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Nonlinear analysis and prediction of soybean futures

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Abstract: We use chaotic artificial neural network (CANN) technology to predict the price of the most widely traded agricultural futures – soybean futures. The nonlinear existence test results show that the time series of soybean futures have multifractal dynamics, long-range dependence, self similarity, and chaos characteristics. This also provides a basis for the construction of a CANN model. Compared with the artificial neural network (ANN) structure as our benchmark system, the predictability of CANN is much higher. The ANN is based on Gaussian kernel function and is only suitable for local approximation of nonstationary signals, so it cannot approach the global nonlinear chaotical hidden pattern. Improving the prediction accuracy of soybean futures prices is of great significance for investors, soybean producers, and decision makers.

Keywords: artificial neural network (ANN); chaos; forecasting; long-range dependence; multifractal

The efficient market hypothesis (EMH) is the cornerstone of financial economics. The pioneering work by Fama (1976) proposed a classic definition: market is informationally efficient if it "fully reflects all available information". As an inevitable result of the EMH, people cannot accept the existence of long-range dependence in financial time series because its existence will allow a risk-free, profitable trading strategy. If the market is information-efficient, arbitrage can prevent the emergence of this strategy. However, many scholars have questioned the EMH through empirical studies. They found that the stock market, exchange rate, gold, and other financial markets did not fully comply with the EMH, and found many financial anomalies: such as nonlinearity, long-range dependence, predictability, and so on. In order to solve the shortcomings of the EMH in explaining many practical situations of the capital market, the fractal market hypothesis (FMH) as the frontier of econophysics has opened up a new situation in the study of the financial market.

According to FMH theory (Haugen 1999), the changes of asset prices are not random walks, but have the durability of strengthening trends. The changes of asset prices today or in the future and initial state are not independent from each other, but are continuously related. It is also pointed out that the financial system should be a complex nonlinear system, and should not be considered as linear by EMH theory. At present, the study of nonlinear financial market mainly includes multifractal theory and chaos theory.

Multifractal and chaos theories reveal different aspects of the nonlinear nature of financial markets: on the one hand, multifractal theory (Peters 1991; Rizvi et al. 2014; Mensi et al. 2017; Shahzad et al. 2017; Zhu

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and Zhang 2018) shows the spatiotemporal organization process of financial markets and reveals the long-range dependence and self similarity of financial time series. On the other hand, chaos theory (Hanias et al. 2010; Pandey et al. 2010; Lahmiri 2017) provides for the time evolution process of financial market. Although the external performance of the financial market price time series is irregular, its internal structure has inherent certainty and nonlinearity, revealing that the financial time series has internal generation mechanism and can be further forecast in the short-term.

The investigation of chaotic and multifractal dynamics in nonlinear systems is also of paramount importance in terms of their predictability. A chaotic system (signal) may have limited short-term predictability, whilst multifractal and self similarity can increase the possibility of accurate prediction of future sequences of such signals.

Forecasting the price of financial time series can help investors avoid risks and get higher returns. It is a hot and challenging topic in the financial field. At present, there are many research studies from various fields to take on the challenge and it is an effective way to perform the research using artificial neural networks (ANNs). ANN can deal with both linear and nonlinear data for forecasting the prices. Some researchers thus have applied ANN technologies such as radial basis function (RBF) neural network and back propagation (BP) neural network to study the fluctuations and predictions of the financial prices. Ma (2010) used the BP neural network model to predict the electric power shares and the Bank of China shares in 2009. Through the construction of BP neural network prediction model, Liu (2009) selected the gold futures contract delivered by the New York Futures Exchange in April 2008 as the empirical research object. The monthly closing price data with the Shanghai Composite Index from January 1993 to December 2009 were used to illustrate the application of the BP neural network based algorithm in predicting the stock index (Wang et al. 2011). Falat and Marcek (2014) applied feed-forward ANN of RBF type into the process of modelling and forecasting the future value of USD/CAD time series.

The futures price of agricultural products has an important function of resource allocation. Moreover, the Chicago Board of Trade (CBOT) is the largest soybean futures exchange, and soybean futures is one of the most active agricultural futures contracts. However, there are few articles on price prediction of soybean futures market, as far as we know: a futures forecast model was presented by Gebremariam and Marchetti (2018) providing season-average price forecasts and using monthly futures prices, cash prices received, basis values (cash prices less futures), and marketing weights; Chan and Wan (2013) applied range-based method to forecasting the daily high and low prices of corn and soybeans futures; Wang and Gao (2018) built a model to predict high and low prices of soybean futures with the neural network. Therefore, another problem of this paper is the prediction of soybean futures price using the model based on the internal generation mechanism of time series and ANN.

Thus, the purpose of our current research has basically two aspects. First, we try to evaluate the predictability of soybean futures by examining their inherent nonlinear dynamics, including inherent chaoticity and multifractality. We used the largest Lyapunov exponent (LLE) and the multifractal detrended fluctuation analysis (MF-DFA) based on the extracted time-series generalized Hurst exponent to detect the chaotic and/or multifractal characteristics of soybean futures. Specifically, the former allows the existence of nonlinear deterministic maps to be checked, while the latter reveals the existence of long-range correlations without assumptions about stationarity. Second, we aim to use a special ANN as a potential dynamic system topology to automatically extract hidden patterns and reveal the nonlinear dynamics of their time series. In other words, we construct an intelligent signal data mining and prediction system based on chaos through ANN topology, namely chaotic neural network. It is hoped that the prediction accuracy of the chaotic artificial neural network (CANN) models can be higher than that of the existing ANN benchmark models, so as to avoid the model misspecification.

We contribute to the literature in the following way: *i*) We try to study the nonlinear statistical characteristics of soybean futures comprehensively and systematically from the perspective of econophysics. As far as we know, no literature has studied it from this perspective. *ii*) By examining whether chaos is intrinsic, we can clarify the short-term predictability of soybean futures. *iii*) Differing from the previous work of financial market forecasting (Hsu 2013; Shynkevich 2017; Lei 2018; Das and Mishra 2019), we try to establish an ANN based on chaos to extract and mine the hidden pattern in the original data of soybean futures in order to make accurate predictions. The latter is very important in modern trading practice. Our results from the perspective of nonlinear dynamics are expected to show that whether soybean futures are predictable in the short-term or not depends on the multifractal

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and chaotic nature of the measurements, and our results introducing ANNs base on chaos will prove the consistency and accuracy of their predictive ability.

METHODOLOGY

Multifractal detrended fluctuation analysis (MF-DFA) and generalized Hurst exponent. The multifractal detrended fluctuation analysis (MF-DFA) is an effective tool for detecting multifractal behavior. This method is proposed by Kantelhardt et al. (2002). The MF-DFA procedure is conducted as follows:

Suppose $\{x_i\}_{i=1}^{N}$ be a time series of length N, where: x_i – the i^{th} value in the time series; i – the ordering in the time series; N – length of the time series.

Step 1: Divide the profile $y(k)$ into

$N_s = \text{int}\left(\frac{N}{s}\right)$ non-overlapping segments, and obtain the local trend for each segment, where:

$$y(k) = \sum_{i=1}^{k}\left[x_i - \frac{1}{N}\sum_{\text{i}=1}^{N} x_i\right];$$

s – the number in each segment; k – 1, 2, ..., N.

Step 2: Construct $F^2(s,\nu)$ and calculate the q^{th} order fluctuation function for the overall segments, as in Equation (1).

The generalized Hurst exponent $H(q)$ is defined by $F_q(s) \sim s^{H(q)}$. The Hurst exponent defines the fractal structure of the time series: by how fast $F_q(s)$ of local fluctuations grows with increasing scale s. When the series is multifractal, a significant dependence of $H(q)$ on q should be observed. If the series is monofractal, $H(q)$ should be equal regardless of different q values.

When the q is equal to 2, the value of $H(2)$ is the classic Hurst exponent (HE). If $HE > 0.5$, it indicates that the trend change is persistent (long-range dependence). This also means that we can make predictions about future prices based on past price information; if it is antipersistent, $HE < 0.5$; and $HE = 0.5$ for the random walk process.

$\Delta H = H(q_{\min}) - H(q_{\max})$ means the multifractal degree of the market. When the value of ΔH is very high, it indicates that the time series will have a big rise and fall, while when the value of ΔH is very small, it shows that the time series has little fluctuation and is relatively stable.

Determining chaos by largest Lyapunov exponent (LLE). Chaos is determined by largest Lyapunov exponent (LLE). The LLE's specific algorithm by Wolf et al. (1985) is as follows:

Step 1: Let $\{x_i : i = 1, 2, \ldots, N\}$ be a time series of length N. By using phase space reconstruction technology, a new sequence of m-dimensional phase space is:

$$X_i = \{x_i, x_{i+\tau}, \ldots, x_{i+(m-1)\tau}\} \tag{2}$$

where: m – the embedding dimension; τ – the delay time.

Step 2: With the initial phase point X_1 as the base point, in the rest of the phase point set $\{X_j\}$, find the nearest neighbor point X_j of X_1 as the endpoint and form the initial vector, denoted as:

$$L(t_0) = \min_j \left\| X_1 - X_j \right\| \tag{3}$$

where t_0 – the initial time.

Step 3: Calculate the linear exponential growth rate of the system:

$$\lambda_1 = \frac{1}{k}\ln\frac{L(t_1)}{L(t_0)} \tag{4}$$

where: λ_1 – linear exponential growth rate of the system; $L(t_1)$ – the distance when $t_1 = t_0 + k$; k – the increment of time; t_1 – time.

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{\nu=1}^{2N_s}\left[F^2(s,\nu)\right]^{\frac{q}{2}}\right\}^{\frac{1}{q}} \tag{1}$$

where:

$$F^2(s,\nu) = \begin{cases} \frac{1}{s}\sum_{i=1}^{s}\left\{y\left[(\nu-1)s+i\right] - \widehat{y_\nu(i)}\right\}^2, \text{ for } \nu = 1, \ldots, N_s \\ \frac{1}{s}\sum_{i=1}^{s}\left\{y\left[N-(\nu-N_s)s+i\right] - \widehat{y_\nu(i)}\right\}^2, \text{ for } \nu = N_s+1, \ldots, 2N_s \end{cases};$$

$\widehat{y_\nu(i)}$ – the n-order fitting polynomial in segment ν; ν – 1, 2, ..., N_s.

Step 4: Continue like this until the end of the time series, and then take the average growth rate of each exponent as the estimate of the *LLE*.

In the regard, *LLE* > 0 represents time series with chaotic dynamics. On the contrary, *LLE* < 0 indicates that time series does not have chaotic dynamics characteristics.

DATA DESCRIPTION AND EMPIRICAL RESULTS

Data. In this paper, we use the CBOT's daily price of soybean futures from January 3, 2000 to December 20, 2019, encompassing 5 025 points of data. The data source is Wind – a commercial database widely used in China (Wind 2020). For convenience, we denote the time sequence for each data set as t and the corresponding price sequence as $p(t)$, where $t = 1, 2, \ldots, 5025$. We divide the whole sample (5 025 data points in total) into two samples, one called training sub-sample data (the first 5 015 data points) and the other called the testing sub-sample data (the last 10 data points) to compare the predicted results.

Figure 1 exhibits the whole soybean futures price time series ranging from January 3, 2000 to December 20, 2019. The x-coordinate represents time and the y-coordinate represents the price of soybean futures, and the unit is cents per bushel. Figure 1 shows two major upward trends: from January 2000 to March 2004, and from February 2005 to February 2008. It also experienced a big bear market: it was in decline from March 2012 until November 2019. At the same time, the price changes from around USD 500 cents per bushel to around USD 1 700 cents per bushel, indicating that the price fluctuates greatly.

The multifractal and chaotic nature of the soybean futures. In the MF-DFA model, in order to avoid overfitting, we choose the fitting order n as 1, q-orders between –5 and 5 and set the scale s as 10 (Lashermes et al. 2004; Ihlen 2012). The generalized Hurst exponent of the soybean futures price is shown in Figure 2. When $q = -5$, $H(q)$ is 0.9, higher than 0.5, and decreases smoothly with a rising q value between –5 and 5. It shows that the value of $H(q)$ is apparently dependent on q values. The decreasing $H(q)$ indicates that the price series of the soybean futures have significant multifractal properties.

At the same time, MF-DFA method was applied to the whole sample and the training sub-sample to obtain Table 1. It can be seen from Table 1 that *HE* values of the two samples are equal to 0.51 and 0.52, respectively [$H(2)$ value], indicating that the time series of soybean futures prices of the two samples have long-range memory. At the same time, as the incidental conclusion of MF-DFA method, ΔH value is equal to 0.85 and 0.86, respectively, indicating that the multifractal degree of the market is very high, which also means that the soybean futures price market will have a big rise and fall.

In order to identify the chaos of the whole sample soybean futures price time series, it is necessary to re-

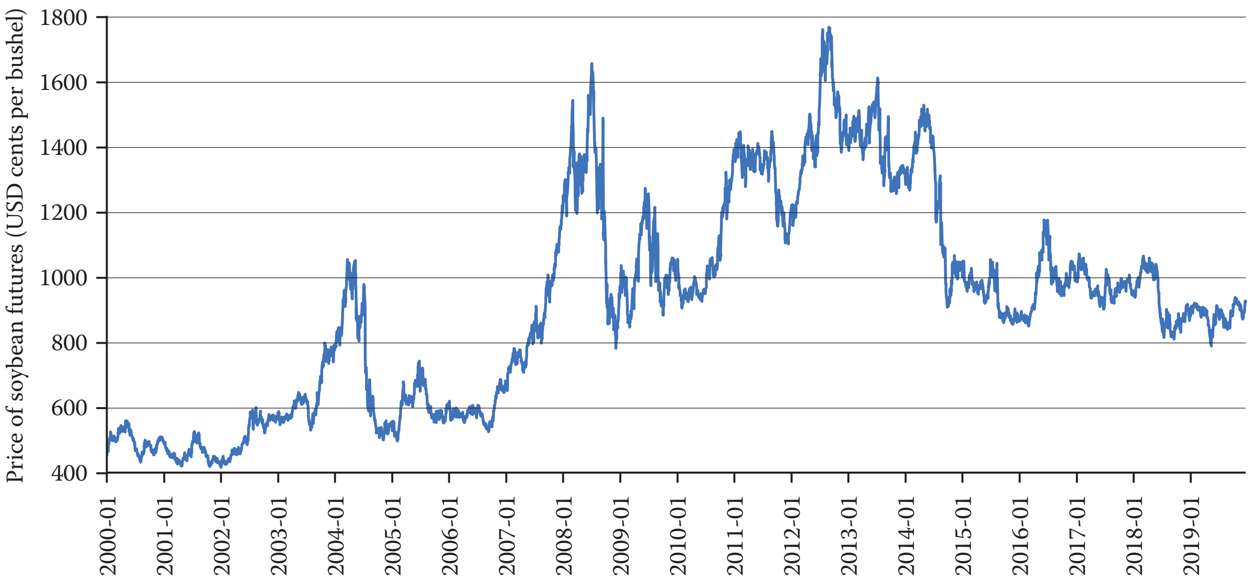

Figure 1. The historical daily price of the whole sample (from January 3, 2000 to December 20, 2019)

Source: Wind (2020)

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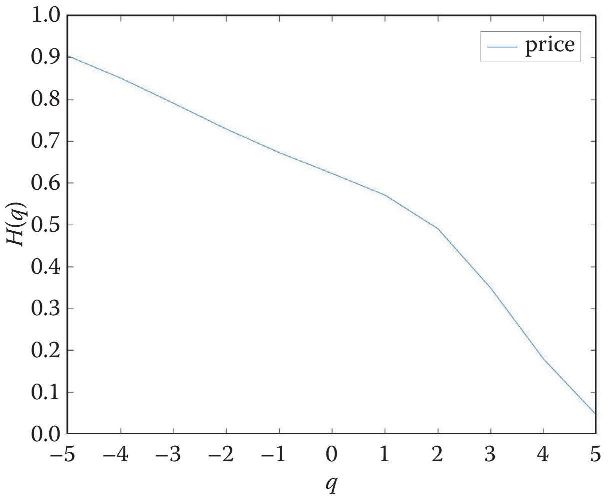

Figure 2. The generalized Hurst exponent of the whole sample

$H(q)$ – the generalized Hurst exponent; q – the order of fluctuation function

Source: Calculations by the authors based on Wind (2020)

Table 1. Generalized Hurst exponent $H(q)$ and their range over $q \in [-5,5]$

Order q	$H(q)$ for the whole sample	$H(q)$ for the training sub-sample
–5	0.90	0.91
–4	0.85	0.82
–3	0.79	0.74
–2	0.72	0.69
–1	0.67	0.67
0	0.62	0.61
1	0.57	0.56
2	0.51	0.52
3	0.34	0.35
4	0.17	0.19
5	0.04	0.05
ΔH	0.85	0.86

$H(q)$ – the generalized Hurst exponent; q – the order of fluctuation function

$\Delta H = H(q_{min}) - H(q_{max})$; the value of $H(2)$ is the classic Hurst exponent (HE)

Source: Calculations by the authors based on Wind (2020)

construct the phase space, which needs to determine two parameters: embedding dimension m and delay time τ. First, we use the mutual information function method (Fraser and Swinney 1986) to get the delay time τ = 3, and use the Gao method (Gao and Zheng 1993) to determine the embedding dimension m = 3. According to Wolf algorithm, largest Lyapunov exponent *LLE* = 0.0378.

Estimates of *LLE* and MF-DFA-based *HE* for soybean futures whole sample and training sub-samples are given in Table 2.

As illustrated in Table 2, the *LLE*s associated with the whole sample and training sub-sample are positive. Therefore, the soybean futures price shows chaotic dynamics in both the whole sample and the training sub-sample, indicating that the characteristics of soybean futures price in different time stages show a seemingly random behavior, but are driven by chaotic behavior. In addition, the estimated value of soybean futures *HE*s greater than 0.5 shows that they have long-range dependence characteristics, suggesting that the price will not follow the random walk, but will show a persistent dynamic. It also shows that soybean futures prices can be predicted based on past historical price.

In general, the results of the study of chaos in the form of intrinsic multifractal characteristic provide strong evidence for the short-term predictability of price dynamics, just as in the case of chaotic systems. In other words, a chaotic neural network nonlinear pattern recognition system can effectively model and predict.

Table 2. Estimated *HE* and *LLE* values

	Whole sample	Training sub-sample
Panel A		
Fitting order n	1	1
Fluctuation function's order q	[–5,5]	[–5,5]
Scale s	10	10
HE	0.51	0.52
Panel B		
Embedding dimension m	3	2
Delay time τ	3	3
LLE	0.0378	0.0382

HE –the Hurst exponent; *LLE* – the largest Lyapunov exponent

The whole sample range from January 3, 2000 to December 20, 2019, including 5 025 points of data; while the training sub-sample is from January 3, 2000 to December 6, 2019, containing 5 015 points of data; due to the small amount of test sample data, there are only 10 points of data, so the *HE* value and *LLE* value of testing sub-sample are not estimated; in order to get the value of *HE*s and *LLE*s, it is necessary to give values or intervals for three parameters (n, q, and s), and the two parameters (m, τ), respectively

Source: Calculations by the authors based on Wind (2020)

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PREDICTION AND COMPARISON

In the simulation experiment, we use training sub-sample data (5 015 points of data in total) for learning, and testing sub-sample data (10 points of data in total) to compare the prediction results. The original testing sub-samples and the predicted samples are $x(n)$ and $x_p(n)$, respectively, and the experiment uses the absolute error (AE) $e(n) = x_p(n) - x(n)$, the mean absolute error (*MAE*) and the percentage error (*Perr*) as the evaluation criteria of the prediction accuracy. The smaller *MAE* and *Perr* values are, the more predictive effect of the model is, where *MAE* and *Perr*, respectively, are defined as:

$$MAE = \frac{1}{N}\sum_{n=1}^{N_P}\left|x(n) - x_p(n)\right|,$$

$$Perr = \sum_{n=1}^{N_P}\left(x(n) - x_p(n)\right)^2 \Big/ \sum_{n=1}^{N_P} x^2(n)$$

where: N_p – the number of predicted samples.

The chaotic neural network (CANN) and artificial neural network (ANN) were used for prediction. The CANN models contain the RBF-CHAOS model and the BP-CHAOS model, while the ANN models contain the RBF model and the BP model. The results are shown in Figure 3. Observed (true) and forecasted values from CANN and ANN are presented. From the left, the top line is the hybrid back propagation neural network and chaos model (BP-CHAOS) prediction data line; the second line is the observed (true) data line; the third line is the the hybrid radial basis function neural network and chaos model (RBF-CHAOS) prediction data line; the fourth line is the back propagation neural network model (BP) prediction data line; the bottom line is the radial basis function neural network model (RBF) prediction data line [for details see the electronic supplementary material (ESM); for ESM see the electronic version].

This shows that all these four models can predict the futures price of soybean, especially the short-term prediction (within 5 days). When the predicted days are longer than 5 days, the error will increase. In particular, The BP-CHAOS model works well in predicting the first five days: compared with the true value, it is consistent in the direction of price change and the value is very close; whilst the RBF-CHAOS model can follow true data on trends.

As shown in Figure 3, for the soybean futures price time series, compared with the ANN topology, the predicted value based on CANN follows the observed value more closely.

Accordingly, the *MAE*s calculated by CANN are no more than 20, while those of ANN are all over 20. Meanwhile, the *Perr*s calculated by CANN do not exceed 0.06%, while those by ANN exceed 0.1% (Table 3). Compared to ANN, *MAE* and *Perr* of CANN are significantly reduced: the *MAE* value is reduced by 11.2% at least, 58% at most, and will reach 60%; the *Perr* value is reduced by 40% to 80%. In terms of specific models, RBF-CHAOS has the highest prediction accuracy

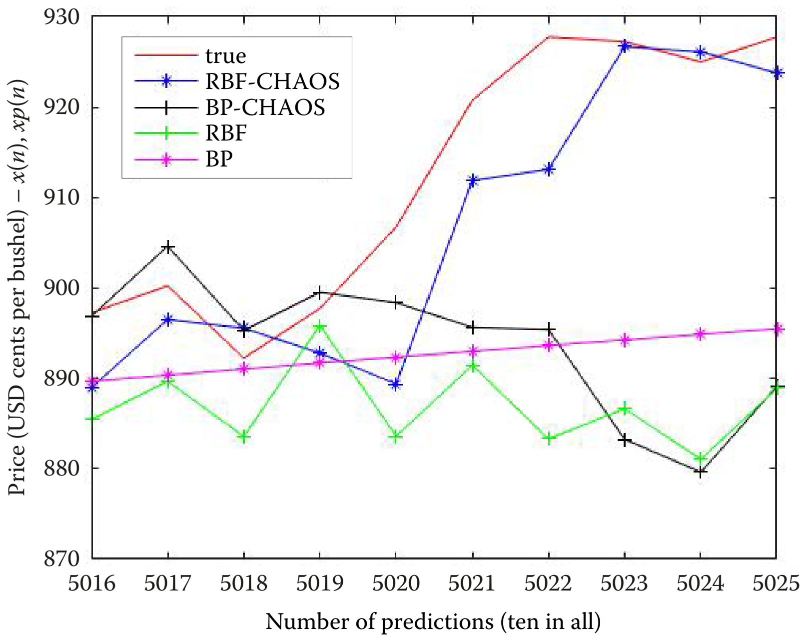

Figure 3. Prediction based on CANN and ANN models

ANN – artificial neural network; BP – back propagation; CANN – chaotic artificial neural network; RBF – radial basis function; $x(n)$ – the original price; $xp(n)$ – the predicted price

"True" stands for real data and, "RBF-CHAOS, BP-CHAOS, RBF and BP" represent the data predicted by the corresponding model; the CANN models contain RBF-CHAOS model and BP-CHAOS model, while the ANN models contain RBF model and BP model [for details on the four models see the electronic supplementary material (ESM); for ESM see the electronic version]

Source: The true data is from the Wind database (Wind 2020), and the predicting data is calculated by the authors based on Wind (2020)

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Table 3. Prediction errors of the CANN and ANN models

	Model	*MAE*		*Perr*	
		USD cents per bushel	Rank	%	Rank
CANN	RBF-CHAOS	10.62	1	0.03	1
	BP-CHAOS	19.34	2	0.06	2
ANN	RBF	25.31	4	0.15	4
	BP	21.78	3	0.10	3

In this paper, CANN contains two models, namely RBF-CHAOS and BP-CHAOS; meanwhile ANN contains RBF and BP; the rule of ranking is: the smaller the *MAE* value and *Perr* value, the higher the corresponding model ordering is
ANN – artificial neural network; BP – back propagation; CANN – chaotic artificial neural network; *MAE* – mean absolute error; *Perr* – percentage error; RBF – radial basis function
Source: Calculations by the authors based on Wind (2020)

for soybean futures. Thus, *MAE* and *Perr* scores confirmed that CANN was superior to ANN in predicting future soybean futures prices. In general, compared with the ANN structure, the CANN system can better learn the chaotic and self-similar patterns of soybean futures, and can better predict its future dynamics. Thus, the effectiveness of CANN in modeling and forecasting chaotic financial data structure in soybean futures market is verified.

CONCLUSION AND ECONOMIC IMPLICATIONS

In this paper, we firstly use MF-DFA and largest Lyapunov exponent to check the multifractal, long-range memory and chaos characteristics of the time series of soybean futures prices from January 3, 2000 to December 20, 2019.

As $H(q)$ value will change with the change of q, we know that this time series has multifractal characteristics, and ΔH is much larger than 0, indicating a high multifractal degree which means that the soybean futures price will fluctuate greatly and it will rise and fall sharply. At the same time, we found that $HE > 0.5$, indicating that this time series has long-range memory. At the same time, the value of $LLE > 0$ indicates that this time series has chaotic characteristics, so it also indicates that the price of soybean futures seems to be random, but the generation mechanism of soybean futures price is in fact deterministic.

The investigation of chaotic and multifractal dynamics in nonlinear systems is of paramount importance in terms of their predictability. An unstable or noisy system (signal) may have limited short-term predictability, whilst multifractal and self similarity can increase the possibility of accurate prediction of future sequences of such signals. By studying the chaotic characteristics of soybean futures, we evaluate its predictability with sufficient historical data, and contribute to the literature of econophysics. We compare the prediction ability of CANN with that of ANN in soybean futures market. Interestingly, the literature on this path that we explored is still very limited. When we apply CANN and ANN to soybean futures, we find that CANN is superior to ANN in term of the mean absolute error (*MAE*) and the percentage error (*Perr*). The reason is that CANN is obviously effective in extracting hidden patterns from potential signals and accurately modeling time series. In addition, because the ANN is based on the Gaussian kernel local approximation of non-stationary signal, the ANN cannot approximate the global model with chaotic characteristics. In general, the CANN model is very effective in predicting soybean futures. At the same time, it can be found that RBF-CHAOS model has the highest prediction accuracy from *MAE* and *Perr*.

Finally, this paper also informs that, from a technical point of view, it is feasible to predict and analyze the fluctuations in the soybean futures market, and this feasibility makes market arbitrage possible. Arbitrage opportunities can attract speculative capital, thereby increasing risks in the soybean futures market. Government departments and investors can use predictive models to design hedging strategies for the soybean futures market and effectively manage risks in the soybean futures market. At the same time, the government departments can formulate corresponding agricultural laws and policies to avoid the risks.

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