Research Article

A Novel Agricultural Commodity Price Forecasting Model Based on Fuzzy Information Granulation and MEA-SVM Model

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The scientific and effective forecasting method is conducive to correctly guide agricultural production, realize the balance of supply and demand of agricultural commodities, increase peasants’ income, and provide decision-making basis for the government to adjust agricultural economic structure and implement targeted macro-control [1–3].

Nowadays, the agricultural price forecasting methods can be divided into two categories: qualitative forecasting methods and quantitative forecasting methods. As a supplement to other agricultural commodity price forecasting methods, qualitative forecasting methods generally do not occupy the mainstream position, with low accuracy and high subjectivity. According to the sequence of occurrence time, the quantitative prediction methods can be divided into econometric method, time series analysis method, and intelligent prediction method. The econometric method finds the supporting economic theory according to the research problem, then puts forward the hypothesis, and establishes the econometric model to verify the hypothesis [4–9]. However, most empirical studies do not prove that the prediction effect of the classic econometric model is better than that of the time series analysis method [10–12]. Therefore, the time series analysis method gradually replaced the econometric method in the 1990s. Due to the complexity and difficulty of price prediction of agricultural commodities, price fluctuations always show the characteristics of repeated ups and downs, instability, benign or vicious circle, etc. The advantages of self-adaptation, self-learning, and self-organization possessed by the intelligent prediction method can well adapt to the characteristics of market price fluctuations of agricultural commodities. Therefore, in recent years, the intelligent prediction method has been increasingly applied to the prediction of agricultural price [13–17]. Intelligent prediction methods usually include artificial neural network, chaos theory, entropy analysis, extreme learning machines, radial basis function, and support vector regression.

The deficiency of the above prediction methods is to use a single model to predict the time series data of agricultural commodities.
commodities. Meanwhile, most forecasting methods provide a point estimation rather than a value range. In the real world, peasants and governments pay more attention to the fluctuation range and trend of agricultural prices. Our study firstly transforms time series data of prices index into fuzzy information granulation particles made up of $Low$, $R$, and $Up$, which represent the trend and magnitude of price movements, then employs a hybrid method that combines the support vector machine (SVM) with mind evolutionary algorithm (MEA) to predict the fuzzy information granulation particles $Low$, $R$, and $Up$, and finally captures the fluctuation range and change trend exhibited in agricultural commodity futures prices, contributing to existing studies and filling the research gap.

Besides, if the SVM model wants to achieve a relatively ideal regression effect, it must set and adjust relevant parameters; the most important parameters are the penalty parameter $c$ and the kernel function parameter $g$. Previous studies applied grid search method (GSM) to seek the optimal parameters $c$ and $g$ of SVM [18–21]. Although GSM can obtain the global optimal solution, that is, the optimal regression accuracy, it is usually conducted within the specified range. Once the search range is expanded, the algorithm training time will be very long [22–24]. To further improve the optimization performance and overcome the deficiencies of traditional algorithms, the Chinese scholar Sun Cheng-Yi et al. raised the mind evolutionary algorithm (MEA) in 1998 [25]. MEA is an evolutionary algorithm simulating the progress of human mind and has the positive and negative feedback mechanism, wherein the positive feedback mechanism improves toward being more beneficial to the population survival to consolidate and develop the evolution achievement. The negative feedback mechanism prevents the algorithm premature to avoid that the algorithm is caught in local optimal solution. The structural parallelism of MEA guarantees the high search efficiency of the algorithm, overcomes the defects of traditional evolutionary algorithms such as time-consuming computation and premature, and also has extreme robustness on interference [26, 27]. Although the MEA has been applied in some technical fields [28–30], there are little credible researches employing MEA to optimize the parameters of the SVM model. This study utilized MEA to optimize the penalty parameter $c$ and the kernel function parameter $g$ of SVM and established the novel MEA-SVM model, which provides a methodological perspective for the agricultural price forecasting, extending the prior researches.

The rest of this article is organized as follows. The fuzzy information granulation theory, SVM model, and MEA are introduced, and the MEA-SVM model is constructed in Section 2. The empirical analysis is given, six agricultural commodity price indexes are predicted, and the performance of MEA-SVM model and GSM-SVM model is compared in Section 3. At last, conclusions are summarized and future research is suggested in Section 4.

2. Model Construction

2.1. Fuzzy Information Granulation Theory. The concept of information granulation was first proposed by American scholar Zadeh [31]. Information granules are collections of objects, which are combined together due to functional similarity, proximity, indivisibility, and functionality. Granulation calculation is a new computing paradigm covering gruanelation theory, technology, method, and tools. It integrates computing theory, entropy space theory, rough set theory, and interval calculation and is one of the hot spots in the field of artificial intelligence and soft computing science.

Information granulation methods mainly include rough set information granulation theory, fuzzy set information granulation theory, and entropy space information granulation theory. Wherein, the information grains represented by fuzzy sets are called fuzzy information grains. When the fuzzy set method granulates the time series data, it mainly includes two steps: window division and fuzzy processing. The original time sequence is divided into several subsequences, which is called window division; the divided subwindows are fuzzified to generate fuzzy sets, which is called fuzzification. The combination of the two treatments is fuzzy information granulation, also known as $f$ granulation. Assuming that the time series data $X$ is regarded as one window, the task of fuzzy processing is to establish a fuzzy information particle $P$, which can replace the original window data. In other words, the fuzzy concept $G$ (fuzzy set with $X$ as the theoretical domain) is determined reasonably so as to describe $X$ [32, 33].

Therefore, the essence of fuzzy process is the process of determining the membership function $A$ of the fuzzy concept $G$. The general membership functions of fuzzy particles include triangle, parabola, Gaussian, and trapezoid. In this study, triangular fuzzy particles are adopted and their membership functions are shown as follows.

$$A(x,a,m,b) = \begin{cases} 0, & x < a; \\ \frac{x-a}{m-a}, & a \leq x \leq m; \\ \frac{b-x}{b-m}, & m \leq x \leq b; \\ 0, & x > b \end{cases}$$

(1)

In the formula, the original time series data is represented by $x$, and the minimum, average, and maximum values of the original data are, respectively, described by fuzzy particle parameters $a$, $b$, and $m$.

2.2. Support Vector Machine. The support vector machine (SVM) model was first proposed by Vapnik in 1995 [34].
It can be used for both pattern classification and nonlinear regression analysis. SVM model is a supervised learning algorithm based on the structure risk minimum principle and statistical Vapnik-Chervonenkis dimension theory. The main idea of SVM model is to transform the nonlinear classification problem into a multidimensional linear convex quadratic programming problem through kernel function mapping and establishment of classification higher-dimensional decision surface. The complexity of SVM algorithm is independent from the sample dimension. It has the advantages of universality, robustness, validity, simple calculation, perfect theory, etc. The obtained solution is unique and globally optimal, which avoids the problem that the neural network method falls into local extreme value [35–37].

In the case of linear separability, the core of SVM algorithm is to find the optimal classification decision plane. It is assumed that the sample data set of linear separable training is $T$.

$$T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l)\} \in (x \times y)^l$$  \hspace{1cm} (2)

In the formula, $x_i \in R^n$, $y_i \in \{-1, 1\}, i = 1, \ldots, l$.

The construction of the secondary planning problem is expressed as follows.

$$\min_{\omega, b} \frac{1}{2} \|\omega\|^2,$$

$$\text{s.t. } y_i ((\omega \cdot x_i) + b) \geq 1, \quad i = 1, \ldots, l$$  \hspace{1cm} (3)

The classification surface determined by the optimal solution is expressed as follows.

$$(\omega^* \cdot x) + b^* = 0$$  \hspace{1cm} (4)

The decision function is constructed as follows.

$$f(x) = \text{sgn} ((\omega^* \cdot x) + b^*)$$  \hspace{1cm} (5)

SVM model is characterized by sparsity and uses a few support vectors to represent decision functions. In order to guarantee this important characteristic, when SVM algorithm is applied to solve nonlinear regression problems, the loss function needs to be introduced. Taking the standard insensitive loss function $\varepsilon$ as an example, the form of the $\varepsilon$-SVM model is as follows.

$$\min_{\omega} \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{m} (\xi_i + \xi_i^*)$$

$$\begin{align*}
& y_i - \omega \cdot x_i - b \leq \varepsilon + \xi_i \\
& \omega \cdot x_i + b - y_i \leq \varepsilon + \xi_i^* \\
& \xi_i, \xi_i^* \geq 0
\end{align*}$$  \hspace{1cm} (6)

In the formula, $\xi_i$ and $\xi_i^*$ are relaxation variables and represent the model error requirements; $C$ is the penalty parameter, which is used to measure the degree of matching between empirical risk and confidence range.
and populations only if the scores of every individual and subpopulation are recorded all the time. The individuals in the subpopulation post up their own information on the local billboard, and the information of each subpopulation is posted up on the global billboard.

2.3.5. MEA-SVM Model. In this study, the prediction accuracy of training set was taken as the fitness function, and MEA was applied to seek the best penalty parameter \( c \) and kernel function parameter \( g \) of SVM model. The overall process of the algorithm is shown in Figure 1.

The main forecasting process of agricultural commodity price based on fuzzy information granulation and MEA-SVM model is described below.

Step 1. Extract time series data of agricultural commodity price index.

Step 2. The triangular fuzzy information granulation theory is applied to process the time series data of the original agricultural commodity price index, and three fuzzy information particles representing the lowest, average, and highest prices of the original agricultural commodity price are obtained.

Step 3. MEA was adopted to search for the optimal parameters \( c \) and \( g \) of SVM model.

Step 4. The hybrid MEA-SVM model is applied to predict the agricultural commodity price index for 1-6 and 7-12 months in the future.

Step 5. Verify and evaluate the predicted results.

2.4. Model Assessment Criteria. In this study, mean squared error (MSE), squared correlation coefficient \( (R^2) \), and computation time (second) are employed to measure the prediction accuracy and computation speed of MEA-SVM model. The calculation formulas of MSE and \( R^2 \) are as follows:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (f(x_i) - y_i)^2
\]

\[
R^2 = \frac{n \Sigma_{i=1}^{n} f(x_i)y_i - (n \Sigma_{i=1}^{n} f(x_i) \Sigma_{i=1}^{n} y_i)^2}{(n \Sigma_{i=1}^{n} f(x_i)^2 - (\Sigma_{i=1}^{n} f(x_i))^2)(n \Sigma_{i=1}^{n} y_i^2 - (\Sigma_{i=1}^{n} y_i)^2)}
\]

3. Empirical Analysis

3.1. Data Sources. This study selected the time series data of FAO price index (http://www.fao.org/home/en/) as the empirical research object. The FAO food price index is a measure of the monthly change in international prices of a basket of food commodities. It consists of the average of six commodity group price indexes (Food Price Index, Cereal Price Index, Vegetable Oil Price Index, Meat Price Index, Dairy Price Index, and Sugar Price Index). The MEA-SVM model takes the time series data of price index of six commodities from January 1990 to June 2017 as training data and the time series data from July 2017 to June 2018 as testing data. As an example, the FAO food price index from January 1990 to June 2017 is shown in Figure 2. Based on this, the highest price, lowest price, average price, and the variation trend of the FAO food price index from July 2017 to June 2018 will be predicted.

3.2. Fuzzy Information Granulation. The time series data of 330 months from January 1990 to July 2017 were regarded as the training set and every 6 months was treated as one information granulation window. Finally, the FAO food price index is transformed into 55 fuzzy information particles, each containing 3 parameters of Low, \( R \), and Up, as shown in Figure 3. For one single fuzzy information particle, parameters Low, \( R \), and Up describe the minimum, mean, and maximum values of original data changes, respectively.

3.3. Regression Prediction of Granulation Data. The hybrid MEA-SVM model was employed to predict the Low, \( R \), and Up. Firstly, the granulation data was preprocessed, then MEA was applied to search the best penalty parameter \( c \) and kernel function parameter \( g \) for establishing the MEA-SVM model. Finally, the MEA-SVM model was used for training and prediction. For example, the prediction process of parameter Low is as follows.

3.3.1. Data Preprocessing. In this study, the granulation data of Low was normalized and data normalization range was \([100, 500]\), as shown in Figure 4.

3.3.2. Searching for the Optimal Parameters \( c \) and \( g \). In this study, MEA was adopted to search for the best parameters \( c \)
Mathematical Problems in Engineering

Support Vector Machine (SVM)

Determine network topology

SVM parameters \( c \) and \( g \)

Obtaining the optimum SVM parameters

Establishing PSO-SVM model

Testing model accuracy

Meeting termination conditions?

Meeting termination conditions?

Yes

Yes

No

No

Forecasting agricultural price

Figure 1: The process of SVM parameters optimized by MEA.

Figure 2: The FAO food price index (1990.01~2017.06).

Figure 3: Visualization diagram of fuzzy information granulation.

The optimal parameter search processes of MEA for granulated data Low were shown in Figures 5 and 6.

In order to verify the superiority of MEA, GSM was also employed to search the optimal parameters \( c \) and \( g \) of SVM model. The population size was set to 200, the numbers of superior population and temporary population size were set to 5, subpopulation size was set to 20, and evolution generations are set to 200. The minimum-value and maximum-value of \( c \) were 500 and 10. The minimum-value and maximum-value of \( g \) were 0.01 and 1. The minimum-value and maximum-value of \( p \) were 0.01 and 100.

and \( g \) of SVM model. The population size was set to 200, the numbers of superior population and temporary population size were set to 5, subpopulation size was set to 20, and evolution generations are set to 200. The minimum-value and maximum-value of \( c \) were 500 and 10. The minimum-value and maximum-value of \( g \) were 0.01 and 1. The minimum-value and maximum-value of \( p \) were 0.01 and 100.
model on the basis of the same parameter settings. The GSM first looks for the optimal parameters roughly (Figure 7) and then delicately seeks for the optimal parameter after observing the cursory search results (Figure 8).

In Figures 7 and 8, the X-axis represents the log base 2 of \( c \), the Y-axis represents the log base 2 of \( g \), the contour line represents the MSE corresponding to \( c \) and \( g \).

Finally, the optimal parameters obtained by the MEA and GSM for granulation data \( \text{Low} \) are shown in Table 1.

3.3.3. Model Training. The optimal parameters \( c \) and \( g \) were obtained and then substituted into the SVM model to establish the MEA-SVM model. The lowest, average, and highest prices of FAO food price index from January 1990 to June 2017 were predicted by using the MEA-SVM model.

The predicted values, actual values, and relative errors obtained by MEA-SVM for granulation data \( \text{Low} \) of FAO food price index were shown in Figures 9 and 10. Meanwhile, the performance of MEA-SVM in predicting granulation data \( \text{Low} \) is compared with GSM-SVM, as shown in Table 2.

In Table 2, the lower the MSE and the higher the \( R^2 \), the more accurate the model’s prediction. Excluding oils price index, the comparison results of the other five agricultural commodity price indexes show that the prediction accuracy of the MEA is superior to the GSM. At the same time, the calculation speed is improved.

3.3.4. Model Prediction. The 6-month FAO price index of granulation data \( \text{Low} \) is regarded as one period, and the fluctuation range and change trend of the 12-month FAO food price index in the next two periods are predicted.

Table 1: The optimal parameters obtained by the MEA and GSM.

<table>
<thead>
<tr>
<th>Price Index</th>
<th>MEA</th>
<th>GSM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Price Index</td>
<td>c=291.8520 0.0692</td>
<td>c=256.0000 0.0313</td>
</tr>
<tr>
<td>Meat Price Index</td>
<td>c=155.9980 0.0292</td>
<td>c=64.0000 0.0313</td>
</tr>
<tr>
<td>Dairy Price Index</td>
<td>c=306.3320 0.2151</td>
<td>c=256.0000 0.1768</td>
</tr>
<tr>
<td>Cereals Price Index</td>
<td>c=287.6840 0.0634</td>
<td>c=256.0000 0.0625</td>
</tr>
<tr>
<td>Oils Price Index</td>
<td>c=115.0080 0.1410</td>
<td>c=181.0190 0.2500</td>
</tr>
<tr>
<td>Sugar Price Index</td>
<td>c=159.9830 0.4890</td>
<td>c=181.0190 0.2500</td>
</tr>
</tbody>
</table>

Table 2: The prediction of food price index for granulation data Low.

<table>
<thead>
<tr>
<th>Price Index</th>
<th>MSE</th>
<th>MEA</th>
<th>Time(s)</th>
<th>MSE</th>
<th>GSM</th>
<th>Time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Price Index</td>
<td>1199.1000</td>
<td>0.8970</td>
<td>14.7905</td>
<td>1523.8400</td>
<td>0.8687</td>
<td>17.2127</td>
</tr>
<tr>
<td>Meat Price Index</td>
<td>1235.8600</td>
<td>0.8500</td>
<td>7.2805</td>
<td>1309.0300</td>
<td>0.8417</td>
<td>10.1516</td>
</tr>
<tr>
<td>Dairy Price Index</td>
<td>471.6220</td>
<td>0.9436</td>
<td>10.0107</td>
<td>680.0180</td>
<td>0.9238</td>
<td>10.4906</td>
</tr>
<tr>
<td>Cereals Price Index</td>
<td>1465.9800</td>
<td>0.8697</td>
<td>9.0348</td>
<td>1473.0900</td>
<td>0.8765</td>
<td>11.1705</td>
</tr>
<tr>
<td>Oils Price Index</td>
<td>1611.9100</td>
<td>0.8012</td>
<td>10.5295</td>
<td>1229.6400</td>
<td>0.8993</td>
<td>10.9678</td>
</tr>
<tr>
<td>Sugar Price Index</td>
<td>656.3550</td>
<td>0.9452</td>
<td>10.5295</td>
<td>1229.6400</td>
<td>0.8993</td>
<td>10.9678</td>
</tr>
</tbody>
</table>

Figure 8: The delicate parameter searching results of GSM for granulated data Low.

By repeating the above data preprocessing, searching for the optimal parameters c and g, model training and model prediction for the granulation data of R and Up, the predicted values of 3 fuzzy particles Low, R, and Up in the next two periods were finally obtained (Table 3).

3.4. Predictive Performance Evaluation. The actual price indexes of six commodities from July 2017 to June 2018 were compared with the predicted price indexes to test the prediction effect of fuzzy information granulation and MEA-SVM model (Tables 4 and 5). For instance, from July 2017 to December 2017, the highest price, average price, and lowest price of FAO food price index are 144.4461, 150.3121, and 152.9865, respectively, and the corresponding predicted values are 147.3770, 145.7625, and 143.4025, with the relative prediction errors of 2.03%, -3.03%, and -6.26%.

In terms of mean value R of the price index, the predictions of cereals price index and meat price index are the most accurate; the dairy price index has the biggest forecasting error. For many FOA price indexes, the predicted values of granulation data Low, R, or Up are lower than the actual observed values, and there are risks of price underestimation. Overall, the prediction error of the second period is higher than that of the first period, so the further the prediction period is, the larger the prediction error is. The minimum and maximum values of the mean prediction relative errors are -10.05% and 10.05%, respectively.
Table 3: The prediction of FAO price indexes fluctuation range and change.

<table>
<thead>
<tr>
<th>Price Index</th>
<th>2017.07-2017.12</th>
<th>2018.01-2018.06</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>R</td>
<td>Low</td>
</tr>
<tr>
<td>Food Price Index</td>
<td>147.3770</td>
<td>145.7625</td>
</tr>
<tr>
<td>Meat Price Index</td>
<td>152.0103</td>
<td>145.1837</td>
</tr>
<tr>
<td>Dairy Price Index</td>
<td>160.0152</td>
<td>142.1009</td>
</tr>
<tr>
<td>Cereals Price Index</td>
<td>124.0533</td>
<td>129.9318</td>
</tr>
<tr>
<td>Oils Price Index</td>
<td>129.8639</td>
<td>134.1359</td>
</tr>
<tr>
<td>Sugar Price Index</td>
<td>139.3746</td>
<td>187.3576</td>
</tr>
</tbody>
</table>

Table 4: Predictive performance evaluation for FAO price indexes from July 2017 to December 2017.

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Food Price Index</td>
<td>[144.4461, 150.3121, 152.9865]</td>
<td>[147.3770, 145.7625, 143.4025]</td>
<td>[2.03%, −3.03%, −6.26%]</td>
</tr>
<tr>
<td>Meat Price Index</td>
<td>[144.9577, 148.2275, 150.0517]</td>
<td>[132.0103, 145.1837, 149.2589]</td>
<td>[−8.93%, −2.05%, −0.53%]</td>
</tr>
<tr>
<td>Dairy Price Index</td>
<td>[157.5603, 179.7687, 191.5383]</td>
<td>[160.0152, 142.0818, 174.9399]</td>
<td>[1.56%, −20.95%, −8.67%]</td>
</tr>
<tr>
<td>Cereals Price Index</td>
<td>[129.7582, 131.7769, 138.5574]</td>
<td>[124.0533, 129.9318, 136.9791]</td>
<td>[−4.40%, −1.40%, −1.14%]</td>
</tr>
<tr>
<td>Oils Price Index</td>
<td>[137.0251, 142.0297, 147.0943]</td>
<td>[129.8639, 134.1359, 149.2905]</td>
<td>[−5.23%, −5.56%, 1.49%]</td>
</tr>
<tr>
<td>Sugar Price Index</td>
<td>[168.5479, 174.9175, 181.7145]</td>
<td>[139.3746, 187.3576, 200.8544]</td>
<td>[−17.31%, 7.11%, 10.53%]</td>
</tr>
</tbody>
</table>

Table 5: Predictive performance evaluation for FAO price indexes from January 2018 to June 2018.

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>Food Price Index</td>
<td>[143.9263, 147.6488, 150.4290]</td>
<td>[144.6949, 136.3491, 134.4704]</td>
<td>[0.53%, −7.65%, −10.61%]</td>
</tr>
<tr>
<td>Meat Price Index</td>
<td>[143.1188, 145.0220, 146.0823]</td>
<td>[130.0265, 142.0818, 141.1972]</td>
<td>[−9.15%, −2.03%, −3.34%]</td>
</tr>
<tr>
<td>Dairy Price Index</td>
<td>[153.7400, 171.0197, 183.8850]</td>
<td>[142.9604, 124.0123, 163.0491]</td>
<td>[−7.01%, −27.49%, −11.33%]</td>
</tr>
<tr>
<td>Cereals Price Index</td>
<td>[133.8120, 141.0704, 147.4464]</td>
<td>[122.4561, 123.7291, 133.262]</td>
<td>[−8.49%, −12.25%, −10.30%]</td>
</tr>
<tr>
<td>Oils Price Index</td>
<td>[124.8099, 132.3246, 139.3903]</td>
<td>[119.2376, 124.1266, 138.5303]</td>
<td>[−4.46%, −6.20%, −0.62%]</td>
</tr>
<tr>
<td>Sugar Price Index</td>
<td>[149.7763, 157.6108, 170.8406]</td>
<td>[135.7445, 166.7963, 176.4463]</td>
<td>[−9.37%, 5.83%, 3.28%]</td>
</tr>
</tbody>
</table>

Figure 10: The prediction error of granulation data Low.

In the first period, the prediction error was -1.40% and -20.95% for the first period, and -2.03% and -27.49% for the second period. The prediction of the future fluctuation range of FAO price index time series data by fuzzy information granulation and MEA-SVM model is generally accurate.

As for the forecast of price indexes change trend, the price of the second period is lower than that of the first period, which is consistent with the observation of FAO price indexes. The prediction of future change trend of FAO price index time series data by fuzzy information granulation and MEA-SVM model is correct.

4. Conclusion and Discussion

Many uncertainties and random factors exist in agricultural commodity market. Therefore, it is difficult to forecast the agricultural commodity price. In this study, the time series data of agricultural commodity price indexes were granulated by triangular fuzzy information granulation theory. Then the MEA was applied to seek the optimal parameters $c$ and $g$ to establish the hybrid MEA-SVM model. Finally, the trained MEA-SVM model was used to predict the fluctuation range and change trend of agricultural commodity price index in the future. The empirical results are as follows.

The fuzzy information granulation method can granulate the time series data of the original agricultural commodity
price index and use the fuzzy information particles Low, R, and Up to represent the lowest, average, and highest values of agricultural commodity price fluctuation.

The MEA can seek the global optimal parameters of SVM model in a wider range without having to traverse all the parameter points, which improves the calculation speed and prediction accuracy.

The MEA-SVM regression model based on fuzzy information granulation is more accurate and effective in predicting the fluctuation range and variation trend of agricultural commodity price index, which indicates that the model has certain advantages in nonlinear simulation, adaptive learning, and processing of incomplete complex information.

The MEA-SVM model can be generalized to predict the price fluctuations of other commodity and help to provide some reference for the time series data prediction in other fields. Nonetheless, the MEA-SVM model based on fuzzy information granulation still has some deficiencies, such as underestimation and the long-term prediction error being larger. In future studies, the penalty parameter $c$ and kernel parameter $g$ of SVM model can be further optimized through other intelligence algorithms to improve the prediction accuracy and stability.

Data Availability

Our research data comes from the Food and Agriculture Organization of the United Nations (FAO). The research data is authoritative and reliable. The FAO food price index is a measure of the monthly change in international prices of a basket of food commodities. It consists of the average of six commodity group price indexes (Food Price Index, Cereal Price Index, Vegetable Oil Price Index, Meat Price Index, Dairy Price Index, and Sugar Price Index). At the same time, the research data is public and can be accessed and obtained through the url http://www.fao.org/home/en/. Research data can be accessed and downloaded by anyone at any time.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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