0.034006250	2018.5.7-2018.5.13	0.016842105
2017.10.9-2017.10.15	0.034006250	2018.5.14-2018.5.20	0.030400000
2017.10.16-2017.10.22	0.034006250	2018.5.28-2018.6.3	0.037315436
2017.10.23-2017.10.29	0.034006250	2018.6.4-2018.6.10	0.037315436
2017.10.30-2017.11.5	0.034006250	2018.6.11-2018.6.17	0.037315436
2017.11.6-2017.11.12	0.034006250	2018.6.18-2018.6.24	0.037315436
2017.11.13-2017.11.19	0.034006250	2018.7.23-2018.7.29	0.044324324
2017.11.20-2017.11.26	0.034006250	2018.7.30-2018.8.5	0.044324324
2017.11.27-2017.12.3	0.034006250	2018.8.6-2018.8.12	0.044324324
2017.12.4-2017.12.10	0.034006250	2018.8.13-2018.8.19	0.044324324
2017.12.11-2017.12.17	0.034006250	2018.8.20-2018.8.26	0.044324324
2017.12.18-2017.12.24	0.034006250	2018.8.27-2018.9.2	0.010196078
2017.12.25-2017.12.31	0.034006250	2018.9.3-2018.9.9	0.015541401
2018.1.1-2018.1.7	0.034000000	2018.9.10-2018.9.16	0.021772152
2018.1.8-2018.1.14	0.034000000	2018.9.17-2018.9.23	0.021772152
2018.1.15-2018.1.21	0.034000000	2018.9.24-2018.9.30	0.131685393
2018.1.22-2018.1.28	0.034000000	2018.11.5-2018.11.11	0.186526316
2018.1.29-2018.2.4	0.034000000	2018.11.12-2018.11.18	0.186526316
2018.2.5-2018.2.11	0.034000000	2018.11.19-2018.11.25	0.186526316
2018.2.12-2018.2.18	0.034000000	2018.11.26-2018.12.2	0.186526316
2018.2.19-2018.2.25	0.034000000	2019.4.15-2019.4.21	0.264000000

VI. EMPIRICAL STUDY OF MULTI-CHARACTERISTIC ENTERPRISE PRODUCT

According to the previous empirical research result, this part conducts an empirical study on the pricing of multi-characteristic enterprise products.

A. SAMPLE SELECTION

The sample was four products that reflected the multi-characteristic of enterprise products, and the weekly price data from 2012-2020 and weekly data of price impact factor. Set the input layer of four products according to the empirical result of Ji [26], see Table 12. Due to short pricing time causes frequent price change, thus not conducive to the product sale, while long time cause the company can not adjust the price timely, thus against the market actual condition. Besides, according to the characteristic of the method, prediction accuracy becomes less over time, so this article pricing the price for the next 12 weeks.

TABLE 9. Product 2 relative error of best training result during no bubble period.

Date	Relative error	Date	Relative error
2019.2.25-2019.3.3	0.039833333	2019.10.7-2019.10.13	0.104822917
2019.3.4-2019.3.10	0.000594340	2019.10.14-2019.10.20	0.082275510
2019.3.25-2019.3.31	0.017935185	2019.10.21-2019.10.27	0.082275510
2019.4.1-2019.4.7	0.017935185	2019.10.28-2019.11.3	0.082275510
2019.4.8-2019.4.14	0.017935185	2019.11.4-2019.11.10	0.082275510
2019.4.15-2019.4.21	0.017935185	2019.11.11-2019.11.17	0.082275510
2019.4.22-2019.4.28	0.017935185	2019.11.18-2019.11.24	0.082275510
2019.4.29-2019.5.5	0.017935185	2019.11.25-2019.12.1	0.082275510
2019.5.6-2019.5.12	0.017935185	2019.12.2-2019.12.8	0.082275510
2019.5.13-2019.5.19	0.017935185	2019.12.9-2019.12.15	0.071343434
2019.5.20-2019.5.26	0.082275510	2019.12.16-2019.12.22	0.010123810
2019.5.27-2019.6.2	0.082275510	2019.12.23-2019.12.29	0.010123810
2019.6.3-2019.6.9	0.082275510	2019.12.30-2020.1.5	0.010323810
2019.6.10-2019.6.16	0.082275510	2020.1.6-2020.1.12	0.010323810
2019.6.17-2019.6.23	0.082275510	2020.1.13-2020.1.19	0.010323810
2019.6.24-2019.6.30	0.082275510	2020.1.20-2020.1.26	0.010323810
2019.7.1-2019.7.7	0.082275510	2020.1.27-2020.2.2	0.010323810
2019.7.8-2019.7.14	0.082275510	2020.2.3-2020.2.9	0.010323810
2019.7.15-2019.7.21	0.082275510	2020.2.10-2020.2.16	0.010323810
2019.7.22-2019.7.28	0.082275510	2020.2.17-2020.2.23	0.010323810
2019.7.29-2019.8.4	0.082275510	2020.2.24-2020.3.1	0.010323810
2019.8.5-2019.8.11	0.082275510	2020.3.2-2020.3.8	0.010323810
2019.8.12-2019.8.18	0.093432990	2020.3.9-2020.3.15	0.035600000
2019.8.19-2019.8.25	0.104822917	2020.3.16-2020.3.22	0.035600000
2019.8.26-2019.9.1	0.104822917	2020.3.23-2020.3.29	0.035600000
2019.9.2-2019.9.8	0.104822917	2020.3.30-2020.4.5	0.035600000
2019.9.9-2019.9.15	0.104822917	2020.4.6-2020.4.12	0.035600000
2019.9.16-2019.9.22	0.104822917	2020.4.13-2020.4.19	0.035600000
2019.9.23-2019.9.29	0.104822917	2020.5.4-2020.5.10	0.035600000
2019.9.30-2019.10.6	0.104822917	2020.5.11-2020.5.17	0.035600000

B. MULTI-CHARACTERISTIC ENTERPRISE PRODUCT PRICING

The whole sample of product 1-4 are the weekly price data from June 12,2012 to March 21,2021, a total of 458 weekly price data, 446 data as training set, and 12 data as prediction value

1) PRODUCT 1 PRICING

According to the previous empirical result, the input layer is set to 6. When the number of neurons in the hidden layer is 10, the obtained price is relatively reasonable. The result is shown in Table 13. The forecast price of product 1 is low, which is quite different from the previous price. The main reason is that the price bubble factor is not considered, and according to the product characteristic, there has been a price bubble. Therefore, the product price bubble range is added to get the product's final price.

2) PRODUCT 2 PRICING

According to the previous empirical result, the input layer is set to 5. When the number of neurons in the hidden layer is 5, the obtained price is relatively reasonable. The result is shown

TABLE 10. Product 4 relative error of best training result during no bubble period.

Date	Relative error	Date	Relative error
2015.10.26-2015.11.1	0.008227273	2016.2.8-2016.2.14	0.001548387
2015.11.2-2015.11.8	0.008227273	2016.2.15-2016.2.21	0.001548387
2015.11.9-2015.11.15	0.008227273	2016.2.22-2016.2.28	0.001548387
2015.11.16-2015.11.22	0.008227273	2016.2.29-2016.3.6	0.001548387
2015.11.23-2015.11.29	0.008227273	2016.3.7-2016.3.13	0.001548387
2015.11.30-2015.12.6	0.008227273	2016.3.14-2016.3.20	0.001548387
2015.12.7-2015.12.13	0.008227273	2016.3.21-2016.3.27	0.001548387
2015.12.14-2015.12.20	0.008227273	2016.3.28-2016.4.3	0.001548387
2015.12.21-2015.12.27	0.030266667	2016.4.4-2016.4.10	0.001548387
2015.12.28-2016.1.3	0.001548387	2016.4.11-2016.4.17	0.001548387
2016.1.4-2016.1.10	0.001548387	2016.4.18-2016.4.24	0.001548387
2016.1.11-2016.1.17	0.001548387	2016.4.25-2016.5.1	0.001548387
2016.1.18-2016.1.24	0.001548387	2016.5.2-2016.5.8	0.001548387
2016.1.25-2016.1.31	0.001548387	2016.5.9-2016.5.15	0.001548387
2016.2.1-2016.2.7	0.001548387	2016.5.16-2016.5.22	0.001548387

TABLE 11. Prediction accuracy result of GSADF-TOPSIS-BP model.

Product	MSE	MAE	MRE
Product 1	0.005797006	0.050234332	0.009767869
Product 2	0.003886143	0.052238631	0.011362015
Product 4	0.000051366	0.004312197	0.000959020

TABLE 12. Input layer of four products.

Product	Price impact factor
Product 1	YIL_2、ECO_3、YSF_3、CSD_3、ECO_4、PSD_2
Product 2	YIL_2、ECO_3、YSF_3、CSD_3、ECO_4
Product 3	YIL_2、ECO_3、YSF_3、CSD_3、ECO_4、PSD_2、PSD_1、YSF_2、YIL_1、PSD_3、YSF_1
Product 4	YIL_2、ECO_3、YSF_3、CSD_3、ECO_4

in Table 14. The forecast price of product 2 is low, which is quite different from the previous price. The main reason is that the price bubble factor is not considered, and according to the product characteristic, there has been a price bubble. Therefore, the product price bubble range is added to get the product's final price.

3) PRODUCT 3 PRICING

According to the previous empirical result, the input layer is set to 11. When the number of neurons in the hidden layer is 11, the obtained price is relatively reasonable. The results is shown in Table 15. The final pricing of product 3 has increased compared with the previous price, because there is no price bubble in the product, and we don't need to consider the price bubble factor.

4) PRODUCT 4 PRICING

According to the previous empirical result, the input layer is set to 5. When the number of neurons in the hidden layer is 11, the obtained price is relatively reasonable.

TABLE 13. Product 1 pricing.

Date	Forecast price	Price bubble	Final pricing
2020.12.28-2021.1.3	301.539	(320,1770)	(621.539,2071.539)
2021.1.4-2021.1.10	301.539	(320,1770)	(621.539,2071.539)
2021.1.11-2021.1.17	301.539	(320,1770)	(621.539,2071.539)
2021.1.18-2021.1.24	301.539	(320,1770)	(621.539,2071.539)
2021.1.25-2021.1.31	301.539	(320,1770)	(621.539,2071.539)
2021.2.1-2021.2.7	301.539	(320,1770)	(621.539,2071.539)
2021.2.8-2021.2.14	301.539	(320,1770)	(621.539,2071.539)
2021.2.15-2021.2.21	301.539	(320,1770)	(621.539,2071.539)
2021.2.22-2021.2.28	301.539	(320,1770)	(621.539,2071.539)
2021.3.1-2021.3.7	301.539	(320,1770)	(621.539,2071.539)
2021.3.8-2021.3.14	301.539	(320,1770)	(621.539,2071.539)
2021.3.15-2021.3.21	301.539	(320,1770)	(621.539,2071.539)

TABLE 14. Product 2 pricing.

Date	Forecast price	Price bubble	Final pricing
2020.12.28-2021.1.3	82.087	(40,250)	(122.087,332.087)
2021.1.4-2021.1.10	82.087	(40,250)	(122.087,332.087)
2021.1.11-2021.1.17	82.087	(40,250)	(122.087,332.087)
2021.1.18-2021.1.24	82.087	(40,250)	(122.087,332.087)
2021.1.25-2021.1.31	82.087	(40,250)	(122.087,332.087)
2021.2.1-2021.2.7	82.087	(40,250)	(122.087,332.087)
2021.2.8-2021.2.14	82.087	(40,250)	(122.087,332.087)
2021.2.15-2021.2.21	82.087	(40,250)	(122.087,332.087)
2021.2.22-2021.2.28	82.087	(40,250)	(122.087,332.087)
2021.3.1-2021.3.7	82.087	(40,250)	(122.087,332.087)
2021.3.8-2021.3.14	82.087	(40,250)	(122.087,332.087)
2021.3.15-2021.3.21	82.087	(40,250)	(122.087,332.087)

TABLE 15. Product 3 pricing.

Date	Final pricing	Date	Final pricing
2020.12.28-2021.1.3	167.052	2021.2.8-2021.2.14	167.052
2021.1.4-2021.1.10	167.052	2021.2.15-2021.2.21	167.052
2021.1.11-2021.1.17	167.052	2021.2.22-2021.2.28	167.052
2021.1.18-2021.1.24	167.052	2021.3.1-2021.3.7	167.052
2021.1.25-2021.1.31	167.052	2021.3.8-2021.3.14	167.052
2021.2.1-2021.2.7	167.052	2021.3.15-2021.3.21	167.052

The result is shown in Table 16. The forecast price of product 4 is low, which is not much different from the previous price. According to the product characteristic, there has been a price bubble. Therefore, the product price

TABLE 16. Product 4 pricing.

Date	Forecast price	Price bubble	Final pricing
2020.12.28-2021.1.3	119.423	(57,69)	(176.423,188.423)
2021.1.4-2021.1.10	119.423	(57,69)	(176.423,188.423)
2021.1.11-2021.1.17	119.423	(57,69)	(176.423,188.423)
2021.1.18-2021.1.24	119.423	(57,69)	(176.423,188.423)
2021.1.25-2021.1.31	119.423	(57,69)	(176.423,188.423)
2021.2.1-2021.2.7	119.423	(57,69)	(176.423,188.423)
2021.2.8-2021.2.14	119.423	(57,69)	(176.423,188.423)
2021.2.15-2021.2.21	119.423	(57,69)	(176.423,188.423)
2021.2.22-2021.2.28	119.423	(57,69)	(176.423,188.423)
2021.3.1-2021.3.7	119.423	(57,69)	(176.423,188.423)
2021.3.8-2021.3.14	119.423	(57,69)	(176.423,188.423)
2021.3.15-2021.3.21	119.423	(57,69)	(176.423,188.423)

TABLE 17. Risk level and characteristic of enterprise product.

Product	Risk level	Risk characteristic
Product 1	High risk	1.Total days of bubble accounted for 33.63% of the total sample days; 2.During the sample period, 10 bubble events occurred; 3.Maximum bubble duration are 616 days; 4.Overall price is high.
Product 2	High risk	1.Total days of bubble accounted for 35.65% of the total sample days; 2.During the sample period, 9 bubble events occurred; 3.Maximum bubble duration are 441 days; 4.Overall price is high.
Product 3	Low risk	1.There is no price bubble; 2.Low price.
Product 4	Medium risk	1.Total days of bubble accounted for 67.71% of the total sample days; 2.During the sample period, 2 bubble events occurred; 3.Maximum bubble duration are 1680 days; 4.Overall price is low.

bubble range of the product is added to get the product's final price.

C. PRICING ANALYSIS

According to the empirical result of Table 13-16, the final pricing range of product 1 is (621.539,20 71.539), the final pricing range of product 2 is (122.087,332.087), two products' final pricing range are relatively big, mainly due to the extensive price bubble range, which makes it more difficult for enterprise pricing according to the result. Due to product 3 has no price bubble, there is no need to consider the price bubble factor, the price can be used as a final price. The final pricing range of product 4 is not extensive, which reduces the product pricing range to a certain extent. Enterprises can balance risk and profit, to determine the final price of product 4 within the final pricing range.

D. FINAL PRICING OF PRODUCT BASED ON PRICE BUBBLE RISK LEVEL AND RISK ALERT

Through the empirical study of the final pricing of multi-characteristic enterprise products, it can be seen that the most controversial product are product 1 and product 2. Due

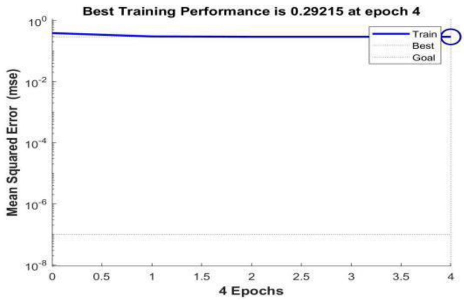

FIGURE 6. Training error curve of product1 no bubble period data.

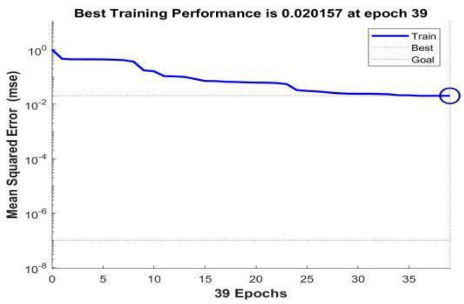

FIGURE 7. Training error curve of product 2 no bubble period data.

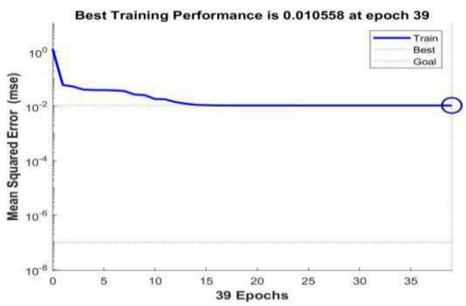

FIGURE 8. Training error curve of product 4 no bubble period data.

to the extensive final pricing range, enterprises cannot be pricing according to the result. Although there is a certain final pricing range of product 4, but the difference is not big and less controversial. Therefore, this section will further discuss the product pricing dispute to determine the final price. Price bubble lead to an extensive range of product pricing, but the existence of bubble has a two-way effect on the market. A moderate price bubble can flourish the market economy, but too large bubble leads to the collapse of the market. A bubble burst can cause a series of chain reaction, and even trigger financial crisis, with negative impact on the economy [27]. Therefore, based on the necessity of price bubble and risk control principle, the controversial products is priced based on the risk level and risk alert, identifying the product that needs to be focused on through the risk level, and the product price is determined by risk alert classification, the controllable price is used as the final product price.

1) RISK LEVEL AND CHARACTERISTIC

For the price bubble risk level, Li and Li [21] divided agricultural future into three grades: high-risk, medium-risk, and low-risk commodities according to the three risk indicators of bubble length, bubble frequency, and bubble strength. According to the research object characteristic in this article, it is planned to add the product price as the fourth risk index, to classify the risk grade of the multi-characteristic enterprise product and evaluate the risk characteristic, as shown in Table 17. According to the risk grade classification, product 1 and product 2 are high-risk products, product 3 is a low-risk product, and product 4 is medium-risk product.

2) ALERT LEVEL

The alert standard is according to the judgment and interpretation standard of the historical risk level of commodities [28]. The reference value of the alarm standard is:

$$s\tan\ dard_i = \mathrm{int}(\frac{\mathrm{sum}_{i,T} - \mathrm{max}_{i,T} - \mathrm{min}_{i,T}}{n-2}) \tag{15}$$

i represents the ith commodity, T represents the historical sample length, and n represents the number of price bubble events within the sample period T, $\mathrm{standard}_i$ represents the ith commodity alert standard, and its value calculation rule is: calculate the total number of bubble events ($\mathrm{SUM}_{i,T}$) in the sample period T minus maximum bubble days ($\mathrm{max}_{i,T}$) and minimum bubble days ($\mathrm{min}_{i,T}$) value; divide the result value by (n-2) and rectify it. Product 1 contains 10 price bubble events, total bubble days of 1050 days, the maximum bubble duration are 616 days, a minimum bubble duration are 7 days, according to the formula, the product 1 alert standard are 53 days. That is, product 1 level 1 (1-53 days), level 2 (54-106 days), and so on. During the sample period, event 1 occurred in level 4 alert, events 2-8 occurred in level 1 alert, event 9 occurred in level 3 alert, and event 10 occurred in level 12 alert, as shown in Fig. 9. With the increase in alert level, the color in the figure also changes. Alert 1-3 are primary, is still a reasonable price bubble, alert 4-6 are intermediate, still within the controllable range, above 6 are senior, need to pay great attention to it. Event 10 has reached the high alert level, the price bubble last a long time, and the risk factor are enormous. Once the price bubble breaks down, it will lead to a sharp drop in the product price. The final pricing range of product 1 is (621.539,2071.539), if the enterprise chooses to pricing at the highest point, there is a greater risk, set at the lowest point causing damage to corporate profits. Since the alert level of event 10 is advanced and the risk factor of a price bubble burst is significant, we can't be pricing according to this price. In addition, at the beginning of the product 1 price bubble, the price and bubble degree are still under control, and product pricing damages the enterprise profits. After considering the above factors, the pricing of product 1 is still within the pricing range of event 10, but it is appropriate to set the product 1 price at 1400 RMB within a reasonable and controllable range of alert level, combined with the price situation during the period.

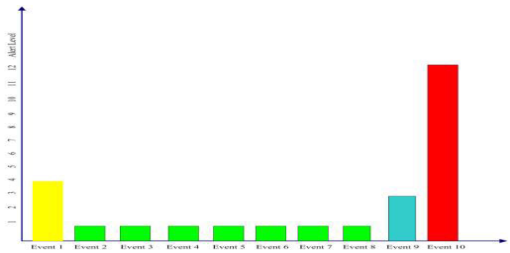

FIGURE 9. Product 1 bubble event alert level.

Product 2 has 9 price bubble events, the total bubble days are 1113 days, the maximum bubble duration are 441 days, and the minimum bubble duration are 14 days. The alert level of product 2 are 94 days according to the formula, product 2 level 1 (1-94 days), level 2 (95-188 days), and so on. During the sample period, events 1-3 occurred in level 2 alert, events 4-5 occurred in level 1 alert, event 6 occurred in level 5 alert, events 7-8 occurred in level 1 alert, and event 9 occurred level 3 alert, as shown in Fig.10. With the increase of alert level, the color in the figure also changes. According to the alert level, the product 2 bubble event belongs to the primary and intermediate alert levels, and is still within the controllable range. The final pricing range of product 2 (122.087,332. 087), the enterprise can set the price at the highest level of 332.087 RMB based on the consideration of product profit.

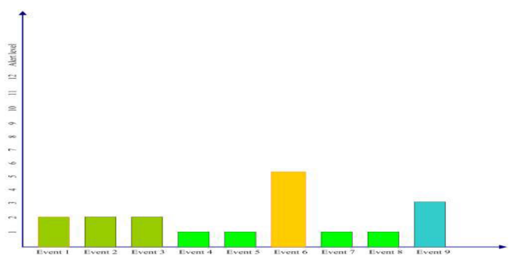

FIGURE 10. Product 2 bubble event alert level.

Note: The horizontal axis represents the price bubble event, and the vertical axis represents the alert level.

VII. CONCLUSION

This article constructed GSADF-TOPSIS-BP model to pricing training, and multi-characteristic enterprise product intelligent pricing method is determined and final pricing. According to the empirical research result, the final pricing price range of product 1 and product 2 is extensive, mainly due to the extensive price bubble range. Product 3 has no price bubble, so there is no need to consider the price bubble factor, the price can be predicted the product pricing range to a certain extent. The enterprise need to balance risk and profit, to determine the final price of product 4 within the final pricing range. Based on the necessity of price bu bble and risk control principle, the controversial products are priced based on the risk level and risk alert, and the disputed product price is finally determined.

A. PAY FULL ATTENTION TO THE PHENOMENON OF MULTI-CHARACTERISTIC ENTERPRISE PRODUCT PRICE BUBBLE, AND ESTABLISH AN EARLY ALERT SYSTEM FOR PRICE BUBBLE

The state attaches great importance to the issue of an asset bubble. On July 26, 2016, the Political Bureau CPC Central Committee for the first time explicitly proposed to "curb asset bubbles", the meeting of Political Bureau CPC Central Committee held on October 28 again clarified that "focus on curbing asset bubble and preventing economic and financial risk". The state has taken a series of measures to conduct risk identification, early warning and prevention, and has achieved certain results. However, due to the lack of experience in risk identification and insufficient risk early alert and prevention ability, the enterprises often takes action after the price bubble bursts, with certain blindness and lag, which seriously damages the interests of the enterprise. The price bubble detection, risk level determination, and alert assessment method in this article provide convenient and scientific methods for the enterprises. Enterprise should establish an alert system: firstly, detect the price bubble; secondly, calculate the duration of the price bubble; thirdly, calculate alert standard; then, determine alert level; finally, take relevant measures, tolerate the existence or adjust the price strategy according to the alert level. Through this system, enterprises can identify the risk of the product price bubbles and carry out certain early alert and prevention, to take relevant measures to avoid risk and reduce losses. The multi-characteristic enterprise product price bubble early alert system and implementation steps are shown in Fig. 11.

B. ESTABLISH A PRICING ANALYSIS SYSTEM, AND USE AN INTELLIGENT PRICING METHOD TO DETERMINE PRODUCT PRICING

Product pricing is an important strategy of enterprise, which directly affects the product sales volume and profit, and even are related to the future development of enterprise. However, most enterprise conduct product pricing based on past experience and market prediction. There are certain blindness and subjectivity with experience as the pricing basis, and there are also a problem such as inaccurate market prediction. Therefore, the product pricing of the enterprise should be scientific, reasonable, and systematic. Aiming for reasonable profit maximization is not ideal, enterprises need to establish a perfect, scientifics, and intelligent pricing system, reduce the subjectivity and uncertainty of pricing, analyze multi-characteristic product prices, and set a price impact factor index system, clarify the weight of price impact factor, intelligent pricing based on price bubble risk level and risk alert, to achieve the balance between profit and risk control.

By constructing the GSADF-TOPSIS-BP model, this article research multi-characteristic enterprise product intelligent pricing method, and obtains good empirical results. It reflects

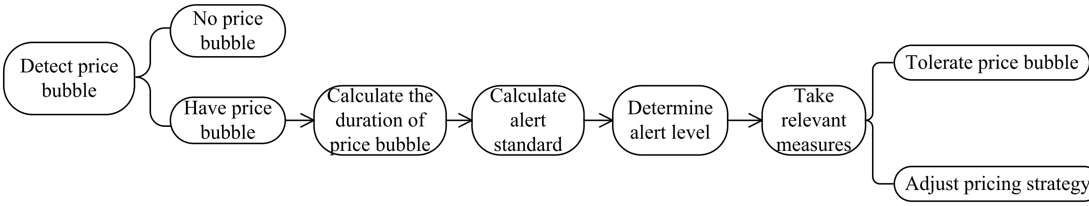

FIGURE 11. **Early alert system of enterprise product price bubble and implementation steps.**

the intelligence and superiority compared with the traditional pricing method model, and provides new ideas and methods for multi-characteristic enterprise product pricing. This article mainly selects the product in the high level of the first stage of product financialization. The limitation of the research sample and data restrict the depth and breadth of this research. Therefore, in the subsequent research, relevant data will be further collected and sorted out to expand the research sample and data. This article constructs a multi-characteristic index system of impact factor of the enterprise product price from three aspects-supply and demand factor, economic development factor and technological factor. The selection of the price impact factor index needs to be further improved and enriched. The current empirical research method still has some drawback and limitations. With the continuous updating and improvement of empirical research methods, it needs to be continuously improved in the subsequent research.

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