Research Article

Research on Forecast of Macroeconomic Indicators Based on Multiobjective Optimization

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In recent years, with China’s economic development entering a new normal, the total scale and complexity of economic development have increased unprecedentedly, and the requirements of government management and regulation of the economy are getting higher and higher. Traditional management concepts, methods, and tools are difficult to meet the needs of the new situation. Therefore, using computer science and technology to fully consider the correlation between various industries and explore new laws of economic operation under the new normal can provide new technical support for promoting the precision of government governance. In previous studies, Most of them take statistics and econometrics as the theoretical basis of macroeconomic decision-making research. This study is based on the analysis of the relationship between the macroeconomic indicators, the establishment of forecasting models to predict the trend of the macroeconomic indicators, and according to the relationship between various economic indicators to build a multiobjective optimization problem, through the multiobjective optimization algorithm to obtain optimal data for the government decision-making basis. In the research process, we focus on solving the problem of prediction overfitting caused by small samples of economic index data and high feature dimension of samples and how to balance the convergence and diversity of solution set in high-dimensional multiobjective optimization problems. In view of the above problems, we propose two economic index forecasting models to solve a variety of fitting problems. On the premise of optimizing space decomposition, an adaptive generation strategy based on inflection point and center point is proposed, and an adaptive solution set selection strategy based on included angle, inflection point, and strong dominance relationship is proposed to balance the convergence and diversity of the multiobjective optimization algorithm.

1. Introduction

Usually, the weighting method is generally used to solve the optimization problem. Now, the genetic algorithm improves the way of dealing with multiobjective problems by introducing the concept of Pareto control [1]. This paper describes the probabilities and methods of continuous nonlinear multiobjective optimization. The methods are divided into three categories: prior preference, posterior preference, and no preference [2]. In this paper, the relationship between theory and practice of mathematical models of nonlinear systems is studied in consideration of many computational techniques [3]. In this paper, three different methods are proposed to determine whether the multiobjective evolutionary algorithm is superior to solving different two-objective optimization problems when dealing with two or more objectives [4]. This paper introduces the decision-making of multiobjective optimization in detail under the condition of making and characterizing the unified decision-making framework of multifunction optimization [5]. This paper studies some representative algorithms to solve multiobjective optimization problems and also discusses some methods related to their use and future research trends [6]. This paper introduces a single-objective elite method based on success rule with selection and step size control and then compares this method with the standard method. Experimental results show that MO-CMA-ES is superior to NSGA-II and multiobjective differential evolution algorithm [7]. There are many problems in multiobjective optimization, and there are conflicts among them. Therefore, the demand for efficient...
and reliable solutions is gradually increasing. Because multiobjective optimization is not a single optimal solution, this task is extremely challenging [8]. The study of multiobjective optimization is mainly to study its fitness. This paper introduces the history and classification of multiobjective optimization, especially five famous multiobjective optimization algorithms [9]. This paper first discusses some general problems of macroeconomic forecasting and then further expands the analysis [10]. This paper analyzes investors’ reaction to macroeconomic news. Every day, news organizations publish forecasts for important macroeconomic indicators. When the published value of an indicator is different from the predicted value, investors must modify their strategies. The intensity of investor reaction depends on the real difference between the published value and the expected value [11]. This paper makes a high-frequency forecast on six macroeconomic indicators: unemployment rate, exchange rate, industrial output, base currency, inflation, and household savings [12]. Research shows that autoregressive econometric models and general equilibrium models cannot make predictions when the economic crisis comes; so, it is necessary to create a series of models that can respond to the dynamic changes of the economic environment faster and more accurately [13]. There is a long-term equilibrium relationship between Shanghai Composite Index and many macroeconomic indicators, and SSM Composite Index can be used as a barometer of economy [14]. Macroeconomic situation is the overall performance of the economic situation of a country or region. At present, many macroeconomic indicators are obtained through statistical calculation, step-by-step reporting, sampling survey, and other processes and then released by the Bureau of Statistics; so, there is a relatively serious lag. In this paper, high-frequency and relatively accurate big data sources are used to build a multiple regression prediction model for traditional national economic indicators, so as to provide more timely, reliable and easy-to-understand national socioeconomic prediction values [15]. In this paper, a small R2SM model is used to simulate the medium-term development plan, and the reasons for the impact on economy are revealed. Then, two alternatives are proposed, and the results are compared with those of the Dobrescu model under the same assumptions [16]. In the forecast of macroeconomic growth, there is a problem of inaccurate single target. However, there is randomness in the application of a single target, and the error is large. In view of the problems of poor prediction effect and low accuracy of macroeconomic growth, this paper puts forward multiobjective macroeconomic forecasting, so as to improve the prediction accuracy.

2. Algorithms for High-Dimensional Multiobjective Optimization Problems

2.1. High-Dimensional Multiobjective Optimization Algorithm Based on Decomposition Strategy. The high-dimensional multiobjective optimization algorithm based on decomposition strategy is to transform multiobjective optimization into multisingle-objective optimization. Subsequently, many algorithms with better performance were proposed. Previous researchers are mainly on the basis of MOEA/D in the selection of convergence and diversity of better solutions, design adaptive strategies, and generate better convergence solutions such as MOEA/D-SAS, MOEA/D-NBI, MOEA/D-AWA, and MOEA/D-OGS. The method based on multiobjective optimization space decomposition is very effective for solving optimization problems.

To make multiple objectives as best as possible in a given area at the same time, the solution of multiobjective optimization is usually a set of equilibrium solutions (that is, a set of optimal solutions composed of many Pareto optimal solutions, and each element in the set is called Pareto optimal solution or noninferior optimal solution).

(1) Noninferior solution: there is no optimal solution for a multiobjective optimization problem, and all possible solutions are called noninferior solutions, also called Pareto solutions

(2) Pareto optimal solution: it is impossible to improve any objective function without weakening at least one other objective function. This solution is called nondominated solution or Pareto optimal solution

2.2. High-Dimensional Multiobjective Optimization Algorithm Based on Dominance Relation. In multiobjective optimization problems, the number of Pareto dominance relations will increase with the increase of the number of objectives. In order to enhance the selection pressure of nondominated solutions, many dominating methods are proposed, such as dominating, dominating, arbitrary dominating, fuzzy dominating, and dominating. Besides the five dominating methods mentioned above are effective for obtaining high-quality solution sets, diversity evaluation mechanism is also introduced to reduce the selection pressure of solution sets. Pareto dominance relation is not suitable for multimodal and multidimensional multiobjective optimization problems because its ability to distinguish the solutions in the solution set is getting worse and worse with the iteration going on when solving the multimodal and high-dimensional multiobjective optimization problems; so, Pareto dominance relation is not suitable for multimodal and high-dimensional multiobjective optimization problems.

2.3. High-Dimensional Multiobjective Optimization Algorithm Based on Performance Index. In order to reduce the computational complexity of hypervolumetric, a hypervolumetric adaptive mesh algorithm is proposed, which divides the optimization target space into several meshes, and then calculates hypervolumetric according to the solutions in the meshes, thus reducing the computational cost of hypervolumetric. In 2007, Igel and others introduced HV index on the basis of (evolution strategy with covariance matrix adaptation, CMA-ES) and put forward (multiobjective covariance matrix adaptation evolution strategy, MO-CMA-ES) algorithm, which performed well in some benchmark problems. Because of the high correlation between R2 index and HV index, after 2013, excellent multiobjective optimization algorithms such as R2-IBEA, R2-MOACO, and iR2-MOACO were proposed based on R2 index.
3. Forecast of Economic Indicators

3.1. Analysis of the Relationship between Economic Indicators

3.1.1. Relational Expression Construction. There is a relationship between multiple macroeconomies in the same period. In this section, the relationship between each economic index is obtained by linear analysis as shown in Formula (1):

\[ x_1 = w_{11}x_2 + d_{11}, \quad x_M = w_{M1}x_1 + d_{M1}, \]
\[ x_1 = w_{12}x_3 + d_{12}, \quad x_M = w_{M2}x_2 + d_{M2}, \]
\[ \vdots \]
\[ x_1 = w_{1M-1}x_M + d_{1M-1}, \quad x_M = w_{M,M-1}x_{M-1} + d_{M,M-1}. \]  
(1)

where \( X = \{x_1, x_2, \ldots, x_M\} \) represents \( M \) macroeconomic indicators, \( W = \{w_1, w_2, \ldots, w_M\} \) represents the coefficients of corresponding macroeconomic indicators, and \( \mathbf{w}_M = (w_{11}, w_{12}, \ldots, w_{M,M-1})^T \) represents the coefficients of the relationship between the \( M \) index and other indicators. The missing data is calculated by using the above relationship, and the data is completed.

3.1.2. Causality Analysis. Because macroeconomic indicators belong to time sequence, this paper uses historical data to forecast the development of macroeconomic indicators. The relationship between economic indicators is very complex. Using a number of historical data related to forecasting indicators to predict the development situation of macroeconomic indicators is to get more accurate forecasting results of economic indicators. Causality analysis is to determine the existence of causality by judging whether one time series data can promote the regression accuracy of another time series data. Granger causality analysis based on Copula is used to determine the causality between economic indicators, which can be used to explore the causality between nonlinear and high-order moments, as shown in Formula (2):

\[
G_{X \rightarrow Y} = E \left[ \log \frac{f(y_{t+1} | y_{t}^i, x_{t}^m)}{f(y_{t+1} | y_{t})} \right] = E \left[ \log \frac{h(y_{t+1}, x_{t}^m | y_{t}^i)}{f(y_{t+1} | y_{t}) \times g(x_{t}^m | y_{t}^i)} \right],
\]  
(2)

where \( h \) is the conditional joint distribution density of \((X, Y)\), and \( f \) and \( g \) are the conditional boundary densities of \( X \) and \( Y \), respectively. According to Sklar theorem and its application in conditional Copula, \( h \) can be expressed as formula (3):

\[
h(y_{t+1}, x_{t}^m | y_{t}^i) = f(y_{t+1} | y_{t}^i) \times g(x_{t}^m | y_{t}^i) \times c(u, v | y_{t}^i),
\]  
(3)

where \( u = F(y_{t+1} | y_{t}^i), \) \( v = G(x_{t}^m | y_{t}^i). \) \( F \) And \( G \) denote the conditional marginal distributions of \( X \) and \( Y \), respectively. Therefore, the Granger causality of \( X \rightarrow Y \) is obtained by substituting formula (3) into formula (2) in the following simple form as shown in formula (4):

\[
G_{X \rightarrow Y} = E[\log c(F(y_{t+1} | y_{t}^i), G(x_{t}^m | y_{t}^i) | y_{t}^i)].
\]  
(4)

3.2. Feature Extraction

3.2.1. Decomposition of Economic Indicators. Due to the time and quantity limitation of data release, the amount of macroeconomic indicators data available is small; so, the useful information for predicting the development trend of macroeconomic indicators can be directly obtained through data is also small. The purpose of decomposing macroeconomic index data is to obtain more useful information. Firstly, an improved empirical mode decomposition algorithm is used to decompose a macroeconomic index data into several groups of mixed time series data, and then independent component analysis is used to obtain independent time series data from the decomposed mixed time series data as sample features. The specific process is shown in Figure 1.

3.2.2. Main Feature Extraction. Due to the limitation of data release and other factors, there are few available macroeconomic indicators; so, predicting a single economic indicator through multiple causal indicators is easy to lead to dimensional disaster. In order to solve the dimension disaster problem, we use partial least square method to extract the main features. PLS has many advantages in feature extraction of small samples.

After pretreatment, \( X \) and \( Y \) are decomposed into formula (5):

\[
\begin{align*}
X &= \sum_{i=1}^{q} t_i p_i^T + E, \\
Y &= \sum_{j=1}^{r} u_j q_j^T + F,
\end{align*}
\]  
(5)

where \( t_i = (t_{i1}, t_{i2}, \ldots, t_{ip})^T \) denotes the \( i \)-th feature extracted from \( X \), \( u_j = (u_{j1}, u_{j2}, \ldots, u_{jm})^T \) denotes the \( j \)-th feature extracted from \( Y \), \( p_i = (p_{i1}, p_{i2}, \ldots, p_{im})^T \) and \( q_j = (q_{j1}, q_{j2}, \ldots, q_{jm})^T \) denote regression coefficients, and \( E \) and \( F \) denote residuals. It can be simplified to formula (6):

\[
\begin{align*}
X &= TP^T + E, \\
Y &= UQ^T + F,
\end{align*}
\]  
(6)

where \( T = (t_1, t_2, \ldots, t_p) \) and \( U = (u_1, u_2, \ldots, u_r) \), \( P = (p_1, p_2, \ldots, p_p) \), and \( Q = (q_1, q_2, \ldots, q_r) \).

3.3. Virtual Sample Construction. Because the sample size is small and there is missing information, in order to avoid overfitting, this paper constructs virtual samples to supplement the missing information. At present, the commonly used methods of generating virtual samples are MTD, GTD, GAVSG, and so on. The support vector regression algorithm has good advantages in learning small samples.
It also has a good effect in generating virtual samples by kernel function. Therefore, this method is used to construct virtual samples, and the support vector regression model is used to predict the development trend of economic indicators. The construction of virtual samples is shown in Formula (7):

\[
K(v, \varphi(x)) = \frac{K(\varphi(x), \varphi(x))}{2} + \frac{K(\varphi(x), \varphi(x))}{2}. \tag{7}
\]

The kernel function matrix obtained after constructing the virtual sample is shown in Formula (8):

\[
K_{(n+1) \times (n+1)} = \begin{bmatrix}
K_{nn} & K(\varphi(x_1), v) \\
\vdots & \ddots \\
K(v, \varphi(x_1)) & \cdots & K(v, \varphi(x_n))
\end{bmatrix}, \tag{8}
\]

where \(K_{nn}\) represents the kernel function matrix between the original samples.

3.4. Forecasting Model. The prediction model proposed in this paper is shown in Figure 2.

The model uses EEMD and ICA to decompose the original sample data to obtain independent time series data, then uses partial least squares method to extract the main features of the samples from the independent time series data, and then obtains \(\{t(1), t(2), \cdots, t(m)\}\) in the graph. Then, these features are used as inputs of the prediction model, and they are mapped to high-dimensional space to obtain the kernel function values between two samples. By using the linear regression characteristic of the support vector regression model, the kernel function between the constructed virtual sample and the original sample is calculated, and finally, the prediction result is obtained by linear regression.

Because the macroeconomy is greatly influenced by the subjectivity of government regulation and control, therefore, based on the prediction results obtained by using support vector regression model (as shown in Figure 2), the final prediction results are obtained by adjusting the prediction results through the relationship between vertical macroeconomic indicators. Firstly, the development trend of economic indicators is predicted one by one through the prediction model to get \(\{Y_1, Y_2, \cdots, Y_{23}\}\), and the linear relationship formula (1) among the indicators is obtained. Then, using a set of relations corresponding to \(Y_i\) in formula (1), several values of \(Y_i\) are obtained, and \(Y_i'\) is obtained by taking the average value. Finally, whether \(Y_i''\) is 10% larger than \(Y_i\) is judged to determine the final value \(Y_i'\) of \(Y_i\). The specific process is shown in Algorithm 1.

3.5. Comparative Analysis of Experiments

3.5.1. Experimental Data. Due to the limitation of data release and other factors, the available macroeconomic index data is missing. This paper obtains the linear relationship between two economic indicators through the economic index data from 2015 to 2017 and completes the missing data through the formula (1) mentioned in Section 3.1.1. According to the relationship between the index of missing data and other indexes, several estimated values of the index are obtained by using the relationship (1) of the data of other indexes in the same period. The data marked in red in Table 1 is the data that was missing and then retrieved:

3.5.2. Forecast Results of Economic Indicators. In the process of feature extraction, firstly, each economic index data is decomposed into four mixed time series data by using equalizer. Then, according to the lag number between causal indexes obtained in the process of causal analysis, the data corresponding to the independent time series data of economic indicators with causal relationship with prediction indicators are integrated as independent variable \(X\), and the independent time series data of prediction indicators are taken as dependent variable \(Y\). The main features are extracted from \(X\) by phase-locked loop in Section 3.2.2, and the number of principal components required is 7 by cross-effective test.

According to the macroeconomic indicators data of a province in recent ten years, the data from 2009 to 2016 are used as training samples to predict the development trend of macroeconomic indicators in 2017 and 2018. The obtained results are shown in Table 2. 2017pre_no and 2018pre_no represent the results without the adjustment of the relationship between indicators, and 2017pre and 2018pre represent the results adjusted by the relationship between indicators.
The red data under 2017pre and 2018pre in Table 2 is the case where the adjusted result is better.

4. Forecast of Macroeconomic Indicators Based on Multiobjective Evolutionary Optimization

4.1. Construction of Multiobjective Optimization Problem

4.1.1. Correlation Analysis among Economic Indicators. Because the pull or contribution between economic indicators is linear, the relationship between macroeconomic indicators with correlation in general is shown in Formula (9)

\[ Y_t = \omega_1 X_t + \omega_2 Z_t + \cdots + b, \]

where \( Y_t, X_t, \) and \( Z_t \) represent the values of economic indicators \( Y, X, \) and \( Z \) at time \( t \), and \( \omega_1, \omega_2, \) and \( b \) represent the corresponding coefficients and the intercept of regression formula.

In this study, according to the production level to which each economic index belongs, it is aggregated into three categories: primary industry, secondary industry, and tertiary industry.

It can be seen from Table 3 that all three industries are synthesized by the comprehensive economic indicators of the industry; so, the small indicators in an industry have a cointegration relationship with the industry.

In this section, the cointegration relationship is obtained by cointegration analysis of GDP and three industries. The test results are shown in Table 4, and \( \text{Ind}_1, \text{Ind}_2, \) and \( \text{Ind}_3 \) are used to represent the three industries, respectively.

4.1.2. Obtain the Relationship between Indicators. Through the cointegration analysis in Section 4.1.1, it is found that there is a cointegration relationship among various macroeconomic indicators. Therefore, this paper constructs a multiobjective optimization problem by establishing multiple linear regression among macroeconomic indicators. The multiple linear regression relationship among macroeconomic indicators is described as shown in the following formula (10):

\[
\begin{align*}
x_1 &= w_{1,1}x_1 + w_{1,2}x_2 + \cdots + w_{1,M}x_M + d_1, \\
x_2 &= w_{2,1}x_1 + w_{2,2}x_2 + \cdots + w_{2,M}x_M + d_2, \\
    &\vdots \\
x_M &= w_{M,1}x_1 + w_{M,2}x_2 + \cdots + w_{M,M-1}x_{M-1} + d_M,
\end{align*}
\]

where \( X = (x_1, x_2, \cdots, x_M)^T \) represents a one-dimensional
array composed of economic indicators, \( w_{ij}, i, j = 1, 2, \cdots, M \) represents the contribution rate of the variables on the right side to the dependent variables on the left side of the above equation, and \( d_i, i = 1, 2, \cdots, M \) represents the intercept of each multivariate linear regression formula. Write formula (10) as a matrix as shown in formula (11):

\[
X = \begin{bmatrix}
0 & w_{1,2} & \cdots & w_{1,M} & d_1 \\
0 & w_{2,1} & \cdots & w_{2,M} & d_2 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
w_{M,1} & w_{M,2} & \cdots & 0 & d_M
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
\vdots \\
x_M \\
1
\end{bmatrix} = W_0X_1.
\]  

(11)

After obtaining the multiple linear regression relationship between macroeconomic indicators, the difference between the macroeconomic indicators \( X \) and the expected target value \( Z_{\text{ideal}} \) of the plan is taken to make the overall difference of all macroeconomic indicators minimum to construct a multiobjective optimization problem, as shown in the following formula:

First, make \( f_i(x) = |x_i - z_{i,\text{ideal}}| \), and get formula (12):

\[
f_1(x) = |w_{1,2}x_2 + w_{1,3}x_3 + \cdots + w_{1,M}x_M + d_1 - z_{1,\text{ideal}}|, \\
f_2(x) = |w_{2,1}x_1 + w_{2,3}x_3 + \cdots + w_{2,M}x_M + d_2 - z_{2,\text{ideal}}|, \\
\vdots \\
f_M(x) = |w_{M,1}x_1 + w_{M,2}x_2 + \cdots + w_{M,M-1}x_{M-1} + d_M - z_{M,\text{ideal}}|.
\]  

(12)

Finally, a multiobjective optimization problem such as formula (13) is constructed:

\[
\text{Min } F(x) = (f_1(x), f_2(x), \cdots, f_2(x)), \\
\text{subject to } x_i \in R_p, \\
G = x_{\omega} + d.
\]  

(13)

4.1.3. Fitness Calculation. The judgment of a solution set is based on the difference \( L_1 \) between the solution and the expected target solution. If the difference \( L_1 \) between the solution and the expected target solution is directly used as the basis for judging the good or bad solution, the final solution set will be biased towards the optimization target with a
smaller value range. Therefore, $L_1$ of the difference between the solution set POP and the expected target point $Z_{\text{ideal}}$ is normalized so that the range of $L_1$ of the difference between the respective targets is $[0, 1]$. $L_1$ normal form is used to measure the difference between each target value in the solution and the corresponding value in the expected target solution as the fitness of the solution. The smaller the difference, the better the fitness, as shown in Formula (14):

$$\text{val}_i^k = \left\lVert p_i^k - z_{\text{ideal}}^k \right\rVert_1, \quad k = 1, 2, \cdots, M, \quad i = 1, 2, \cdots, N.$$  \hfill (14)

The normalized fitness value of the $k$ objective of the $i$ solution of the fitness normalization process for each optimization objective is shown in formula (15):

$$\text{normal}\_\text{val}_i^k = \frac{\text{val}_i^k}{R_{\text{up}}^k - R_{\text{down}}^k}, \quad k = 1, 2, \cdots, M, \quad i = 1, 2, \cdots, N,$$

where $R_{\text{up}}^k, R_{\text{down}}^k$ represents the upper and lower limits of the value range, respectively.

4.2. Multiobjective Optimization Algorithm Framework. It is also a challenge to ensure the convergence and diversity of the solution set in the optimization process. After the multi-objective problem is constructed through Section 4.1.2, the selection pressure of the solution set is small in the optimization process because of the large number of objectives in the optimization problem, and the solutions in the solution set cannot be effectively graded. As shown in Figure 3, firstly, the adaptive solution set generation strategy based on better solution set prediction improves the convergence and diversity of the generated solution set. Then, the optimization space is reduced and divided into several subspaces, and the number of optimization targets in each subspace is small; so, the solutions in the solution set can be effectively graded by using nondominated sorting. Finally, the proposed adaptive solution set selection strategy based on strong dominance relation is used to balance the diversity and convergence of solution sets in the corresponding subspace, and then the optimal solution set $\text{pop}_i$ is obtained, then the optimal solution set POP is obtained by combining these

### Table 2: Forecast results.

| Year | Pre 2017 | Pre 2018 | Pre 2017 | Pre 2018 | Pre 2017 | Pre 2018 |
|------|---------|---------|---------|---------|---------|---------|
| 2017 | 4.3     | 3.2     | 4.2     | 4.1     | 4.2     | 4.1     |
| 2018 | 12.6    | 14.1    | 10.38   | 10.38   | 8.8     | 8.8     |
|      | 7.4     | 7.8     | 7.7     | 7.9     | 7.7     | 7.3     |
|      | 4.4     | 8.6     | 6       | 6       | 5.8     | 5.8     |
|      | 8.7     | 4.3     | 0.2     | 0.2     | 1.8     | 3.7     |
|      | 9.3     | 9.2     | 11.2    | 12      | 9.1     | 10.4    |
|      | 6.9     | -2.5    | 6.4     | 2       | 3.7     | 2.3     |
|      | 12.3    | 12.3    | 12.6    | 12.2    | 12.4    | 12.3    |
|      | 40      | 28.6    | 35.5    | 35.2    | 36.2    | 32.7    |
|      | 12.4    | 14.1    | 11.4    | 11.4    | 11.3    | 10.9    |
|      | 13.8    | 14.3    | 13.8    | 14.3    | 13.8    | 14.3    |
|      | 14.1    | 13.6    | 13.1    | 13.1    | 12.3    | 11.8    |
|      | 15.1    | 15.1    | 15.3    | 16.2    | 15.3    | 15.8    |
|      | 13      | 11.1    | 13.8    | 14.1    | 13.8    | 14.1    |
|      | 11.4    | 13.8    | 40.9    | 29.8    | 35.2    | 20.2    |
|      | 29.3    | 5.7     | 19      | 15.5    | 22.2    | 21.2    |
|      | 9.8     | 11.4    | 14.5    | 14.5    | 10.9    | 11.9    |
|      | 15.1    | 13.8    | 9.4     | 11.9    | 11.8    | 10.5    |
|      | 20.5    | 21      | 21.9    | 20.3    | 22.9    | 23.5    |
|      | 60.5    | 143.3   | 45.8    | 45.1    | 58.6    | 64.7    |
|      | 27.6    | 23.2    | 23.9    | 23.9    | 24.7    | 25      |
|      | 13      | 7.2     | 15.2    | 14.5    | 15.2    | 14.5    |
|      | 7.8     | 7.8     | 8.4     | 8.5     | 8.2     | 8.1     |
Table 4: Cointegration test results.

| Category | Category | t-stat | 1% critical value | 5% critical value | 10% critical value | Cointegration |
|----------|----------|--------|-------------------|-------------------|--------------------|---------------|
| Ind1     | Ind2     | -2.208 | -5.789            | -4.207            | -3.6171            | No            |
| Ind1     | Ind3     | -4.319 | -5.789            | -4.207            | -3.6171            | Yes           |
| Ind1     | GDP      | -1.666 | -5.789            | -4.207            | -3.6171            | No            |
| Ind2     | Ind1     | -3.819 | -5.789            | -4.207            | -3.6171            | Yes           |
| Ind2     | Ind3     | -4.206 | -5.789            | -4.207            | -3.6171            | Yes           |
| Ind2     | GDP      | -2.664 | -5.789            | -4.207            | -3.6171            | Yes           |
| Ind3     | Ind1     | -2.51  | -5.789            | -4.207            | -3.6171            | No            |
| Ind3     | Ind2     | -2.474 | -5.789            | -4.207            | -3.6171            | No            |
| Ind3     | GDP      | -1.6   | -5.789            | -4.207            | -3.6171            | No            |
| GDP      | Ind1     | -3.754 | -5.789            | -4.207            | -3.6171            | Yes           |
| GDP      | Ind2     | -3.417 | -5.789            | -4.207            | -3.6171            | No            |
| GDP      | Ind3     | -3.728 | -5.789            | -4.207            | -3.6171            | Yes           |

Figure 3: General flow chart of the multiobjective optimization algorithm.
solution sets, and the final optimal solution set is obtained by \( g \) max generation cyclic optimization.

4.3. Multiobjective Reduction Method Based on Subspace Extraction. With the increase of the number of optimization objectives, the number of nondominated solutions in the solution set also increases, which leads to the decrease of the selection pressure of the solution set. Therefore, this paper uses a multiobjective reduction method based on subspace extraction, which selects the larger conflicting objectives as the main body, and constructs a suboptimization space with the smaller conflicting objectives to select the solution set. The specific process of the multiobjective reduction method based on subspace extraction is shown in Figure 4.

4.3.1. Conflict Value Calculation and Target Classification. In order to choose the target of constructing subspace, it is necessary to quantify the conflict between targets first and divide the targets into strong conflict targets and weak conflict targets based on the contribution rate of conflict between targets. Target conflict is defined as Formula (16).

**Theorem 1.** For two objective functions \( f_i(x) \) and \( f_j(x) \), if there is an individual \( x_i, x_j \in P \) so that

\[
\begin{align*}
[f_i(x_i) > f_i(x_j)] \land [f_j(x_i) < f_j(x_j)]
\end{align*}
\]

\[
\begin{align*}
[f_i(x_i) < f_i(x_j)] \land [f_j(x_i) > f_j(x_j)]
\end{align*}
\]

There is a conflict between the two targets.

The total number of combinations of solutions in the solution set is \( C_N^2 \); assuming that there are \( K \) combinations satisfying Theorem 1, then the conflict values of objective functions \( f_i(x) \) and \( f_j(x) \) are shown in formula (17):

\[
c_{ij} = \frac{K}{C_N^2}.
\] (17)

The conflict contribution rate of Goal \( i \) is shown in Formula (18):

\[
\lambda_i = \frac{\sum_{j=1}^{M} c_{ij}}{\sum_{j=1}^{M} \sum_{i=1}^{M} c_{ij}}.
\] (18)

According to the role of objective function in the overall multiobjective conflict, that is, the contribution rate of conflict, the goal is divided into strong conflict and weak conflict goals.

4.3.2. Multiobjective Reduction Based on Subspace Extraction. Firstly, the conflict rate of each target in Section 4.3.1 is sorted from large to small. The target whose conflict contribution rate is greater than \( \sigma \) is a strong conflict target, and the target whose conflict contribution rate is less than \( \sigma \) is a weak conflict target. The strong conflict target set is \( S_{\text{main}} \), and the weak conflict target set is \( S_{\text{second}} \). Then, using the multiobjective reduction method based on subspace extraction will lead to repeated convergence in the multiobjective optimization process. According to the fitness value calculation formula (15), it can be concluded that when a solution \( X \) dominates the solution \( Y \), the sum \( I_X \) of the fitness values of the optimization objectives of the solution \( X \) must be less than the sum \( I_Y \) of the fitness values of the optimization objectives of the solution \( Y \). Therefore, after obtaining the subspace \( \psi_i \), the sum \( I \) of the normalized fitness values of the remaining optimization objectives is added to the subspace \( \psi_i \) as a new optimization objective to alleviate the convergence repetition in the evolution process. The specific process is shown in Algorithm 2.
4.4. Experimental Results and Analysis

4.4.1. GDP Growth Rate. This paper takes GDP as the target research object, selects industry, agriculture, forestry, animal husbandry, fishery, financial industry, real estate, and other target indicators, and makes a correlation analysis of the most effective indicators. The historical values of economic indicators are shown in Table 5.

The line chart can compare the relationship between data more intuitively; so, the four types of economic index data can be built into a line chart for comparison to get Figure 5.

A variety of prediction models are used for error analysis. The results are shown in Table 6.

The error analysis results of the prediction model are shown in Figure 6.
Figure 5: Comparison chart of four types of indicators.

Table 6: Error analysis results (%).

| Model                     | Relative error |
|---------------------------|----------------|
| Moving average method     | 3.6            |
| Multiple regression analysis | 2.2            |
| ARIMA                     | 2.9            |
| BP neural network         | 3.1            |
| Value smoothing method    | 3.3            |
| GM (1.1)                  | 5.6            |
| LASSO regression          | 2.9            |
| Trend extrapolation method| 4.5            |
| Box-Jenkins               | 7.8            |
| Ridge regression          | 2.9            |
Through the histogram, we can clearly observe that the Box-Jenkins model has the largest error, and the multivariate regression model has the smallest error. Taking $X_1, X_2, X_3$, and $Y$ as independent variables and $E$ as dependent variable, the multivariate regression analysis model was established as shown in Formula (19)

$$Y = 0.54X_1 + 0.35X_2 + 0.07X_3 + 0.08X_4 + 1.11.$$  \hspace{1cm} (19)

The significance of the coefficients in the above model is that every 1% increase in the growth rate of industry, agriculture, forestry, animal husbandry and fishery, finance, and real estate can promote the GDP growth rate by 0.54%, 0.35%, 0.07%, and 0.08% and then predict that the GDP growth rate of China in 19 years will be 6.39%. The prediction chart is shown in Figure 7.

Seven principal components are used to predict China’s GDP growth rate, and the relative error is 6.13%. The algorithm in this paper only uses four correlation indexes, and the relative error of prediction is 2.2%; so, it has more advantages in simplicity and prediction accuracy of correlation indexes.

**4.4.2. Other Key Macroeconomic Indicators.** Taking the selected key macroeconomic indicators and more than 200 effective index classes as input, the algorithm in this paper can automatically select the related index set with the greatest comprehensive impact on a key macroeconomic indicator and calculate the average relative error of the forecast results over the years and the forecast value in 2019, as shown in Tables 7 and 8. It can be seen that because the algorithm in this paper chooses the best treatment for related indicators and forecasting models, only through a
small set of related indicators, the prediction error of most key macroeconomic indicators can be smaller, and the prediction accuracy can be higher.

In other articles, the particle swarm optimization- (PSO-) BP neural network algorithm based on principal component analysis is used to predict China’s GDP growth rate, with a relative error of 6.13%. The algorithm in this paper only uses four correlation indexes, and the relative error of prediction is 2.2%; so, it has more advantages in simplicity and prediction accuracy of correlation indexes.

5. Conclusion

Macroeconomic analysis and prediction have always been a comprehensive problem. The traditional selection method of factors affecting economic indicators is highly dependent on professional economic knowledge. This paper puts forward a forecasting algorithm of macroeconomic indicators based on correlation analysis from the mathematical point of view, which can automatically select the associated indicators set with the greatest comprehensive influence on the target indicators from a large number of macroeconomic indicators, analyze the contribution of each associated indicator, and predict the target indicators with various forecasting models. Traditional macroeconomic indicators have many problems, such as strong time lag; so, we should use timely updated microeconomic big data indicators and combine machine learning algorithms to construct the relationship between traditional macroeconomic indicators and microeconomic big data indicators, so as to improve the timeliness of traditional macroeconomic indicators prediction. In this paper, the prediction results of the multi-objective optimization model have obvious advantages compared with the traditional prediction performance and have good results in practice. Future work will focus on in-depth analysis of the accuracy and accuracy of economic growth targets, using a variety of analysis models for comprehensive evaluation, in order to reduce the dimensions in the multiobjective prediction and find out the most critical target attributes.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declared that he/she has no conflicts of interest regarding this work.

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