улучшить метод опорных векторов (SVM), основанный на эффекте прогнозирования модели раннего предупреждения финансового кризиса.

**Методика.** С учетом усовершенствованного способа функции ядра, экспортируемой римановой геометрической структурой, построена система раннего предупреждения финансового кризиса на основе алгоритма SVM.

**Результаты.** Улучшенная модель SVM позволяет эффективно уменьшать число опорных векторов так, чтобы модель имела лучшую способность к обобщению, обеспечивала более точную классификацию для неизвестных образцов. Улучшенная модель SVM повысила точность классификации для первоначального обучения и тестирования выборки.

**Научная новизна.** Проведен конкретный анализ усовершенствованного алгоритма для функции ядра на основе информационных данных, в соответствии с уровнем масштабирования информационных данных с возможностью регулировки отображения. Получено выражение алгоритма мер Римана на функцию полиномиального ядра. На данный момент не существует другой литературы с описанием подобных исследований.

**Практическая значимость.** Для вопроса раннего предупреждения финансового кризиса, если его масштаб не велик, а также с учетом реальных интересов предприятия, часто бывает целесообразно добиваться лучшего прогнозирующего эффекта. В этом случае применение модели SVM с улучшенной функцией ядра является хорошим решением.

**Ключевые слова:** *метод опорных векторов (SVM), функция ядра, раннее предупреждение банкротства предприятия*

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# SELF-ADAPTIVE OPTIMIZED MARKET PREDICTION MODEL BASED ON GREY MODEL

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# САМОАДАПТИВНА ОПТИМІЗОВАНА МОДЕЛЬ ПРОГНОЗУВАННЯ РИНКУ НА ОСНОВІ СІРОЇ МОДЕЛІ

**Purpose.** Market prediction refers to prediction of internal rules and future development trends of various market indexes and factors based on exploration and in-depth research of various factors influencing market demand and supply changes through scientific theories and systematic model algorithms. This paper analyses optimization results of the traditional prediction algorithms and the intelligent prediction algorithms.

**Methodology.** In order to analyse differences between the results obtained by prediction algorithms and practical situations, it is necessary to unify the model analysis parameters. The model predicting the grey system is applicable to predicting situations with an index variation trend. The time sequence model is suitable to data with certain trend and periodical changes.

**Findings.** It has been found that the neural network and model and the support vector model have no requirements of data, so they are suitable to any situations. And when the market demand changes show index changes, the dynamic pricing and inventory control optimization model based on the grey prediction model is of vital guiding significance towards planning of commodity sales.

**Originality.** Through simulation, the predicted value of models is close to the final optimization target earnings.

**Practical value.** The following fact has been also considered: when market demand changes tend to show index changes, the dynamic pricing and inventory control optimization model based on the grey prediction model can guide the planning of commodity sales.

**Keywords:** *grey model, self-adaptive optimization, model prediction, specific power function*

**Introduction.** Market prediction refers to prediction of internal rules and future development trends of various market indexes and factors based on exploration and in-depth research of various factors influencing market demand and supply changes through scientific theories and systematic model algorithms [1]. Based on the rules of market supply and demand changes, it provides reliable guidance and bases for operation decision-making of enterprises. Prediction can help improve the scientific level of management and reduce the blindness of decision-making. Therefore, the purpose of market prediction is actually to reduce future uncertainties and potential risks, and facilitate realization of decision-making goals based on prediction of economic development or relevant trend of future market changes. Below is the classification of market prediction and prediction content.

The paper focuses on analysing optimization results of the traditional prediction algorithm and the intelligent prediction algorithm. In order to analyse differences between the results obtained by prediction algorithms and practical situations, model analysis parameters should be unified. As to the prediction of the grey system, the prediction model is applicable to predicting data showing trend of index changes; while the time sequence model is suitable to predicting data with certain trend and periodical changes. To the neural network model and the support vector model, there are no requirements of data. In other words, the neural network model and the support vector model are applicable to any situation.

**Design of model analysis methods.** Model analysis steps designed in this paper are as follows:

*Step 1:* to unify relevant parameters for the model simulation according to characteristics of various models. Refer to Table 1 below for practical data analysed by the grey prediction model. We use data in Table 2 for simulation analysis of the time sequence model, the neural network model and the support vector model. The model adopts the specific power demand function.

*Step 2:* to adopt the data in the previous eight periods as the input value of various prediction models for training and to adopt the data of the remaining four periods as the predicted value.

*Step 3:* to adopt the practical value of 12 periods as the input data of the dynamic pricing and inventory joint model, and to obtain optimization results of actual data in every period.

*Step 4:* to combine various market index data in the remaining four periods obtained by each prediction model and the actual value of previous eight periods as the input data of the dynamic pricing and inventory joint model to obtain optimization results of the prediction data in every period.

*Step 5:* to analyse and compare optimization results of various prediction models and actual data, and assess advantages and disadvantages of each prediction system.

*Table 1*

Simulation analysis of practical data based on the grey model

| Period ($t$) | Consumer income ($m$) | Interest rate ($r$) | Commodity order price ($p_{0t}$) | Inventory unit cost ($C$) |
|---|---|---|---|---|
| 1 | 9700 | 3.1 | 10.7 | 0.83 |
| 2 | 9900 | 3 | 10.8 | 0.84 |
| 3 | 10100 | 3 | 11 | 0.85 |
| 4 | 10150 | 2.95 | 11.2 | 0.86 |
| 5 | 10200 | 2.9 | 11.3 | 0.87 |
| 6 | 10250 | 2.83 | 11.28 | 0.91 |
| 7 | 10300 | 2.8 | 11.4 | 0.92 |
| 8 | 10350 | 2.78 | 11.43 | 0.91 |
| 9 | 10380 | 2.73 | 11.47 | 0.93 |
| 10 | 10430 | 2.71 | 11.5 | 0.91 |
| 11 | 10500 | 2.65 | 11.6 | 0.93 |
| 12 | 10600 | 2.55 | 11.76 | 0.95 |

*Table 2*

Simulation analysis of practical data based on the time sequence model, the neural network model and the support vector model

| Period ($t$) | Consumer income ($m$) | Interest rate (r) | Commodity order price ($p_{0t}$) | Period (t) |
|---|---|---|---|---|
| 1 | 9700 | 3.1 | 10.7 | 0.83 |
| 2 | 9900 | 3.08 | 10.8 | 0.84 |
| 3 | 9800 | 3.05 | 10.9 | 0.85 |
| 4 | 9450 | 2.95 | 10.5 | 0.84 |
| 5 | 9600 | 2.9 | 10.3 | 0.82 |
| 6 | 9850 | 2.93 | 10.38 | 0.85 |
| 7 | 9630 | 3.04 | 10.4 | 0.86 |
| 8 | 9550 | 3.08 | 10.53 | 0.82 |
| 9 | 9480 | 3.13 | 10.6 | 0.81 |
| 10 | 9630 | 3.02 | 10.5 | 0.82 |
| 11 | 9600 | 3.05 | 10.6 | 0.81 |
| 12 | 9500 | 3.05 | 10.62 | 0.82 |

**Self-adaptive optimized market modelling and prediction based on grey model.** Since historical data are hard to collect, modelling based on a small number of data can reflect the role of recent data better [2–3]. Besides, impacted by various unpredictable factors, market indexes show huge fluctuations. It is hard to build a model based on the original data. The modelling based on the grey system does not rely on the original data but on the grey modules generated after accumulation. This can greatly weaken the randomness of data and enhance regularity. Moreover, the grey system theory combines qualitative analysis and quantitative analysis. In other words, during the modelling process, a whitening processing is conducted to confirm the system scope, the system elements and behaviours and relationship. In this way, the target system turns from a grey one to a white one. During the process, not only the mathematical model of modern control theories, but also experiential judgement, qualitative and quantitative analysis are combined to explore different relationships among various system factors. In this way, a modelling process from qualitative orientation towards quantitative orientation, from being rough to being refined and from being grey to being white comes into being. In other words, based on the "generated column" obtained through accumulation of a group of time sequence information, the author conducts differential fitting and modelling of "generated columns" with weakened randomness and strengthened regularity obtained through accumulation.

This paper adopts the grey prediction model to study the changing trend of market demand indexes based on the following hypotheses: 1) the grey prediction model calls for a small number of data; 2) various index data of the future market mostly show progressive changes; 3) the grey prediction model has an edge in terms of predicting short-term land demands.

The model, GM (1, 1), for grey prediction is based on the random original time sequence. The rules of the new time sequence formed after accumulation can use the linear first-order differential equation to get the closest simulation. The approximate curve can be adopted as the model [4–5]. At last, the predicted value of the model undergoes one inverse accumulated generating operation so as to predict the system. Below are steps to build the model, GM (1, 1):

**1.** ***Data pre-treatment.***

Let us assume the original data column as

$$x^{(1)}(i)=\left\{\sum_{j=1}^{i}x^{(0)}(j)\middle|i=1,2,\ldots,n\right\}.$$

The column generated through accumulation

$$x^{(1)}(i)=\left\{\sum_{j=1}^{i}x^{(0)}(j)\middle|i=1,2,\ldots,n\right\}.$$

In order to revert the accumulated data column into the original one, it is necessary to conduct subtraction-based generation, which refers to subtraction results between the former column and the latter column. (See Eq. 1 below)

$$\Delta x^{(1)}(i)=x^{(1)}(i)-x^{(1)}(i-1)=x^{(0)}(i). \tag{1}$$

Where, $i = 1, 2, \ldots, \mathrm{I}$, $x^{(0)}(0) = 0$. The column generated weakens the randomness and instability of the original data column and increases its regularity. We conduct the index rule test and the smoothness test of $x^{(0)}$ and $x^{(1)}$, respectively:

class-compare

$$\sigma(i)=\frac{x^{(1)}(i)}{x^{(1)}(i-1)};$$

smooth ratio

$$\rho(i)=\frac{x^{(0)}(i)}{x^{(1)}(i-1)}. \tag{2}$$

When $i > 3$, if $\rho(i) < 0.5$ and $\sigma(i) < 2$, the data meets the smoothness conditions and the index rules. After that, $GM(1, 1)$ of $x^{(1)}$ can be built.

**2.** ***Modelling principle.***

Provide the observation data column

$$x^{(0)}=\{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}. \tag{3}$$

After one accumulation,

$$x^{(1)}=\{x^{(1)}(1), x^{(1)}(2), \ldots, x(1)(n)\}. \tag{4}$$

We assume that $x^{(1)}$ meets the first-order differential equation

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=u. \tag{5}$$

Where $a$ stands for the constant coefficient which is called the development grey number; $u$ stands for the internal control grey number, which is a common fixed input of the system; the first "1" stands for the number of order and the second "1" stands for the number of variables. The equation meets the following initial condition:

when $t = t_0$, the solution of $x^{(1)}(t) = x^{(1)}(t_0)$ is

$$x^{(1)}(t)=\left[x^{(1)}(t_0)-\frac{u}{a}\right]e^{-a(t-t_0)}+\frac{u}{a}.$$

The discrete value ($t_0 = 1$) based on the equal interval sampling is

$$x^{(1)}(k+1)=\left[x^{(1)}(1)-\frac{u}{a}\right]e^{-ak}+\frac{u}{a}.$$

The grey modelling method is to obtain an accumulation column through one accumulation. The least square method is used to calculate constants, $a$ and $u$, in Eq. (5).

Let us adopt $x^{(1)}(1)$ as the initial value, and put $x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)$ into Eq. (5), respectively. Replace the difference with the differential. Through the equal interval sampling, $\Delta(t) = (t + 1) - t = 1$, and

$$\frac{\Delta x^{(1)}(2)}{\Delta t}=\Delta x^{(1)}(2)=x^{(1)}(2)-x^{(1)}(1)=x^{(0)}(2).$$

Similarly

$$\frac{\Delta x^{(1)}(2)}{\Delta t}=x^{(0)}(2),\ldots,\frac{\Delta x^{(1)}(n)}{\Delta t}=x^{(0)}(n).$$

Therefore, according to Eq. (2–5), there is

$$\begin{cases} x^{(0)}(2)+ax^{(1)}(2)=u \\ x^{(0)}(3)+ax^{(1)}(3)=u \\ \quad\ldots \\ x^{(0)}(n)+ax^{(1)}(n)=u \end{cases}.$$

Let us put $ax^{(1)}(i)$ to the right and write it in the dot product form of the vector

$$\begin{cases} x^{(0)}(2)=[-x^{(1)}(2),1]\begin{bmatrix}a\\u\end{bmatrix} \\ x^{(0)}(3)=[-x^{(1)}(3),1]\begin{bmatrix}a\\u\end{bmatrix} \\ \quad\ldots \\ x^{(0)}(n)=[-x^{(1)}(n),1]\begin{bmatrix}a\\u\end{bmatrix} \end{cases}. \tag{6}$$

Since $\frac{\Delta x^{(1)}}{\Delta t}$ refers to the value of two moments accumulated to $x^{(1)}(1)$, it is more feasible for $x^{(i)}(i)$ to be replaced by the mean value of the previous moment and the next moment. Replace $x^{(i)}(i)$ with

$$\frac{1}{2}[x^{(i)}(i)+x^{(i)}(i-1)],(i=2,3,\ldots,n).$$

Rewrite Eq. (6) into the following matrix expression

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(2)+x^{(1)}(1)] & 1 \\ -\frac{1}{2}[x^{(1)}(3)+x^{(1)}(2)] & 1 \\ \vdots & \\ -\frac{1}{2}[x^{(1)}(n)+x^{(1)}(n-1)] & 1 \end{bmatrix} \begin{bmatrix} a \\ u \end{bmatrix}, \quad (7)$$

$$y = (x^{(0)}(3), x^{(0)}(3), ..., x^{(0)}(n))^T;$$

$$B = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(2)+x^{(1)}(1)] & 1 \\ -\frac{1}{2}[x^{(1)}(3)+x^{(1)}(2)] & 1 \\ \vdots & \\ -\frac{1}{2}[x^{(1)}(n)+x^{(1)}(n-1)] & 1 \end{bmatrix}, \quad U = \begin{bmatrix} a \\ u \end{bmatrix}.$$

The expression of Eq. (7) is shown below

$$y = BU. \quad (8)$$

Therefore, the least square estimation of Eq. (8) is

$$\widehat{U} = \begin{bmatrix} \hat{a} \\ \hat{u} \end{bmatrix} = (B^T B)^{-1} B^T y. \quad (9)$$

We put the estimated value, $\hat{a}$ and $\hat{u}$ into Eq. (8) to obtain the time response equation

$$\widehat{x}^{(1)}(k+1) = \left[ x^{(1)}(1) - \frac{\hat{u}}{\hat{a}} \right] e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}. \quad (10)$$

When $k = 1, 2, ..., n-1$, it can be seen that $\widehat{x}^{(1)}(k+1)$ is a fitted value according to Eq. 10. When $k \geq n$, $\widehat{x}^{(1)}(k+1)$ is a predicted value. $\widehat{x}^{(1)}(k+1)$ is the fitted value of $x^{(1)}$. Let us use the subtraction generation to revert $x^{(1)}$. When $k = 1, 2, ..., n-1$, the fitted value of the original column, $x^{(0)}$, can be obtained, which is $\widehat{x}^{(0)}(k+1)$; when $k \geq n$, the predicted value of the original sequence, $x^{(0)}$, can be obtained, which is $\widehat{x}^{(0)}(k+1)$.

Based on the above calculation method, the predicted value at the position of "$k+1$" can be obtained, which is

$$\widehat{x}^{(0)}(k+1) = \widehat{x}^{(1)}(k+1) - \widehat{x}^{(1)}(k).$$

The residual error, correlation degree and post-error test are adopted to guarantee the accuracy and reliability of the model. After testing, if the model is still not accurate enough, the calibration and optimization test is required [6–8].

**3. *Accuracy test.***

1. Residual examination (Below is the calculation method):

residual error

$$\varepsilon^{(0)}(k) = x^{(0)}(k) - \widehat{x}^{(0)}(k), \quad k = 2,3,\ldots,n;$$

relative residual error

$$e(k) = [x^{(0)}(k) - \widehat{x}^{(0)}(k)] \big/ x^{(0)}(k), \quad k = 2,3,\ldots,n.$$

Let us calculate the absolute error of the corresponding percentage

$$MAPE = \frac{1}{n-1} \sum_{k=2}^{n} \left| \frac{\varepsilon^{(0)}(k)}{x^{(0)}(k)} \right|.$$

Generally speaking, if $MAPE \leq 10$ % and the error of the original point is smaller than 2 %, it can be thought that the accuracy requirement is met.

2. Correlation degree test (Below is the calculation method)

$$\eta(i) = \frac{\min\{\varepsilon^{(0)}(k)\} + \xi \max\{\varepsilon^{(0)}(k)\}}{\varepsilon^{(0)}(k) + \rho \max\{\varepsilon^{(0)}(k)\}}.$$

Where, $\xi$ stands for the resolution ratio, which is generally set to be "0"; the correlation degree is $r = \frac{1}{n}\sum_{i=1}^{n}\eta(i)$. When $\xi = 0.5$ and $r > 0.6$, the prediction accuracy is met.

3. Post-error test (Below is the calculation method):

Mean value of $x^{(0)}$

$$\bar{X} = \frac{1}{n}\sum_{k=1}^{n} x^{(0)}(k).$$

Variance of $x^{(0)}$

$$S_1 = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(x^{(0)}(k) - \bar{X})}.$$

Mean value of the residual error

$$\bar{E} = \frac{1}{n-1}\sum_{k=2}^{n}\varepsilon^{(0)}(k).$$

Variance of the residual error

$$S_2 = \sqrt{\frac{1}{n-1}\sum_{k=2}^{n}[\varepsilon^{(0)}(k) - \bar{E}]}.$$

Specific value of the post-error

$$C = \frac{S_2}{S_1}.$$

Probability of the small error

$$P = P\left\{ \left| \varepsilon^{(0)}(k) - \bar{E} \right| < 0.6745 S_1 \right\}.$$

Generally speaking, the value of $C$ should be small enough even if the original data have no rules to follow [9–10]. In this way, the error scope of the predicted value will not be too huge. The prediction results by the model can be judged by the value of $\alpha$, $C$ and $P$. The larger the value of $\alpha$ and $C$ is, the better; while the smaller the value of $P$ is, the better. Generally speaking, the corresponding accuracy of $P$ and $C$ is shown in Table 3. After the model is built, it can be tested. If the verification results are not qualified, the model built this way should be improved so as to improve its accuracy.

Based on summary of the above discussion, the major modelling steps for GM(1, 1) are shown below:

*Step 1:* we assume that the original data column constitutes $x^{(0)}$ (Eq. 3) and conducts an accumulation of the column to obtain $x^{(1)}$ (Eq. 4).

*Step 2:* we build the matrix form like Eq. (7) and obtain the corresponding $B$ and $y$.

*Step 3:* we work out the inverse matrix of $(B^T B)^{-1}$.

*Step 4:* we work out the estimated value, $\hat{a}$ and $\hat{u}$, according to Eq. (9).

*Step 5:* we work out $\hat{x}^{(1)}(i)$ according to Eq. (10), and use the subtraction generation for restoration, namely

$$x^{(0)}(i) = x(i) - \hat{x}^{(1)}(i-1), \quad i = 2,3,\ldots,n.$$

*Step 6:* Accuracy test and prediction.

We put the data of Table 1 into GM (1, 1) above, and predict the future market indexes. The prediction results, the prediction accuracy indexes and the comparison results of the model are shown in Table 4, Table 5 and Figure, respectively.

We put the predicted data obtained through the original actual data and the grey prediction model, namely the actual data in Table 1 and the predicted data in Table 4, into the optimization model of the specific power demand function for solution. The optimization results of the actual data and the predicted data are shown in Table 6 and Table 7, respectively.

*Table 3*

Reference table of the accuracy test grade

| Indexes Accuracy grade | Relative error ($\alpha$) | Specific value of the post-error ($C$) | Probability of the small error ($P$) |
|---|---|---|---|
| Grade 1 | 0.01 | 0.35 | 0.95 |
| Grade 2 | 0.05 | 0.5 | 0.8 |
| Grade 3 | 0.1 | 0.65 | 0.7 |
| Grade 4 | 0.2 | 0.8 | 0.6 |

*Table 4*

Grey model prediction results

| Period ($t$) | Consumer income ($m$) | Interest rate ($r$) | Commodity order price ($p_{0t}$) | Period ($t$) |
|---|---|---|---|---|
| 9 | 10444.69 | 2.729 | 11.60 | 0.938 |
| 10 | 10512.53 | 2.690 | 11.70 | 0.954 |
| 11 | 10580.81 | 2.651 | 11.81 | 0.969 |
| 12 | 10649.53 | 2.613 | 11.91 | 0.985 |

**Conclusions.** Based on the solution results of the above mode, it can be seen that the overall prediction performance of GM (1, 1) is favourable, and various accuracy indexes have reach Grade 1. The market index value of the prediction results is optimized. The results obtained by the prediction model and the results obtained by the actual model show no huge error.

*Table 5*

Precision results of various indexes based on GM (1, 1)

| Indexes | Development coefficient ($a$) | Grey action ($u$) | Specific value of the standard deviation ($C$) | Average relative error (MAPE) | Degree of correlation ($r$) |
|---|---|---|---|---|---|
| Consumer income | –0.006474 | –1527166 | 0.1248 | 0.0029 | 0.751 |
| Interest rate | 0.014550 | 212.31 | 0.0708 | 0.0045 | 0.563 |
| Commodity order price | –0.008789 | –1224.9 | 0.1766 | 0.0044 | 0.554 |
| Inventory cost unit price | –0.016203 | –50.458 | 0.1717 | 0.0083 | 0.536 |

*Table 6*

Actual optimization results of the specific power demand function model

| T | It | Dt | St | AIt | p1t | Qt | Rt |
|---|---|---|---|---|---|---|---|
| 1 | 200 | 144 | 144 | 134 | 17.264 | 6 | 2291.2 |
| 2 | 62 | 126 | 126 | 76 | 18.774 | 77 | 3754.6 |
| 3 | 13 | 98 | 98 | 50 | 21.153 | 86 | 4858.9 |
| 4 | 1 | 104 | 104 | 106 | 20.744 | 157 | 5252.9 |
| 5 | 54 | 91 | 91 | 129.5 | 21.659 | 121 | 5810.8 |
| 6 | 84 | 103 | 103 | 62.5 | 21.1 | 30 | 7578.9 |
| 7 | 11 | 97 | 97 | 103.5 | 22.362 | 141 | 7956 |
| 8 | 55 | 89 | 89 | 195.5 | 22.567 | 185 | 8088.9 |
| 9 | 151 | 83 | 83 | 128.5 | 22.94 | 19 | 9553.5 |
| 10 | 87 | 86 | 86 | 46 | 22.99 | 2 | 11474 |
| 11 | 3 | 100 | 100 | 99 | 21.27 | 146 | 11978 |
| 12 | 49 | 118 | 118 | 61 | 19.686 | 71 | 13452 |

*Table 7*

Grey prediction optimization results of the specific power demand function model

| T | It | Dt | St | AIt | p1t | Qt | Rt |
|---|---|---|---|---|---|---|---|
| 1 | 200 | 129 | 129 | 182.5 | 18.612 | 47 | 1687.2 |
| 2 | 118 | 111 | 111 | 90.5 | 20.485 | 28 | 3563.6 |
| 3 | 35 | 121 | 121 | 85.122 | 18.377 | 86 | 4808.4 |
| 4 | 0 | 106 | 106 | 207 | 20.46 | 260 | 4033.8 |
| 5 | 154 | 132 | 132 | 210 | 16.99 | 122 | 4771.1 |
| 6 | 144 | 95 | 95 | 126.5 | 22.279 | 30 | 6408.8 |
| 7 | 79 | 100 | 100 | 51 | 21.974 | 22 | 8309.5 |
| 8 | 1 | 100 | 100 | 126 | 20.889 | 175 | 8422.2 |
| 9 | 76 | 93 | 92 | 264.5 | 21.302 | 16 | 10188 |
| 10 | 0 | 155 | 155 | 128.5 | 15.551 | 206 | 10279 |
| 11 | 51 | 99 | 99 | 122.5 | 21.404 | 121 | 11016 |
| 12 | 73 | 119 | 119 | 153.92 | 19.55 | 46 | 12773 |

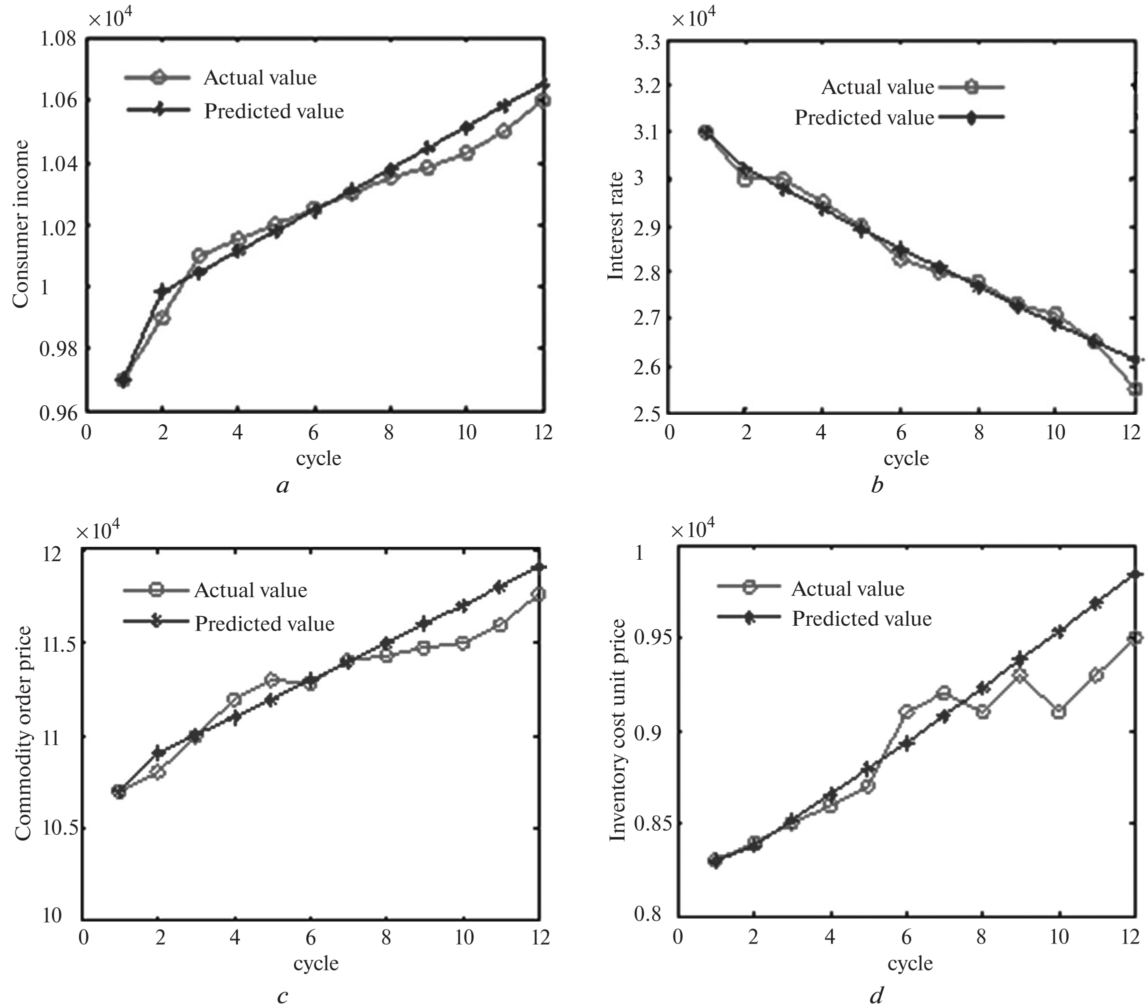


*Fig. Actual value and predicted value of GM (1, 1)*:

*a — actual value and predicted value of Consumer income; b — actual value and predicted value of Interest rate; c — actual value and predicted value of Commodity order price; d — actual value and predicted value of Inventory cost unit price*

Excluding that the commodity sales price is a little low and the commodity demand is too high in the tenth period, the overall predicted value of the model is favourable and the final optimized earnings do not differ greatly from the expectation. Therefore, when the market demand changes show index changes, the dynamic pricing and inventory control optimization model based on the grey prediction model is of vital guiding significance towards planning of commodity sales.

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**Мета.** Прогнозування ринку відноситься до прогнозування внутрішніх правил і майбутніх тенденцій розвитку різних ринкових індексів і чинників на основі вивчення та поглибленого дослідження різних чинників, що впливають на зміни ринкового попиту й пропозиції за допомогою наукових теорій і систематичних модельних алгоритмів. Ця робота аналізує результати оптимізації традиційних і інтелектуальних алгоритмів прогнозування.

**Методика.** Для аналізу відмінностей між результатами, отриманими за допомогою алгоритмів прогнозування, і практичними ситуаціями, необхідно уніфікувати параметри моделі аналізу. Модель прогнозування сірої системи застосовна до прогнозування ситуацій з трендом індексів, що змінюється. Модель часових рядів підходить для даних з певним трендом і періодичними змінами.

**Результати.** Ми виявили, що нейронна мережа, модель і підтримка векторної моделі не мають яких-небудь вимог до даних, тому вони підходять для будь-яких ситуацій. І коли зміни ринкового попиту показують зміни індексу, життєво важливе направляюче значення для планування продажів товарів має динамічне ціноутворення та оптимізаційну модель управління запасами на основі сірої моделі прогнозування.

**Наукова новизна.** За допомогою моделювання, прогнозоване значення моделей близьке до кінцевої цільової оптимізації прибутків.

**Практична значимість.** Зміни ринкового попиту, як правило, показують зміни індексу, динамічне ціноутворення та оптимізаційна модель управління запасами на основі сірої моделі передбачення може служити орієнтиром при плануванні продажів товарів.

**Ключові слова:** *сіра модель, самоадаптивна оптимізація, модельне прогнозування, специфічна функція потужності*

**Цель.** Прогнозирование рынка относится к прогнозированию внутренних правил и будущих тенденций развития различных рыночных индексов и факторов на основе изучения и углубленного исследования различных факторов, влияющих на изменения рыночного спроса и предложения с помощью научных теорий и систематических модельных алгоритмов. Эта работа анализирует результаты оптимизации традиционных и интеллектуальных алгоритмов прогнозирования.

**Методика.** Для анализа различий между результатами, полученными с помощью алгоритмов прогнозирования, и практическими ситуациями, необходимо унифицировать параметры модели анализа. Модель прогнозирования серой системы применима к прогнозированию ситуаций с изменяющимся трендом индексов. Модель временных рядов подходит для данных с определенным трендом и периодическими изменениями.

**Результаты.** Мы обнаружили, что нейронная сеть, модель и поддержка векторной модели не имеют каких-либо требований к данным, поэтому они подходят для любых ситуаций. И когда изменения рыночного спроса показывают изменения индекса, жизненно важное направляющее значение для планирования продаж товаров имеет динамическое ценообразование и оптимизационную модель управления запасами на основе серой модели прогнозирования.

**Научная новизна.** С помощью моделирования, прогнозируемое значение моделей близко к конечной целевой оптимизации прибыли.

**Практическая значимость.** Изменения рыночного спроса, как правило, показывают изменения индекса, динамическое ценообразование и оптимизационная модель управления запасами на основе серой модели предсказания может служить ориентиром при планировании продажи товаров.

**Ключевые слова:** *серая модель, самоадаптивная оптимизация, модельное прогнозирование, специфическая функция мощности*

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