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Multi-Characteristic Product Price Research Based on GSADF-BP Model

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ABSTRACT According to hedonic price theory, people's demand for product is based on the product characteristic. Pu'er tea is geographical indicator product of Yunnan province, which has edible, medicinal, drinking, investment and cultural value. It is a typical multi-characteristic product, the price bubble possibility is large, but the degree of price bubble has not been tested, and the detection effect is not clear. So, this paper applied four Pu'er tea products as study case, generalized sup ADF statistic model (GSADF) to respectively detect price bubble and Back-ProPagation Network model (BP) is used to forecast the four products price in whole sample period and non-price bubble period, so as to verify the detection effect of GSADF model. According to the GSADF result, three products have price bubble and one product have no price bubble. In the whole sample data price prediction, the best forecast effect was product 3, followed by were product 4, product 2 and finally was product 1. In the non-price bubble period sample data price prediction, the best forecast effect was product 4, followed by was product 1, and the last one was product 2. Multi-characteristic product which cover various industries and fields, Pu'er tea is not a unique case. As a pioneering research, the methods and ideas in this paper can be extended to other industries and fields, so as to conduct in-depth analysis of multi-characteristic product in the market and provide suggestion and guidance for the decision making and behavior of relevant stakeholder.

INDEX TERMS Multi-characteristic product, GSADF model, BP model.

I. INTRODUCTION

According to hedonic price theory, people's demand for product is not based on the product itself, but because of the product characteristic. Households buy and use them as an ''input'' and turn them into productive uses, depending on the number of characteristic. With the in-depth study of hedonic price theory and the improvement of calculation tools, scholars have quantitatively studied the impact of different characteristic factors on commercial housing price, mainly including building, traffic, educational facilities, green park and air noise pollution et al [1]–[4]. With the increasing application maturity of hedonic price theory, it has been widely applied in consumer goods fields such as household appliances and agricultural vehicles. With the increasing number of product characteristic, more product take on the characteristic of commodity financialization and future product [5], [6], and their price devite from basic value. Due to the real estate has more characteristics and financialization degree strong, their price are still regulated by government action and do not completely depend on market condition. Although the price of product such as onion, ginger and garlic have caused a wave of fluctuation in China, they have not yet formed a climate. Therefore, this paper takes Pu'er tea as a case study to analysis multi-characteristic product price.

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Pu'er tea is a geographical indicator product of Yunnan province, which has edible, medicinal, drinking, investment and cultural value. It is a typical multi-characteristic product. In 2020, the tea planting area in Yunnan province will be 6.999,000 Mu, accounting for 16.6% of the total tea plantation area in China. The annual output of Pu'er tea is 200,000 tons, accounting for 45% of tea production in Yunnan province and 6.6% of national tea production. In the development process, the price research is becoming a hot topic. On November 24, 2002, 100g Pu'er tea king was auction 160,000 RMB in Guangzhou Tea Fair, which created the highest record of tea auction price in China. Bingdao, Banzhang tea reached 10000 RMB/KG, and this tea is difficult to buy; February 25, 2019, 880,000 RMB transaction 4 kilograms Bingdao ancient tree tea, a series of events made Pu'er tea entitled as 'drinkable antique', 'sky high price Pu'er', 'crazy Pu'er' and other. Related news media carried out a series of tracking reports on Pu'er tea, such as Banzhang village suddenly rich because hundred years tea trees, drying money on the ground; CCTV's economic program called it 'invisible Pu'er tea' and pointed out that the over-mystification and extravagance of Pu'er tea can only keep it away from consumer, and can't make cheating become a habit or hype become normal. Pu'er tea has shown the characteristic of commodity financialization and future product, and become the best selling product in the investment market. The price of Pu'er tea has far exceeded its fundamental value, but the price bubble has not been detected yet, and the detection effect is not clear.

The main detection methods for price bubble include statistical characteristic test [7]–[11], West two-step test [12], [13], unit root-co-integrationtest [14], and endogeneic bubble detection [15] et al, but all the above methods have some disadvantages. In recent years, the econometricians represented by Phillips have made some breakthroughs in the theory of unit root process. By constructing the concept of 'moderately deviated explosive', the distinction between unit root process and (moderately deviated) explosive process is realized [16]. Based on the theory of 'moderate deviation' unit root, Phillips, Wu and Yu [17] by building on the right tail unit root test and supremum ADF statistics of recursive regression, effectively improve the unit root process and moderate deviation from discrimination in the process of explosive, first time explosive for the price bubble identification and made a breakthrough in the detection. However, this method may have insufficient discriminative power when there are multiple bubbles in the sample, especially when the second bubble is larger than the first bubble. Therefore, Phillips, Shi and Yu, in view the deficiency of the model, further adopt the right tail double recursive regression, build the GSADF, which can effectively distinguish and explosive unit root between the price sequence process, so as to realize effective identification and detection of commodity price bubble, this method has a better detection effect on the sequence with multiple bubbles in the sample period [18], [19]. However, scholars have mainly applied this method to shipping [20], [21], agricultural product [22]–[26], real estate [27], stocks [28] and other fields [29]–[32], and few studies used on the Pu'er tea field. Therefore, according to the current research status at home and abroad, this paper applied this method to Pu'er tea field, but the detection effect could not be verified. This paper further verified and studied it through BP model. BP model is one of the most widely used and mature model now [33], [34]. The idea of error back propagation was first proposed by Bryson *et al.* in 1969 [35]. In 1974, Werbos studied error back propagation in his doctoral thesis at Harvard University, but it did not attract academic attention [36]. In 1986, Rumelhart and his research group published their research results in *Nature*, and BP model and its learning algorithm began to attact attention [37]. However, BP model contains some disadvantages, foe example slow convergence speed and difficult to determine the network structure, which makes the method application limited. Recently, scholars had improved BP model from two aspects: learning algorithm [38], [39] and network structure [40]–[43]. Therefore, this method application is gradually expanding. Kimoto *et al.* developed a stock price prediction system by using BP and combining the related theories of multivariate statistics, and the empirical result show that this stock price prediction system can accurately predict the stock price index [44]. Scholars have also applied BP in many fields [45]–[51].

Based on hedonic price theory and multiple characteristic of product, this paper selects Pu'er tea as case study. The GSADF model was applied to the Pu'er tea field, and detected four Pu'er tea products price bubble during the period from June 12, 2012 to December 27, 2020, the every year of Dayi 7542 new raw tea is product 1, the every year of Dayi 7572 new ripe tea is product 2, 2011 product Dayi 7542 raw tea is product 3 and 2011 product Dayi 7572 ripe tea is product 4. According to the detected result, BP model is used to respectively forecast price for the whole sample period and non-price bubble period to test the scientificity and rationality of GSADF model, so as to analysis the product price characteristic and put forward suggestion. This paper based on the hedonic price, applying this theory to the Pu'er tea field is an extension of its application; this theory does not consider the product investment value, but under China's national condition, this is a problem that must be considered, so this paper used Pu'er tea as case, fully considered the product investment value, make the theory match with China's national condition. Then innovatively combined the two methods to detect the price bubble of Pu'er tea and verify its effectiveness, in addition to the application in the field of Pu'er tea, this method can also be applied to other fields.

II. PRICE BUBBLE DETECTION OF PU'ER TEA

The investment value makes Pu'er tea present the commodity financialization and future product characteristic, but it is still in the advanced stage of the first stage of commodity financialization. Compared with the product in the second stage, the financialization degree is relatively low. Pu'er tea has five values, its price is determined by characteristic, and consumer buy it according to the product characteristic. According to the investment product characteristic and analysis the market price of Pu'er tea in recent years, it is very likely to appear asset price bubble and become a part of price composition. Academic circle define asset price bubble as the process in which asset price rise rapidly in a short period and deviate from their fundamental value and eventually cause the rapid decline of asset price. Kindleberger, Aliber described the phenomenon of asset price bubble as the rapid rise in the price

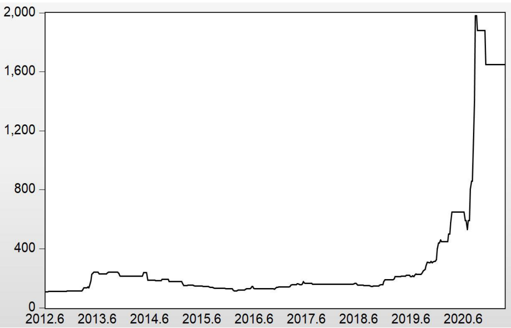

FIGURE 1. Price trend of product 1.

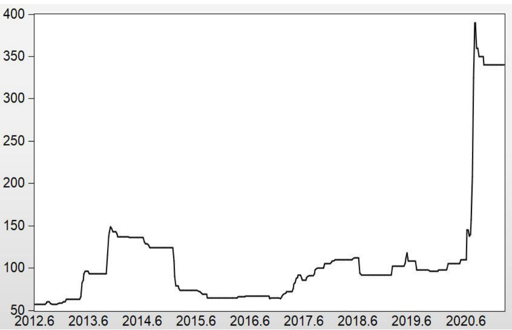

FIGURE 2. Price trend of product 2.

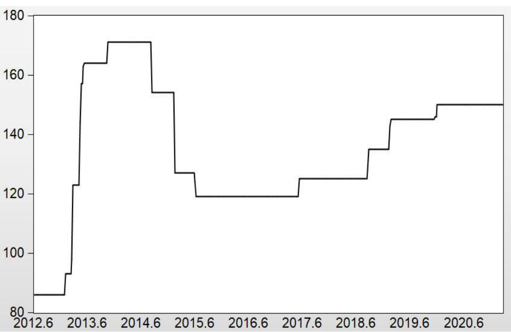

FIGURE 3. Price trend of product 3.

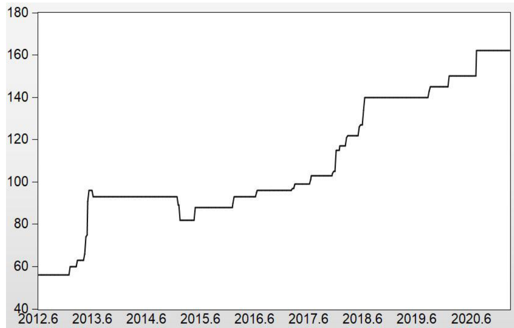

FIGURE 4. Price trend of product 4.

TABLE 1. Descriptive statistics of four Pu'er tea products price.

Product	Average Price	Highest Price	Lowest Price	Price Volatility
1	308.70	1980.00	109.00	1816%
2	109.38	390.00	57.00	684%
3	134.58	171.00	86.00	198%
4	108.22	162.00	56.00	289%
Product	Standard Deviation	Skewness	Kurtosis	
1	404.16	2.99	10.85	
2	68.15	2.76	10.07	
3	22.19	-0.26	2.70	
4	30.11	0.24	2.08	

Note: Price volatility is the ratio of highest to lowest price in the sample period.

of one or a class of assets in a short term. The price rise in the early stage leads to the bullish price expectation and attracts more buyers who seek profits purely for speculation. Thus, asset price are overvalued and eventually fall rapidly [52]. Therefore, this part will realize the price situation and Pu'er tea characteristic through the measurement and analysis of Pu'er tea price bubble.

A. PRICE FLUCTUATION CHARACTERISTIC AND DESCRIPTIVE STATISTICS OF PU'ER TEA

1) PRICE FLUCTUATION CHARACTERISTIC OF PU'ER TEA

To observe Pu'er tea market price fluctuate of the overall situation, this paper selects four kinds tea products, during June 12, 2012 to December 27, 2020, each product has 446 weekly price datas, a total of 1784 price datas, the data source from *China tea network*, four products price movement as shown in Figure 1, 2, 3 and 4.

As can be seen from Figure 1, 2, 3 and 4, the price of raw tea is higher than ripe tea. Compared with raw tea, ripe tea has fermentation procedures during processing, while raw tea is not fermented, so there is more space for subsequent change, which reflects the price superiority of raw tea over ripe tea. Pu'er tea aggregate demand mainly comes from consumer demand, private collection and investment demand, the investment demand will cause price fluctuation, but investor more emphasis on the every year new tea product, because its have large change space, investment value and profit space is large, the other companies launching new product based on the consideration such as sales, will increase investment, so the every year new tea product price is higher than 2011 product.

2) DESCRIPTIVE STATISTICS OF PU'ER TEA PRICE

In order to further analysis the four products prie, this paper will conduct descriptive statistics and unit root test on the four products price. The results are shown in Table 1, 2.

From the perspective of price volatility, the most violent volatility product in the sample period was product 1, with the volatility is 1816%, followed were product 2 and 4, the lowest volatility product was product 3, with the volatility is

TABLE 2. Unit root test of four Pu'er tea products price.

Product	Original Sequence		
	ADF	PP	KPSS
1	0.818	0.451	1.020
	0.994	0.984	
2	-0.237	1.114	0.767
	0.930	0.997	
3	-2.178	-2.154	0.256
	0.214	0.223	
4	-0.663	-0.573	2.425
	0.853	0.873	
Product	First Difference		
	ADF	PP	KPSS
1	-6.625	-15.361	0.337
	0.000	0.000	
2	-7.521	-9.249	0.281
	0.000	0.000	
3	-17.694	-17.685	0.262
	0.000	0.000	
4	-11.645	-17.644	0.077
	0.000	0.000	

only 198%. The lowest price all appeared in the early sample stage, while the highest price of product 1 was from June 8, 2020 to June 21, 2020, the highest price of product 2 was from June 8, 2020 to June 21, 2020, the highest price of product 3 was from October 14, 2013 to August 3, 2014, the highest price of product 4 was from May 18, 2020 to December 27, 2020. The price sequence of the three products has a positive Skewness, indicating that the price has a tendency to jump upward and there may be bubbles. A product with a negative Skewness may not have a price bubble. The result of unit root test show that the price of the four products are I(1) sequence, and it is not appropriate to use the traditional unit root test to identify bubbles. Therefore, based on the research of Phillips, this paper uses GSADF detection method to identify price bubble.

B. MODEL CONSTRUCTION AND DETECTION METHOD

1) MODEL CONSTRUCTION

The price is composed of bubble and actual value. Therefore, the price of Pu'er tea can be expressed as:

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

Among them, P_t is the price of Pu'er tea during the t period, D_{t+i} is the income of Pu'er tea in the $t+i$ period, r_f is the free risk interest rate, U_t is the unknown factor, B_t is speculative bubble of Pu'er tea price. Theoretically, speculative bubble B_t meets the submartingale nature of explosion, and if the Pu'er tea price explodes, it proves that there is bubble.

2) DETECTION METHOD

Referred to Phillips's literature, commodity futures price bubbles follow the process: $P_t = \gamma T^{-\eta} + \rho P_{t-1} + \varepsilon_t$,where, γ is a constant, T is the sample size, $\eta > 1/2$ and ε_t follows the independent identical distribution hypothesis. Under the null hypothesis ($\rho = 1$), P_t is follows the random walk process. Accordingly, under the alternative hypothesis ($\rho > 1$), the commodity price sequence contains an explosive process (price bubble). Then through the double recursion method of setting variable window, the commodity price sequence is sequentially detected the existence of bubble and estimate the bubble starting and ending time.

(1) Build GSADF statistics to detect the existence of price bubble in commodity price series. GSADF statistics are defined as:

$$GSADF\ (r_0) = \sup_{r_2 \in [r_0, 1]} \left\{ \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2} \right\} \tag{2}$$

where, r_0 represents the minimum sample window sequence that can guarantee the validity of the estimation, $r_0 \in (0, 1]$; r_1 represents the starting point of sample window sequence; r_2 represents the end point of sample window sequence. Therefore, $ADF_{r_1}^{r_2}$ represents the standard ADF value calculated from the selected window sequence observations.

(2) Build backward sup ADF statistic (BSADF) sequence to estimate the starting and ending points of the price bubble process. BSADF statistics are defined as:

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

By constructing BSADF statistics, the starting and ending time of bubble in commodity price series can be estimated. If multiple price bubble occur in the commodity price series, then the beginning and ending time of the K time price bubble is defined as:

$$\hat{r}_{ke} = \inf_{r \in [\hat{r}_{k-1}, 1]} \{ r : BSADF(r_0) > cv \} \tag{4}$$

$$\hat{r}_{kf} = \inf_{r_2 \in [\hat{r}_{ke} + L_T, 1]} \{ r_2 : BSADF\ (r_0) < cv \} \tag{5}$$

where, $L_T = \delta \log(T)/T$, δ values are different with sample data frequency (monthly, weekly and daily). $\mathcal{CV}$ represents the sequence of critical values of BSADF statistics, whose values are calculated by Monte Carlo simulation. Through compare the value of BSADF and CV to define the starting and ending time of price bubble, when the value of BSADF greater than CV, it means that price bubble process start, when the value of BSADF less than CV, it means that price bubble process end.

C. EMPIRICAL TEST

1) EXPERIMENTAL TIME

To run of four product respectively, the test run time of product 1 was 44h13’59”, product 2 was 60h11’27”, product 3 was 49h17’13”, product 4 was 62h18’30”.

2) TEXT RESULT

The price bubble detection model constructed above is applied to evaluate and detect the occurrence of four products price bubbles. After Monte Carlo 2000 simulations, the GSADF value was compared with the corresponding 95% confidence threshold value, and the detection result were shown in Figure 5, 6 and 7. Product 1, 2 and 4 price sequence GSADF threshold values were bigger than 95% confidence level, its exist price bubble phenomenon in the price series, product 3 price sequence GSADF value was less than 95% confidence level, there is no price bubble demonstrated in the price series phenomenon, the result such as Table 3.

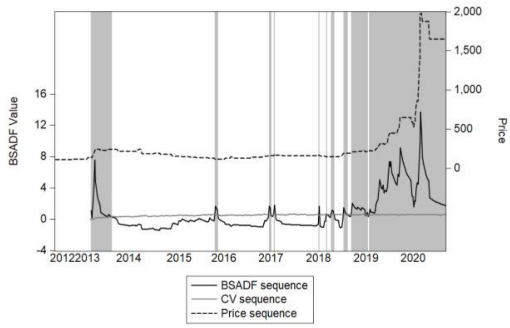

FIGURE 5. Price bubble of product 1.

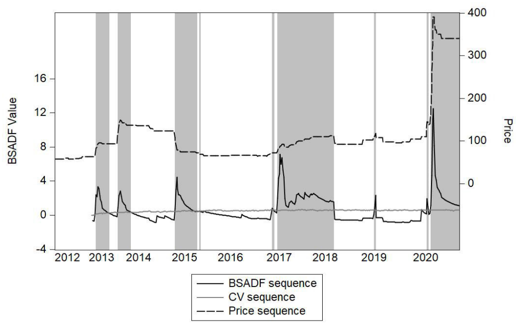

FIGURE 6. Price bubble of product 2.

Figure 5-7 shows the price bubble of the three products, but the picture cannot specifically show the time node of price bubble. Therefore, according to the GSADF test bubble, which are listed in chronological order, see Table 4-6. From these tables, we can know the bubble time, time node and duration.

3) THE FOAMING PROCESS OF PRODUCT 1

There were 10 price bubbles in product 1, mainly in 2013, 2018, 2019 and 2020. Its time nodes and bubble duration are shown in Table 4.

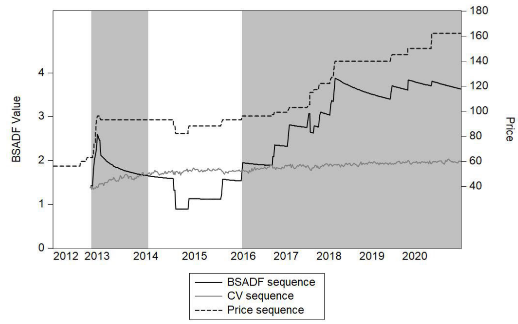

FIGURE 7. Price bubble of product 4.
Note:1. BSADF sequence and CV value sequence are marked in units on the left vertical axis, while price sequence is marked in units on the right vertical axis; 2. CV value sequence refers to the eigenvalue sequence with the confidence of 95%; 3. Commodity price bubbles are marked by shadows.

TABLE 3. Foam detection result of Pu’er tea price sequence.

Product	GSADF Value	CV Value	If Have Bubble
1	13.70	2.26	Yes
2	12.53	2.26	Yes
3	2.60	3.54	No
4	3.88	3.54	Yes

TABLE 4. Price bubble time node and bubble duration of product 1.

Bubble Order	Time Node	Duration (Days)
1	2013.3.25—2013.9.8	168
2	2015.12.7—2016.1.3	28
3	2017.2.13—2017.3.5	21
4	2017.3.27—2017.4.2	7
5	2018.3.19—2018.3.25	7
6	2018.5.21—2018.5.27	7
7	2018.6.25—2018.7.22	28
8	2018.10.1—2018.11.4	35
9	2018.12.3—2019.4.14	133
10	2019.4.22—2020.12.27	616

4) THE FOAMING PROCESS OF PRODUCT 2

There were 9 price bubbles in product 2, mainly in 2013, 2015, 2017 and 2020. It’s time nodes and bubble duration are shown in Table 5.

5) THE FOAMING PROCESS OF PRODUCT 4

There were 3 price bubbles in product 4, which mainly occurred in 2013, 2016 and 2017-2020. The time nodes and bubble duration are shown in Table 6.

TABLE 5. Price bubble time node and bubble duration of product 2.

Bubble Order	Time Node	Duration (Days)
1	2013.4.22—2013.8.4	105
2	2013.10.7—2014.1.19	105
3	2014.12.22—2015.6.14	175
4	2015.6.29—2015.7.12	14
5	2017.1.9—2017.1.29	21
6	2017.2.20—2018.5.6	441
7	2019.3.11—2019.3.24	14
8	2020.4.20—2020.5.3	14
9	2020.5.18—2020.12.27	224

TABLE 6. Price bubble time node and bubble duration of product 4.

Bubble Order	Time Node	Duration (Days)
1	2013.4.1—2014.6.8	434
2	2016.5.23—2020.12.27	1680

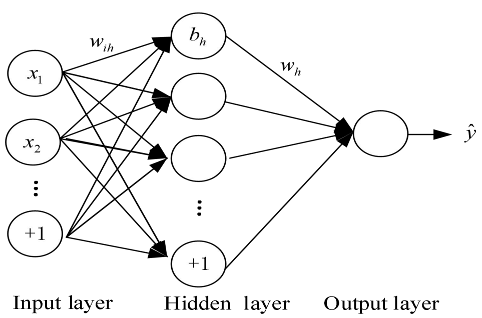

FIGURE 8. BP neural network model.

III. PRICE PREDICTION OF PU'ER TEA

Through four product price bubble measure and analysis, this part through BP model to respectively forecast four product price of the whole sample data and non-price bubble sample data, verify the accuracy and analysis the tea price characteristic, according to the prediction result to provide suggestion for the industry development.

A. BP MODEL CONSTRUCTION

BP model as shown in Figure 8.

B. DETERMINATION OF TRAINING SAMPLES

For the model input layer sample data, namely the Pu'er tea price impact factor, few scholars have research and analysis, Dou [53] established Pu'er tea price evaluation index system. This paper takes weekly price impact factor data[1] of four Pu'er tea products from June 12, 2012 to December 27, 2020 as sample data. For the output layer sample data, weekly price data of four Pu'er tea products from June 12, 2012 to December 27, 2020 are used as sample data, whole sample data and non-price bubble sample data of four products are forecast respectively.

C. DATA PREPROCESSING

This paper use premnmx function to normalize the original data samples. After BP training, the normalized data obtained from the network prediction output need to be reverted the price value of Pu'er tea by inverse normalization processing.

D. BP MODEL STRUCTURE DESIGN

The commonly used calculation formulas for hidden layer node are mainly as follows:

$$m = \sqrt{nl} \tag{6}$$

$$m = \log_2 n \tag{7}$$

$$m = \sqrt{n+l} + \alpha \tag{8}$$

The hidden layer node number is m, the input layer node number is n, the output layer node number is l, and α is a constant between 1 and 10.

Formula (8) which is commonly used, repeated experiments with different node number, and the hidden layer node optimal number is determined according to the training error result. According to the scholars research conclusion, the product 1 input layer neurons number is 4; the product 2 input layer neurons number is 11; the product 3 input layer neurons number is 16; the product 4 input layer neurons number is 6.

The output layer neurons number is 1. The hidden layer excitation function was tansig, the output layer excitation function was purelin, and the training function was trainlm. The epoch iteration was 5000 times, and training error was 0.0000001.

E. VALIDATION OF BP MODEL

Considering the price bubble characteristic of the four products are different, the sample data selected are also different, so the empirical test is conducted on the four products respectively.

1) MODEL VALIDATION OF PRODUCT 1

Price forecast of the whole sample and non-price bubble period sample of product 1. The whole sample data of product 1 are the weekly price data from June 12, 2012 to December 27, 2020, with a total of 446 weekly price datas. The non-price bubble period data of product 1 included

[1] Most of the evaluation index system data are year data, and price data used in this paper are weekly data, the frequency of both is different, so in this paper, in order to meet the requirement of empirical research, the evaluation index system of Pu'er tea price impact mechanism of annual data by default as weekly data, namely default the annual data no change in the current year.

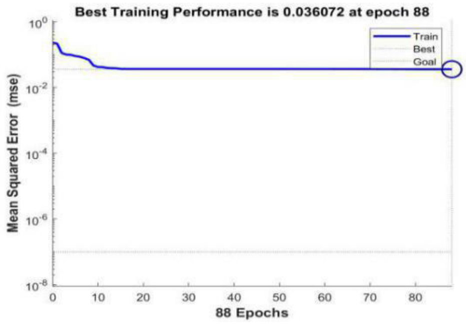

FIGURE 9. Product 1 whole sample training error curve.

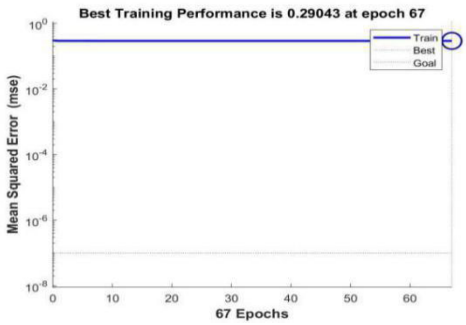

FIGURE 10. Product 1 non-price bubble period sample training error curve.

296 weekly price datas. According to the characteristic of the two kinds of sample data, 386 datas of product 1 were used as training set, and 60 datas were used as verification set in the whole sample; 236 datas of product 1 were used as training set, and 60 datas were used as verification set in the non-price bubble period sample. Through empirical test, when the hidden layer neurons number are 9 and 5 respectively, the forecast accuracy is highest, and the prediction result are shown in Table 7 and 8. After 88 and 67 iterations respectively, the network training errors of the two training samples reached below the target error. See Figure 9 and 10.

2) MODEL VALIDATION OF PRODUCT 2

Price forecast of the whole sample and non-price bubble period sample of product 2. The whole sample forecast data of product 2 are the weekly price data from June 12, 2012 to December 27, 2020, with a total of 446 weekly price datas, the non-price bubble period data of product 2 included 287 weekly price datas. According to the characteristic of the two kinds of sample data, 386 datas of product 2 were used as training set, and 60 datas were used as verification set in the whole sample; 227 datas of product 2 were used as training set, and 60 datas were used as verification set in the non-price bubble period sample. Through empirical test, when the hidden layer neurons number are 8 and 11 respectively, the forecast accuracy is highest, and the prediction result are shown in Table 9 and 10. After 26 and 22 iterations

TABLE 7. Price forecast of product 1 during whole sample.

Whole Sample Price Forecast		
Date	Forecast Price	Relative Error
2019.11.4—2019.11.10	111.060	0.7520
2019.11.11—2019.11.17	111.060	0.7520
2019.11.18—2019.11.24	111.060	0.7520
2019.11.25—2019.12.1	111.060	0.7520
2019.12.2—2019.12.8	111.060	0.7520
2019.12.9—2019.12.15	111.060	0.7778
2019.12.16—2019.12.22	111.060	0.7778
2019.12.23—2019.12.29	111.060	0.8068
2019.12.30—2020.1.5	269.572	0.5852
2020.1.6—2020.1.12	269.572	0.5852
2020.1.13—2020.1.19	269.572	0.5852
2020.1.20—2020.1.26	269.572	0.5852
2020.1.27—2020.2.2	269.572	0.5852
2020.2.3—2020.2.9	269.572	0.5852
2020.2.10—2020.2.16	269.572	0.5852
2020.2.17—2020.2.23	269.572	0.5852
2020.2.24—2020.3.1	269.572	0.5852
2020.3.2—2020.3.8	269.572	0.5852
2020.3.9—2020.3.15	269.572	0.5852
2020.3.16—2020.3.22	269.572	0.5852
2020.3.23—2020.3.29	269.572	0.5852
2020.3.30—2020.4.5	269.572	0.5430
2020.4.6—2020.4.12	269.572	0.5430
2020.4.13—2020.4.19	269.572	0.4913
2020.4.20—2020.4.26	269.572	0.5430
2020.4.27—2020.5.3	269.572	0.5430
2020.5.4—2020.5.10	269.572	0.6651
2020.5.11—2020.5.17	269.572	0.6865
2020.5.18—2020.5.24	269.572	0.6865
2020.5.25—2020.5.31	269.572	0.7715
2020.6.1—2020.6.7	269.572	0.8074
2020.6.8—2020.6.14	269.572	0.8638
2020.6.15—2020.6.21	269.572	0.8638
2020.6.22—2020.6.28	269.572	0.8566
2020.6.29—2020.7.5	269.572	0.8566
2020.7.6—2020.7.12	269.572	0.8566
2020.7.13—2020.7.19	269.572	0.8566
2020.7.20—2020.7.26	269.572	0.8566

TABLE 7. *(Continued.)* **Price forecast of product 1 during whole sample.**

2020.7.27—2020.8.2	269.572	0.8566
2020.8.3—2020.8.9	269.572	0.8566
2020.8.10—2020.8.16	269.572	0.8566
2020.8.17—2020.8.23	269.572	0.8366
2020.8.24—2020.8.30	269.572	0.8366
2020.8.31—2020.9.6	269.572	0.8366
2020.9.7—2020.9.13	269.572	0.8366
2020.9.14—2020.9.20	269.572	0.8366
2020.9.21—2020.9.27	269.572	0.8366
2020.9.28—2020.10.4	269.572	0.8366
2020.10.5—2020.10.11	269.572	0.8366
2020.10.12—2020.10.18	269.572	0.8366
2020.10.19—2020.10.25	269.572	0.8366
2020.10.26—2020.11.1	269.572	0.8366
2020.11.2—2020.11.8	269.572	0.8366
2020.11.9—2020.11.15	269.572	0.8366
2020.11.16—2020.11.22	269.572	0.8366
2020.11.23—2020.11.29	269.572	0.8366
2020.11.30—2020.12.6	269.572	0.8366
2020.12.7—2020.12.13	269.572	0.8366
2020.12.14—2020.12.20	269.572	0.8366
2020.12.21—2020.12.27	269.572	0.8366

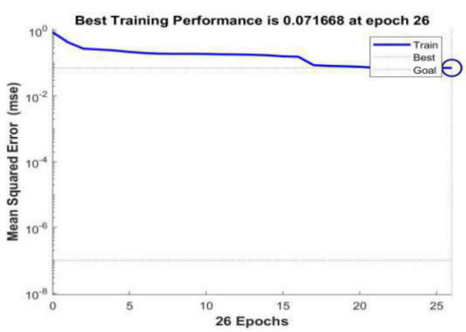

FIGURE 11. **Product 2 whole sample training error curve.**

respectively, the network training errors of the two training samples reached below the target error. See Figure 11 and 12.

3) MODEL VALIDATION OF PRODUCT 3

Price forecast of whole sample data of product 3. The whole sample forecast data of product 3 are the weekly price data from June 12, 2012 to December 27, 2020, with a total of

TABLE 8. **Price forecast of product 1 during non-price bubble period sample.**

Price Forecast during Non-price Bubble Period		
Date	Forecast Price	Relative Error
2017.7.31—2017.8.6	154.204	0.0362
2017.8.7—2017.8.13	154.204	0.0362
2017.8.14—2017.8.20	154.204	0.0362
2017.8.21—2017.8.27	154.204	0.0362
2017.8.28—2017.9.3	154.204	0.0362
2017.9.4—2017.9.10	154.204	0.0362
2017.9.11—2017.9.17	154.204	0.0362
2017.9.18—2017.9.24	154.204	0.0362
2017.9.25—2017.10.1	154.204	0.0362
2017.10.2—2017.10.8	154.204	0.0362
2017.10.9—2017.10.15	154.204	0.0362
2017.10.16—2017.10.22	154.204	0.0362
2017.10.23—2017.10.29	154.204	0.0362
2017.10.30—2017.11.5	154.204	0.0362
2017.11.6—2017.11.12	154.204	0.0362
2017.11.13—2017.11.19	154.204	0.0362
2017.11.20—2017.11.26	154.204	0.0362
2017.11.27—2017.12.3	154.204	0.0362
2017.12.4—2017.12.10	154.204	0.0362
2017.12.11—2017.12.17	154.204	0.0362
2017.12.18—2017.12.24	154.204	0.0362
2017.12.25—2017.12.31	154.204	0.0362
2018.1.1—2018.1.7	154.427	0.0348
2018.1.8—2018.1.14	154.427	0.0348
2018.1.15—2018.1.21	154.427	0.0348
2018.1.22—2018.1.28	154.427	0.0348
2018.1.29—2018.2.4	154.427	0.0348
2018.2.5—2018.2.11	154.427	0.0348
2018.2.12—2018.2.18	154.427	0.0348
2018.2.19—2018.2.25	154.427	0.0348
2018.2.26—2018.3.4	154.427	0.0348
2018.3.5—2018.3.11	154.427	0.0525
2018.3.12—2018.3.18	154.427	0.0640
2018.3.26—2018.4.1	154.427	0.0408
2018.4.2—2018.4.8	154.427	0.0036
2018.4.9—2018.4.15	154.427	0.0036
2018.4.16—2018.4.22	154.427	0.0036
2018.4.23—2018.4.29	154.427	0.0027

TABLE 8. *(Continued.)* **Price forecast of product 1 during non-price bubble period sample.**

2018.4.30—2018.5.6	154.427	0.0159
2018.5.7—2018.5.13	154.427	0.0159
2018.5.14—2018.5.20	154.427	0.0295
2018.5.28—2018.6.3	154.427	0.0364
2018.6.4—2018.6.10	154.427	0.0364
2018.6.11—2018.6.17	154.427	0.0364
2018.6.18—2018.6.24	154.427	0.0364
2018.7.23—2018.7.29	154.427	0.0434
2018.7.30—2018.8.5	154.427	0.0434
2018.8.6—2018.8.12	154.427	0.0434
2018.8.13—2018.8.19	154.427	0.0434
2018.8.20—2018.8.26	154.427	0.0434
2018.8.27—2018.9.2	154.427	0.0093
2018.9.3—2018.9.9	154.427	0.0163
2018.9.10-2018.9.16	154.427	0.0226
2018.9.17—2018.9.23	154.427	0.0226
2018.9.24—2018.9.30	154.427	0.1324
2018.11.5—2018.11.11	154.427	0.1872
2018.11.12—2018.11.18	154.427	0.1872
2018.11.19—2018.11.25	154.427	0.1872
2018.11.26—2018.12.2	154.427	0.1872
2019.4.15—2019.4.21	167.865	0.2006

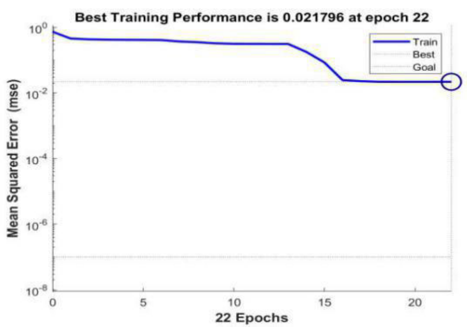

FIGURE 12. **Product 2 non-price bubble period sample training error curve.**

446 weekly price datas. 386 datas of product 3 were used as training set and 60 datas were used as verification set. Through empirical test, when the hidden layer neurons number is 13, the forecast accuracy is highest, and the prediction result are shown in Table 11. After 235 iterations, the network

TABLE 9. **Price forecast of product 2 during whole sample.**

Whole sample price forecast		
Date	Forecast Price	Relative Error
2019.11.4—2019.11.10	95.159	0.0289
2019.11.11—2019.11.17	95.159	0.0289
2019.11.18—2019.11.24	95.159	0.0289
2019.11.25—2019.12.1	95.159	0.0289
2019.12.2—2019.12.8	95.159	0.0289
2019.12.9—2019.12.15	95.159	0.0387
2019.12.16—2019.12.22	95.159	0.0937
2019.12.23—2019.12.29	95.159	0.0937
2019.12.30—2020.1.5	96.588	0.0801
2020.1.6—2020.1.12	96.588	0.0801
2020.1.13—2020.1.19	96.588	0.0801
2020.1.20—2020.1.26	96.588	0.0801
2020.1.27—2020.2.2	96.588	0.0801
2020.2.3—2020.2.9	96.588	0.0801
2020.2.10—2020.2.16	96.588	0.0801
2020.2.17—2020.2.23	96.588	0.0801
2020.2.24—2020.3.1	96.588	0.0801
2020.3.2—2020.3.8	96.588	0.0801
2020.3.9—2020.3.15	96.588	0.1219
2020.3.16—2020.3.22	96.588	0.1219
2020.3.23—2020.3.29	96.588	0.1219
2020.3.30—2020.4.5	96.588	0.1219
2020.4.6—2020.4.12	96.588	0.1219
2020.4.13—2020.4.19	96.588	0.1219
2020.4.20—2020.4.26	96.588	0.3338
2020.4.27—2020.5.3	96.588	0.3338
2020.5.4—2020.5.10	96.588	0.3000
2020.5.11—2020.5.17	96.588	0.3100
2020.5.18—2020.5.24	96.588	0.3847
2020.5.25—2020.5.31	96.588	0.5356
2020.6.1—2020.6.7	96.588	0.7028
2020.6.8—2020.6.14	96.588	0.7523
2020.6.15—2020.6.21	96.588	0.7523
2020.6.22—2020.6.28	96.588	0.7317
2020.6.29—2020.7.5	96.588	0.7317
2020.7.6—2020.7.12	96.588	0.7240
2020.7.13—2020.7.19	96.588	0.7240
2020.7.20—2020.7.26	96.588	0.7240

TABLE 9. ***(Continued.)*** **Price forecast of product 2 during whole sample.**

2020.7.27—2020.8.2	96.588	0.7240
2020.8.3—2020.8.9	96.588	0.7240
2020.8.10—2020.8.16	96.588	0.7159
2020.8.17—2020.8.23	96.588	0.7159
2020.8.24—2020.8.30	96.588	0.7159
2020.8.31—2020.9.6	96.588	0.7159
2020.9.7—2020.9.13	96.588	0.7159
2020.9.14—2020.9.20	96.588	0.7159
2020.9.21—2020.9.27	96.588	0.7159
2020.9.28—2020.10.4	96.588	0.7159
2020.10.5—2020.10.11	96.588	0.7159
2020.10.12—2020.10.18	96.588	0.7159
2020.10.19—2020.10.25	96.588	0.7159
2020.10.26—2020.11.1	96.588	0.7159
2020.11.2—2020.11.8	96.588	0.7159
2020.11.9—2020.11.15	96.588	0.7159
2020.11.16—2020.11.22	96.588	0.7159
2020.11.23—2020.11.29	96.588	0.7159
2020.11.30—2020.12.6	96.588	0.7159
2020.12.7—2020.12.13	96.588	0.7159
2020.12.14—2020.12.20	96.588	0.7159
2020.12.21—2020.12.27	96.588	0.7159

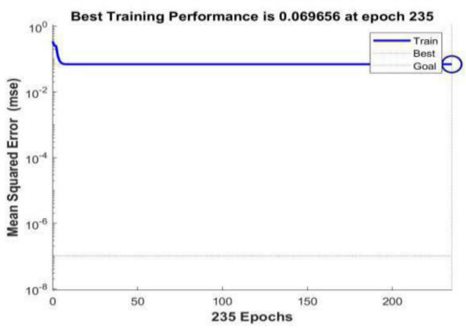

FIGURE 13. **Product 3 whole sample training error curve.**

training errors of training samples reached below the target error. See Figure 13.

4) MODEL VALIDATION OF PRODUCT 4

Price forecast of the whole sample and non-price bubble period sample of product 4. The whole sample forecast data of product 4 are the weekly price data from June 12, 2012 to December 27, 2020, with a total of 446 weekly price datas, the

TABLE 10. **Price forecast of product 2 during non-price bubble period sample.**

Price Forecast during Non-price Bubble Period		
Date	Forecast Price	Relative Error
2019.2.25—2019.3.3	133.811	0.3118
2019.3.4—2019.3.10	133.811	0.2623
2019.3.25—2019.3.31	133.811	0.2389
2019.4.1—2019.4.7	133.811	0.2389
2019.4.8—2019.4.14	133.811	0.2389
2019.4.15—2019.4.21	133.811	0.2389
2019.4.22—2019.4.28	133.811	0.2389
2019.4.29—2019.5.5	133.811	0.2389
2019.5.6—2019.5.12	133.811	0.2389
2019.5.13—2019.5.19	133.811	0.2389
2019.5.20—2019.5.26	133.811	0.3654
2019.5.27—2019.6.2	133.811	0.3654
2019.6.3—2019.6.9	133.811	0.3654
2019.6.10—2019.6.16	133.811	0.3654
2019.6.17—2019.6.23	133.811	0.3654
2019.6.24—2019.6.30	133.811	0.3654
2019.7.1—2019.7.7	133.811	0.3654
2019.7.8—2019.7.14	133.811	0.3654
2019.7.15—2019.7.21	133.811	0.3654
2019.7.22—2019.7.28	133.811	0.3654
2019.7.29—2019.8.4	133.811	0.3654
2019.8.5—2019.8.11	133.811	0.3654
2019.8.12—2019.8.18	133.811	0.3794
2019.8.19—2019.8.25	133.811	0.3938
2019.8.26—2019.9.1	133.811	0.3938
2019.9.2—2019.9.8	133.811	0.3938
2019.9.9—2019.9.15	133.811	0.3938
2019.9.16—2019.9.22	133.811	0.3938
2019.9.23—2019.9.29	133.811	0.3938
2019.9.30—2019.10.6	133.811	0.3938
2019.10.7—2019.10.13	133.811	0.3938
2019.10.14—2019.10.20	133.811	0.3654
2019.10.21—2019.10.27	133.811	0.3654
2019.10.28—2019.11.3	133.811	0.3654
2019.11.4—2019.11.10	133.811	0.3654
2019.11.11—2019.11.17	133.811	0.3654
2019.11.18—2019.11.24	133.811	0.3654
2019.11.25—2019.12.1	133.811	0.3654

TABLE 10. *(Continued.)* **Price forecast of product 2 during non-price bubble period sample.**

2019.12.2—2019.12.8	133.811	0.3654
2019.12.9—2019.12.15	133.811	0.3516
2019.12.16—2019.12.22	133.811	0.2743
2019.12.23—2019.12.29	133.811	0.2743
2019.12.30—2020.1.5	133.811	0.2743
2020.1.6—2020.1.12	133.811	0.2743
2020.1.13—2020.1.19	133.811	0.2743
2020.1.20—2020.1.26	133.811	0.2743
2020.1.27—2020.2.2	133.811	0.2743
2020.2.3—2020.2.9	133.811	0.2743
2020.2.10—2020.2.16	133.811	0.2743
2020.2.17—2020.2.23	133.811	0.2743
2020.2.24—2020.3.1	133.811	0.2743
2020.3.2—2020.3.8	133.811	0.2743
2020.3.9—2020.3.15	133.811	0.2164
2020.3.16—2020.3.22	133.811	0.2164
2020.3.23—2020.3.29	133.811	0.2164
2020.3.30—2020.4.5	133.811	0.2164
2020.4.6—2020.4.12	133.811	0.2164
2020.4.13—2020.4.19	133.811	0.2164
2020.5.4—2020.5.10	133.811	0.0303
2020.5.11—2020.5.17	133.811	0.0442

non-price bubble period data of product 4 include 144 weekly price datas. According to the characteristic of the two kinds of data, 386 datas of product 4 were used as training set, and 60 datas were used as verification set; 114 datas of product 4 were used as training set, and 30 datas were used as verification set. Through empirical test, when the hidden layer neurons number is 4, the prediction accuracy is highest, and the prediction result are shown in Table 12 and 13. After 1 iteration, the network training error of two training samples reached below the target error. See Figure 14 and 15.

IV. RESULT ANALYSIS

Based on the hedonic price theory, this paper carries out empirical study on the multi-characteristic product price. GSADF method is used to detect product bubble, and BP price prediction model is used to verify the scientificity and rationality of GSADF method. This part will conduct specific analysis on the empirical test result.

A. PRICE BUBBLE RESULT ANALYSIS

Through the three indexes—bubble length (total number of bubble days), bubble frequency (price bubble events number)

TABLE 11. **Price forecast of product 3 during whole sample.**

Date	Forecast Price	Relative Error
2019.11.4—2019.11.10	164.130	0.0942
2019.11.11—2019.11.17	164.130	0.0942
2019.11.18—2019.11.24	164.130	0.0942
2019.11.25—2019.12.1	164.130	0.0942
2019.12.2—2019.12.8	164.130	0.0942
2019.12.9—2019.12.15	164.130	0.0942
2019.12.16—2019.12.22	164.130	0.0942
2019.12.23—2019.12.29	164.130	0.0942
2019.12.30—2020.1.5	146.667	0.0222
2020.1.6—2020.1.12	146.667	0.0222
2020.1.13—2020.1.19	146.667	0.0222
2020.1.20—2020.1.26	146.667	0.0222
2020.1.27—2020.2.2	146.667	0.0222
2020.2.3—2020.2.9	146.667	0.0222
2020.2.10—2020.2.16	146.667	0.0222
2020.2.17—2020.2.23	146.667	0.0222
2020.2.24—2020.3.1	146.667	0.0222
2020.3.2—2020.3.8	146.667	0.0222
2020.3.9—2020.3.15	146.667	0.0222
2020.3.16—2020.3.22	146.667	0.0222
2020.3.23—2020.3.29	146.667	0.0222
2020.3.30—2020.4.5	146.667	0.0222
2020.4.6—2020.4.12	146.667	0.0222
2020.4.13—2020.4.19	146.667	0.0222
2020.4.20—2020.4.26	146.667	0.0222
2020.4.27—2020.5.3	146.667	0.0222
2020.5.4—2020.5.10	146.667	0.0222
2020.5.11—2020.5.17	146.667	0.0222
2020.5.18—2020.5.24	146.667	0.0222
2020.5.25—2020.5.31	146.667	0.0222
2020.6.1—2020.6.7	146.667	0.0222
2020.6.8—2020.6.14	146.667	0.0222
2020.6.15—2020.6.21	146.667	0.0222
2020.6.22—2020.6.28	146.667	0.0222
2020.6.29—2020.7.5	146.667	0.0222
2020.7.6—2020.7.12	146.667	0.0222
2020.7.13—2020.7.19	146.677	0.0222

TABLE 11. ***(Continued.)*** **Price forecast of product 3 during whole sample.**

2020.7.20—2020.7.26	146.667	0.0222
2020.7.27—2020.8.2	146.667	0.0222
2020.8.3—2020.8.9	146.667	0.0222
2020.8.10—2020.8.16	146.667	0.0222
2020.8.17—2020.8.23	146.667	0.0222
2020.8.24—2020.8.30	146.667	0.0222
2020.8.31—2020.9.6	146.667	0.0222
2020.9.7—2020.9.13	146.667	0.0222
2020.9.14—2020.9.20	146.667	0.0222
2020.9.21—2020.9.27	146.667	0.0222
2020.9.28—2020.10.4	146.667	0.0222
2020.10.5—2020.10.11	146.667	0.0222
2020.10.12—2020.10.18	146.667	0.0222
2020.10.19—2020.10.25	146.667	0.0222
2020.10.26—2020.11.1	146.667	0.0222
2020.11.2—2020.11.8	146.667	0.0222
2020.11.9—2020.11.15	146.667	0.0222
2020.11.16—2020.11.22	146.667	0.0222
2020.11.23—2020.11.29	146.667	0.0222
2020.11.30—2020.12.6	146.667	0.0222
2020.12.7—2020.12.13	146.667	0.0222
2020.12.14—2020.12.20	146.667	0.0222
2020.12.21—2020.12.27	146.667	0.0222

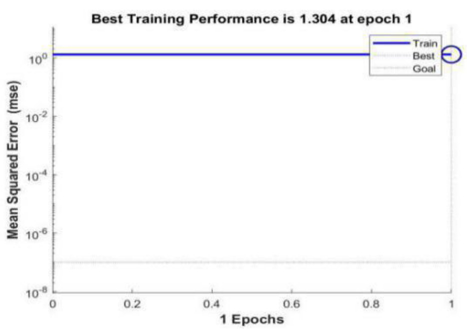

FIGURE 14. **Product 4 whole sample training error curve.**

and bubble intensity (maximum number of bubble days), analyzed and compared the occurrence degree and difference of three products price bubble. In the length index, the largest days was product 4; in the frequency index, the events occurred most frequently was product 1; in the strength index, the longest duration was product 4. This paper analysis the

TABLE 12. **Price forecast of product 4 during whole sample.**

Whole sample price forecast		
Date	Forecast Price	Relative Error
2019.11.4—2019.11.10	145.000	0.0000
2019.11.11—2019.11.17	145.000	0.0000
2019.11.18—2019.11.24	145.000	0.0333
2019.11.25—2019.12.1	145.000	0.0333
2019.12.2—2019.12.8	145.000	0.0333
2019.12.9—2019.12.15	145.000	0.0333
2019.12.16—2019.12.22	145.000	0.0333
2019.12.23—2019.12.29	145.000	0.0333
2019.12.30—2020.1.5	145.000	0.0333
2020.1.6—2020.1.12	145.000	0.0333
2020.1.13—2020.1.19	145.000	0.0333
2020.1.20—2020.1.26	145.000	0.0333
2020.1.27—2020.2.2	145.000	0.0333
2020.2.3—2020.2.9	145.000	0.0333
2020.2.10—2020.2.16	145.000	0.0333
2020.2.17—2020.2.23	145.000	0.0333
2020.2.24—2020.3.1	145.000	0.0333
2020.3.2—2020.3.8	145.000	0.0333
2020.3.9—2020.3.15	145.000	0.0333
2020.3.16—2020.3.22	145.000	0.0333
2020.3.23—2020.3.29	145.000	0.0333
2020.3.30—2020.4.5	145.000	0.0333
2020.4.6—2020.4.12	145.000	0.0333
2020.4.13—2020.4.19	145.000	0.0333
2020.4.20—2020.4.26	145.000	0.0333
2020.4.27—2020.5.3	145.000	0.0333
2020.5.4—2020.5.10	145.000	0.0333
2020.5.11—2020.5.17	145.000	0.0333
2020.5.18—2020.5.24	145.000	0.1049
2020.5.25—2020.5.31	145.000	0.1049
2020.6.1—2020.6.7	145.000	0.1049
2020.6.8—2020.6.14	145.000	0.1049
2020.6.15—2020.6.21	145.000	0.1049
2020.6.22—2020.6.28	145.000	0.1049
2020.6.29—2020.7.5	145.000	0.1049
2020.7.6—2020.7.12	145.000	0.1049

TABLE 12. *(Continued.)* **Price forecast of product 4 during whole sample.**

2020.7.13—2020.7.19	145.000	0.1049
2020.7.20—2020.7.26	145.000	0.1049
2020.7.27—2020.8.2	145.000	0.1049
2020.8.3—2020.8.9	145.000	0.1049
2020.8.10—2020.8.16	145.000	0.1049
2020.8.17—2020.8.23	145.000	0.1049
2020.8.24—2020.8.30	145.000	0.1049
2020.8.31—2020.9.6	145.000	0.1049
2020.9.7—2020.9.13	145.000	0.1049
2020.9.14—2020.9.20	145.000	0.1049
2020.9.21—2020.9.27	145.000	0.1049
2020.9.28—2020.10.4	145.000	0.1049
2020.10.5—2020.10.11	145.000	0.1049
2020.10.12—2020.10.18	145.000	0.1049
2020.10.19—2020.10.25	145.000	0.1049
2020.10.26—2020.11.1	145.000	0.1049
2020.11.2—2020.11.8	145.000	0.1049
2020.11.9—2020.11.15	145.000	0.1049
2020.11.16—2020.11.22	145.000	0.1049
2020.11.23—2020.11.29	145.000	0.1049
2020.11.30—2020.12.6	145.000	0.1049
2020.12.7—2020.12.13	145.000	0.1049
2020.12.14—2020.12.20	145.000	0.1049
2020.12.21—2020.12.27	145.000	0.1049

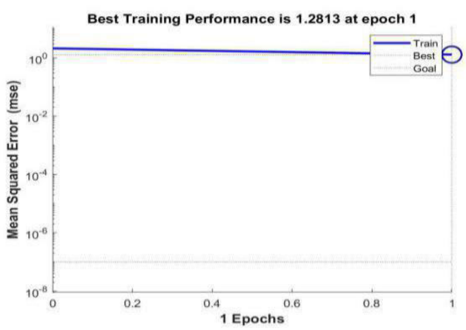

FIGURE 15. **Product 4 non-price bubble period sample training error curve.**

TABLE 13. **Price forecast of product 4 during non-price bubble period sample.**

Price Forecast during Non-price Bubble Period		
Date	Forecast Price	Relative Error
2015.10.26—2015.11.1	93.000	0.0568
2015.11.2—2015.11.8	93.000	0.0568
2015.11.9—2015.11.15	93.000	0.0568
2015.11.16—2015.11.22	93.000	0.0568
2015.11.23—2015.11.29	93.000	0.0568
2015.11.30—2015.12.6	93.000	0.0568
2015.12.7—2015.12.13	93.000	0.0568
2015.12.14—2015.12.20	93.000	0.0568
2015.12.21—2015.12.27	93.000	0.0333
2015.12.28—2016.1.3	93.000	0.0000
2016.1.4—2016.1.10	93.000	0.0000
2016.1.11—2016.1.17	93.000	0.0000
2016.1.18—2016.1.24	93.000	0.0000
2016.1.25—2016.1.31	93.000	0.0000
2016.2.1—2016.2.7	93.000	0.0000
2016.2.8—2016.2.14	93.000	0.0000
2016.2.15—2016.2.21	93.000	0.0000
2016.2.22—2016.2.28	93.000	0.0000
2016.2.29—2016.3.6	93.000	0.0000
2016.3.7—2016.3.13	93.000	0.0000
2016.3.14—2016.3.20	93.000	0.0000
2016.3.21—2016.3.27	93.000	0.0000
2016.3.28—2016.4.3	93.000	0.0000
2016.4.4—2016.4.10	93.000	0.0000
2016.4.11—2016.4.17	93.000	0.0000
2016.4.18—2016.4.24	93.000	0.0000
2016.4.25—2016.5.1	93.000	0.0000
2016.5.2—2016.5.8	93.000	0.0000
2016.5.9—2016.5.15	93.000	0.0000
2016.5.16—2016.5.22	93.000	0.0000

occurrence process of price bubble of the three products and the product without price bubble, then analysis the causes of price bubble, mainly in the following three aspects:

1) ECONOMIC FACTOR

Pu'er tea has drinking and investment value, consumer will make purchase decision by comparing price with substitute in market. Most investor investment behavior will be affected by economic factor, they compare the investment return rate of Pu'er tea and other products then make investment decision according to the market situation and expected returns. After the collapsed of Pu'er tea in 2014, the price of Pu'er tea had a great price advantage compared with other kinds of tea. Therefore, consumer and investor made consumption and investment in response to this favorable price, thus the price bubble of the three products appeared for many time and lasted for a long time.

2) TEA SUPPLY AND DEMAND FACTORS

The impact factor is mainly reflected in the following five aspects: Firstly, the ancient tea tree resources have received unprecedented attention and protection from the government, and the scarcity of resource has led to the price rise, while the mountain tea and ancient tea introduced after 2012 have aroused the consumer's pursuit; Secondly, after mandarin tea was introduced to the consumer market, it became popular all over the country, which greatly released the Pu'er ripe tea market, and many tea companies joined in the ranks of the ripe tea production, then price increases accordingly; Thirdly, the continuous drought in Yunnan and the landing of super typhoon ''Mankhut'' led to the Pu'er tea product and storage decrease, thus cause the price increased; In addition, in recent years, the price of raw material of spring tea has remained high, compared with last year, the price of raw tea in most tea areas has increased by about 30% and even more than 50% in some tea areas. The average daily salary of tea picking worker is 150 RMB, and the salary of tea makers has also risen gradually; Finally, after the implementation of Central Committee's eight point decision, the consumption demand for gifts has gradually decreased, the sales of high value product have been blocked, drinking demand has become the main demand of Pu'er tea consumption.

3) THE CHANGE OF SALES MODE AND CHANNEL OF Pu'er TEA MAKES THE MARKET DEMAND SURGE

Consumer structure changes cause industry change, young group has become the main tea consumption crowd, new consumption population, new consumer supply and new scene was appeared. For the young consumer, they pay more attention to drinking and cultural value, the traditional market way and Internet maked Pu'er tea opened the consumer market quickly, broaden the sales channel and take the Internet as the media to meet the personalized needs of customer.

4) ANALYSIS PRODUCT 3 WITHOUT PRICE BUBBLE

According to the test result, there is no price bubble in product 3. The reasons are mainly as follows: Firstly, Pu'er raw tea has not undergone artificial fermentation, and it needs to be naturally fermented for more than 10 years before it becomes more valuable for drinking. However, the product 3 has not reached the best drinking period, so consumers do not pay attention on it; Secondly, its price is much higher than product 4, so it has no advantage in price factor; Thirdly, throughout the development history of Pu'er tea, the advent of new product will set off the wind of speculation, Pu'er ripe tea was once popular in the market due to the popularity of mandarin tea. In contrast, there was no product similar to mandarin tea in product 3 and this product added value was insufficient. In addition, due to the characteristic and investment value of Pu'er tea, the storage of Pu'er tea in the market has nearly 800,000 tons, far beyond the actual demand, there is a serious imbalance between supply and demand; Finally, There are many types of product in Dayi company. According to the sales volume and other factors, the company will focus on the every year new product, however, Dayi 7542 raw tea is produced in large quantity every year, so the company will not pay attention to the product in 2011 for a long time. Dayi 7542 product is the benchmark product in the industry, which has the characteristic of future product and has presented the property of commodity financialization. However, the product with more hype value and investment space are the every year new product, 2011 product have passed the best hype time.

B. PRICE PREDICTION RESULT ANALYSIS

In this paper, the GSADF method is used to analysis the price bubble of Pu'er tea, and BP model is used to predict price, so as to verify the scientific and reasonable GSADF method. Forecast price of four product in different period, in the whole sample data, the best forecast effect was product 3, followed by were product 4, product 2 and finally was product 1. According to the whole sample data predict result, due to product 3 have no price bubble, therefore the BP model to predict price is better and the forecast precision is higher. Although there have price bubble in product 4, but its price is relatively stable and fluctuate little, so the price prediction effect is good. The price of product 2 is higher than other ripe tea and lower than raw tea in the same year, the price prediction effect of product 2 is inferior to product 4 but superior to product 1. Product 1 is the product with the highest price and biggest fluctuation among the four products, and it has more obvious investment value characteristic, so its price prediction effect is poor.

In the non-price bubble period sample data, the best forecast effect was product 4, followed by was product 1, and the last one was product 2. Because the total price bubble days number of product 4 is longest, the non-price bubble period sample data are excluded to predict, so the prediction effect is best. Although the price of product 1 is high and fluctuate great, but the excessive price is eliminated through price bubble detection, so the price prediction effect is better. The prediction effect of product 2 is poor, which is related to the market's attention to ripe tea in recent years.

V. CONCLUSION AND ENLIGHTENMENT

In this paper, the GSADF model was constructed to detect the price bubble of four products. The test results showed that there were price bubbles in three products-product 1, 2 and 4, but there was no price bubble in product 3. BP model is respectively used to forecast the price of whole sample data and non-price bubble sample data. According to the prediction result, the BP model proved the rationality and scientificity of GSADF method in the price bubble detection of Pu'er tea, which laid a foundation for the follow-up research. Through the current situation of Pu'er tea market and empirical test result, the following enlightenment and suggestion are obtained.

Through price bubble detection and price forecast of Dayi product, we get more scientific and reasonable empirical research result. As a leading enterprise in the industry, Dayi produces product that are hard currency in the market. Its added value such as brand value makes it have storage and investment value. Therefore, the emergence of price bubble is match with the market actual situation. Whether it is the quality of raw material, or the processing technology have storage and investment value, blind storage will inevitably lead to the imbalance between supply and demand, market downturn. Therefore, the product that are not suitable for storage in the market should give full play to their drinking value, accelerate product consumption and reduce inventory, so that the Pu'er tea market will return to rational production and consumption. As the main body of the industry, the government should give full play to its administrative function and play the guide and bridge role; Tea farmers should produce rationally, not expand the planting area and scale blindly; Tea enterprises should reasonably arrange inventory and produce on demand; Consumer and investor should spend and invest in a rational way to prevent the dumping of stocks in the market from hurting their interests.

Based on the hedonic price theory, this paper analysis the multi-characteristic product, they not only have the use characteristic, but also have investment characteristic. However, previous studies have paid little attention to the investment characteristic of product. Pu'er tea is a typical representative of multi-characteristic product. Due to the multiple characteristic of Pu'er tea, it meets the different need of consumer, making its price far beyond the basic value. Through the detection of price bubble of Pu'er tea, the causes of price bubble of four products were analyzed, and the GSADF method was validated by BP model. Multi-characteristic product flood the market, and Pu'er tea is not a unique case. For example, real estate, jade and tulip are all multi-characteristic products, which cover various industries and fields. As a pioneering research, the research methods and ideas of Pu'er tea in this paper can be extended to other industries and fields, so as to conduct in-depth analysis of multi-characteristic product in the market and provide suggestion and guidance for the decision making and behavior of relevant stakeholder.

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