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Research Article

Construction of Inflation Forecasting Model Based on Ensemble Empirical Mode Decomposition and Bayesian Model

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The high explanatory power of the first-order lag term of inflation in the inflation explanatory factor is that, on the one hand, the calculation of annual inflation indicators makes the inflation values of adjacent months cover the high correlation caused by the common price increase, and on the other hand, it also shows that people's perception of inflation is high. Some adaptability is expected. Although there are many Bayesian models available, due to the limitation of high-dimensional characteristics of the economy, most of the current inflation forecasting researches focus on a variety of generalized naive Bayesian models. By summarizing and analyzing the structural characteristics, learning methods, and classification principles of different Bayesian models, this paper finds out the important factors that affect the performance of the models and provides a theoretical basis for further improving the performance of Bayesian inflation forecasting. In this paper, the empirical mode decomposition method is introduced into inflation forecasting, and EEMD has obvious advantages in dealing with nonstationary and nonlinear time series and can decompose the signal according to the time scale characteristics of the data itself. Decompose the original time series step by step to generate eigenmode functions with different time scales. It is divided into high-frequency sequence and low-frequency sequence. Use rolling method and iterative method to construct subsamples for the sample data in this sample interval, forecast the inflation rate of each subsample interval in the next 12 months, and then compare the predicted value with the actual value to obtain a certain constructive conclusion. The predicted value is relatively close to the real value, which has theoretical and practical significance, and the predicted results obtained have no obvious regularity, but the root mean square error can be kept within 60%. By comparing the predicted value and the actual value, it can be seen that the prediction effect of the EEMD model is better.

1. Introduction

This paper evaluates the fit of conditional forecast densities based on Bayesian models to commonly used assumptions of normality to assess the feasibility and accuracy of different output growth and inflation forecasting models. Unlike point forecasting, which is limited to "deterministic equivalence," density forecasting estimates the future conditional probability density function of economic variables based on existing information, which fully describes the uncertainty associated with forecasting. Therefore, based on the fact that decision makers often have asymmetric loss functions, research on density forecasting that can characterize forecast-related uncertainty is particularly important [1]. Governments all over the world regard price stabilization as one of their macrocontrol objectives. Price stabilization can provide policymakers with a stable expected environment and play a guiding role in resource allocation. As the maker and executor of monetary policy, in order to achieve the goal of stabilizing prices, the central bank must enhance the forward-looking of monetary policy, make reasonable judgments about future inflation, and take appropriate measures to bring inflation back to the target range and prevent price fluctuations, to prevent huge fluctuations in the economy [2]. The correct direction of the central bank's regulation depends on the accurate prediction of future inflation, and economists must think deeply and discuss how to model and predict inflation. This is not only because inflation and inflation forecasting are monetary economics and market. The main concern is to establish an inflation forecasting model, which can accurately predict the time and level of future inflation, which can provide reference for policymakers to regulate inflation.

Inflation prediction refers to the process of dividing the economy into different clusters according to the differences in the characteristics of the economy. The purpose is to make the distance between economies in the same cluster as small as possible and the distance between economies in different clusters as large as possible [3]. Inflation is very important in the development of macro control policies, and there is a delay in the influence of monetary policy on inflation, so it is very important to determine the price of prices in advance, and many national governments are estimated by the price level as an intermediary target of monetary policy [4]. In contrast to economic classification, samples in inflation forecasting have no class labels and need to be automatically determined by a clustering algorithm. The uncertainty of the model and parameters and the comprehensive and effective use of information are the main factors that affect the prediction accuracy of macro variables. This paper uses the Bayesian model averaging method to model and predict out-of-sample inflation, synthesizes information from alternative models and variables to control model uncertainty, and effectively utilizes abundant macro data information. For the in-sample fitting of inflation, the Bayesian model averaging (BMA) method is better than the single model; for out-of-sample forecasting, under the RMSE criterion, the Bayesian model averaging method is better than the more popular AR models, main component analysis model, Phillips curve model, interest rate term structure model, single optimal model, and five-variable model [5]. Not only that inflation and inflation forecasting are the main concerns of monetary economics and the market, but also that the establishment of an inflation forecasting model can accurately predict the time and level of future inflation, which can provide a reference for policymakers to regulate inflation.

Therefore, the inflation rate can be kept in a moderate range to promote the rapid, stable, and healthy development of the economy. There is not only one source of price rises, and it is affected by many factors. This paper summarizes the causes of inflation into the following three aspects: first, it is explained from the perspective of the quantity theory of money, highlighting the important influence of money on inflation; second, it is explained from the perspective of supply and demand; third, explain the causes of inflation from the perspective of changes in economic structural factors. Using EEMD can automatically track changes in the data and continuously adjust estimates of short-term trends contained in the series. The premise of using EEMD is that the trend of the time series is stable and regular, so it can accurately predict the future situation. The most recent data can better reflect the regularity of the time series trend than the old data, so a larger weight should be set on the recent data. The short-term forecasting effect of this forecasting method is better. This method has more advantages than the simple average method and the moving average method. It not only considers the past data but also assigns different weights according to the time distance of the data, and the prediction accuracy is very high [6]. In the field of macroeconomics, people pay more attention to long-term trends and cyclical trends in time series. Therefore, decomposing the trend elements and cyclic elements of the time series to obtain useful information is a very important content in time series analysis [6, 7].

The innovation of this paper: the innovation of this paper is mainly in the way of comparison, according to the forecast results of inflation to analyze and compare the pros and cons of the model's predictive ability. In this paper, the sample time period is divided into 12 small sample intervals according to the rolling method and iterative method, and the EEMD model is used for inflation prediction analysis for each small sample interval. In the small sample interval obtained by the rolling method, the number of samples contained in each sample interval is the same, but the historical periods at the beginning and end of each small sample interval are different. In the small sample interval obtained by the iterative method, the initial period of the historical period of each sample interval is the same, but the end period is different, so the number of samples in each small sample interval is different. Such a sample division allows for a more comprehensive comparison of inflation forecasting models.

Chapter arrangement of this paper: Chapter 1 introduces the research on EEMD model and inflation forecasting; Chapter 2 introduces the development and basic theory of ensemble empirical mode decomposition and tests the IMF unit stationarity of EEMD model. The third chapter conducts data analysis experiments on inflation index based on the EEMD model; the fourth chapter summarizes the full text.

2. Related Work

As a new time series analysis tool, the empirical mode decomposition method has been applied in many fields and achieved good results. Starting from the related research and analysis of the empirical mode decomposition method, this paper expounds the research status of the EMD method from the perspective of theory and application.

Inflation is a time-honored topic in economics. Inflation has become a concomitant of human social and economic activities since money was used as a general equivalent for the exchange of goods [8]. Kim studied the performance of stocks in different industries at different stages of the economic cycle and believed that the existence of the economic cycle is conducive to the implementation of industry rotation investment strategies [9]. Franses studied the correlation between the financial and economic cycles in 44 countries from 1960 to 2010. The results show that there is a certain correlation between the economic and financial cycles at different stages, especially when the economy is in recession. The conditions caused by the bursting of real estate and stock price bubbles were longer in duration and farther-reaching than other recessions [10]. Lanne and

Luoto analyze the relationship between economic operation, stock market fluctuation cycle, and industrial development and believe that the development of the industry determines the cycle of economic operation, and the adjustment of the economic cycle is transmitted to the stock market through changes in related industries, thereby affecting the return on financial assets. The stock market fluctuates with the change of the economic trajectory [11]. Espinosatorres et al. use the DCC method to study the relationship between the stock market cycle and the macroeconomic cycle. Through empirical research on the data from 1996.01 to 2010.12, it is found that the volatility of the stock market has a dynamic and time-varying correlation with economic and financial cycles. It is positively correlated during the investigation period. In the economic trajectory of different stages, the correlation coefficient between the cycle of the stock market and the cycle of finance and the real economy is different, reflecting the characteristics of bull and bear markets in different stages. In addition, they also found that the level of dynamic correlation between the up and down cycle of the stock market and the economic cycle is gradually strengthened [12]. Using the stock market and macroeconomic variables from 1999 to 2009, Yang and Guo establish a simultaneous equation model for the return of stock index and macroeconomic variables and empirically analyze the relationship between the return of the stock market and the fluctuation of macroeconomics. The results show that the stock investment return can be used as a leading indicator in the recovery stage of the economic cycle and the pre-prosperity and middle stages, that is, the upward stage of the economic cycle has a certain correlation with stock returns [13]. Kurihara uses the causality test method to empirically test the causal relationship between money supply, economic growth, wage costs, and inflation [14]. McGurk uses the causality test method to analyze the relationship between inflation and economic growth. It is concluded that inflation hinders economic growth. Because they did not test the stationarity of inflation macroeconomic data, they directly used nonstationary time series data to model and analyze, so the conclusions they got were not scientific enough. In recent years, a very small number of scholars have used modern econometrics for empirical research on inflation [15]. Gilenko and Smelkov examined the data of 110 countries and came to the conclusion that the inflation rate and the money supply are related to each other. Changes have a very strong correlation, the correlation coefficient is between and almost close to, and in the long run, the increase in the money supply will eventually lead to the same degree of inflation [16]. Zhu and Peng examined the effects of deficit, financial system variables such as the degree of central bank independence, the degree of financial market development, and the growth rate of money supply on inflation. Countries: the inflation effect of deficit is more significant. It proves that inflation in Slovakia is mainly affected by foreign prices, exchange rates, and wages. The impact of money supply on inflation is direct and rapid, and the impact of interest rates on inflation is moderate but gradual. Scholars have conducted theoretical discussions on inflation [17]. Wang et al. made an in-depth theoretical analysis of the inflation problem and formed the first monograph to systematically analyze the inflation problem in the socialist economy [18]. Beckers started from the actual situation, and while absorbing the foreign inflation research results, he deeply discussed and analyzed the inflation problem. Generality and specificity of inflation: they made a detailed discussion on the causes of inflation, the relationship between economic system and inflation, and governance and achieved certain research results. However, most of these literatures describe it from a qualitative perspective, and few systematically use quantitative analysis [19]. Nyonit used the method of combining econometrics and input-output analysis, extended linear expenditure system to analyze the total amount and structure of inflation, and established a quantitative analysis model of inflation [20]. In the study of Qiao et al., the Granger causality test method for the driving factors of inflation is analyzed, and a regression equation is established, and it is concluded that currency circulation, fixed asset investment, consumption, wages, and savings all play a role in promoting inflation [21]. Castillo et al. uses multiple regression analysis methods to establish a measurement of economic model, and the system investigates the impact of major economic factors on inflation [22].

Since the relationship between inflation and the economy is quite complex, the multivariate model is more reasonable than the bivariate model. In the study of causality, a cointegration test should be carried out. Once a cointegration relationship between variables is found, the cointegration relationship should be calculated as the form of error correction term is incorporated into the model; otherwise, the model will be imperfect. Therefore, it is very urgent to use the ensemble empirical model to systematically examine the main economic factors that affect inflation, to explain their influence on inflation, and to accurately analyze the causes of inflation.

3. Relevant Theoretical Basis

3.1. Bayesian Model. Inflation forecasting is a complex process, including major steps such as economic preprocessing, economic representation, feature selection, classification model design, and performance evaluation. The core of which is the design of classification model, which has the greatest impact on inflation forecasting performance, followed by feature selection. After determining the classification idea and implementation method of the component model in the ensemble, let us analyze how to create more component models and add them to the classifier ensemble, so as to use the complementarity and difference between members to improve the ensemble's ability to understand different languages. Economic adaptability: most of the traditional classification models are only for specific languages and require word segmentation preprocessing. The main reason for the confusion of the EMD algorithm pattern is the discontinuity of the sequence. At the same time, the discontinuity also causes some IMF components to lose their specific physical meaning. First, the intermittent test relies on subjective judgment to a certain extent, and the determination of the intermittent point depends on the experimenter, thus affecting the results of EMD decomposition. In this paper, we apply the classifier ensemble framework to the Bayesian model and propose a language-independent Bayesian ensemble classification model. Each classifier in the model is composed of a combination of N-Gram and a naive Bayesian model. The local conditional probability constraints provided by the order N-Gram model generate differential component models. Based on this, we apply it to the classifier ensemble framework and propose a new ensemble mode and adaptive ensemble method, which utilizes the performance differences of the models on different economic sets to realize the combination of the classifier selection method and the classifier fusion method. Organically combined judgments made on the significance of parameters under the assumption that a single model is correct are almost always wrong under the method. Therefore, the explanatory power of all explanatory variables to inflation cannot be judged by the statistics calculated by a single model.

3.2. EEMD Decomposition Theory. Although the EMD decomposition method can adaptively decompose the signal into different frequencies, if the time series does not fully conform to the definition of white noise, some frequency scale components may be found, resulting in mode confusion, that is, one IMF component contains other different A signal sequence of frequencies or a sequence of frequencies appearing in multiple IMF components. Since most of the data in the real world contains noise, the pattern confusion cannot be completely eliminated in the EMD algorithm, which is also a defect of the EMD algorithm. Subjective measures are feasible only when the order is clear and the specific time scale is; otherwise, intermittent testing has limited effect. Therefore, in order to overcome the above drawbacks, an ensemble empirical mode decomposition method, EEMD, is proposed. The decomposition principle of EEMD is to use the uniform frequency distribution characteristics of white noise sequences. When white noise is added to the time series, the distribution characteristics of the extreme points of the low-frequency components of the sequence will change, so as to ensure that the average value of the upper and lower envelopes of the sequence can be accurately obtained, and the average value of multiple decompositions will be used as the actual IMF sequence. This approach also avoids the shortcomings of prior judgment in intermittent testing [23]. The basic idea of empirical mode decomposition is actually to convert a signal with irregular frequency into the form of multiple single-frequency waves plus aftermath. The essence of the EMD method is to obtain intrinsic fluctuation patterns through the characteristic time scale of the data and then decompose the data. This decomposition process can also be vividly called a “screening” process, and it can be demonstrated that the EMD decomposition is complete and orthogonal.

Since the added white noise obeys a uniform distribution in the time-frequency range, although different white noises are added in each uncorrelated experiment, since the decomposition step finally obtains the IMF component by averaging multiple experiments, the final experiment noise will be removed when averaging is obtained. It should be noted that the additional noise signal is not unlimited, and the amplitude value of the noise signal should be fixed, so that various signal sequences are classified into the corresponding IMFs, so that the average value of the obtained data is closer to reality. The adaptive white noise method should satisfy the following equation:

$$0 < \alpha < \frac{\varepsilon}{2}. \tag{1}$$

The ε is the ratio of the amplitude standard deviation of the highest frequency IMF after the sequence EMD decomposes. Through the endogenous variables to construct the lag value of all endometric variables of the system, it is estimated that the dynamic relationship between endogenous variables is to achieve the effect of “letting the data yourself.” EEMD model expression is shown in (2).

$$X_t = \alpha_1 \sum \Phi_{1t} X_{t-p} + \sum H_{1t} Y_{t-p} + \varepsilon_{1t}, \tag{2}$$

$$Y_t = \alpha_1 \sum \Phi_{2t} Y_{t-p} + \sum H_{2t} Y_{t-p} + \varepsilon_{2t}. \tag{3}$$

Before the parameter estimation of the EEMD model, the appropriate lag order must be determined. When the determined value is determined, on the one hand, it is desirable to eliminate the autocorrelation in the error term, so that the dynamic characteristics of the system are completely reflected, but if excessive, it will result in excessive parameters that need to be estimated and reduce the freedom of the model, which affects the validity of parameter estimation. When determining the lag step, the method that is often used includes the LR test, AIC information guidelines, and SC information guidelines.

The LR test method sets the original hypothesis to be in the lag of rear step $p = i$, the coefficient matrix element is 0, then the x^2 statistic LR is constructed from the maximum hysteresis step, and the critical value of the statistic and 95% confidence is compared. When $x^2_{0.05} > 0$, reject the original hypothesis, indicating that the lag scale can significantly increase greatly; otherwise, it will accept the original hypothesis. Decrease a lag number each time until the rejection is the original hypothesis. SCI is also known as BIC Guidelines; AIC Guidelines and BIC Guidelines are as follows:

$$\mathrm{AIC} = \frac{-2l}{T} + \frac{2n}{T}, \tag{4}$$

$$\mathrm{SC} = \frac{-2l}{T} + \frac{n \ln T}{T}. \tag{5}$$

In the EEMD model, the time series in the equation must be smooth, so the stability of the variable is required to be tested when modeling. The most common method of testing time series is the unit root test, and the unit root inspection includes the ADF method as shown in the following equation:

$$\Delta X_t = \delta X_{t-1} + \sum_{i=1}^{m} \beta_i \Delta X_{t-i} + \varepsilon_t. \tag{6}$$

Suppose zero assumptions in the test $\delta = 0$, that is, one unit root, 1. Check the statistical to measure whether to distribute from the ADF, when the test is rejected, a false holiday H. The original time sequence does not exist in unit roots, it is a smooth sequence, and the test is stopped; otherwise, the model is continued to be 1.

This chapter uses EEMD to decompose fluctuations in inflation different frequency domains. EEMD decomposition is performed on inflation, and the IMF components of different frequency domains are obtained, and the angle of three indicators of Pearson correlation coefficients is evaluated by the average cycle and the point of variance. The IMF is divided into high frequency, low frequency, and trend components according to the frequency domain, and its economic significance is explained. Further, for the low-frequency and high-frequency components of inflation, an appropriate model is established to analyze its influencing factors. The specific idea is shown in Figure 1 below.

Inflation as a macroeconomic phenomenon, and it reflects the general price level rather than a single commodity price change, thereby producing how to measure inflation. To this end, it is necessary to solve the following two questions, how is the price index of general price levels from individual commodities and services? Which price index can be more appropriately measuring inflation? From the statistical point of view, the main principle of choosing the price index is in addition to accuracy, and there is easy understanding, simple, sensitivity, and easy access to the right. Due to the complication of the "ideal index," it is more difficult to obtain the current weight data required to obtain the resort price index calculation, and therefore, widely used is a lass price index and its modified weighted average index. In recent years, many economists have proposed some new methods such as social monetary circulation measurement methods, monetary purchase force measurement, and currency supply and demand measurement, but they cannot accurately calculate money supply and demand. Gaps and currency flow speed: to objectively reflect the changes of inflation, the indicators selected should meet three conditions. First, it is necessary to reflect the reality of the market economy, and in line with the international general practical practice, it is conducive to the international exchange and comparison, and three is to have operation. Sexuality and timeliness can meet the needs of short-term macroeconomic regulation goals. Based on the above three points, many economists believe that choosing as an inflation metric indicator is relatively appropriate.

Inflation caused by changes in aggregate demand is called demand-induced price increases, and aggregate demand is greater than aggregate supply, resulting in a continuous and significant increase in prices. Fluctuations in government spending, investment, and net exports all have an impact on aggregate demand, driving output growth beyond potential productive capacity. Demand-pull inflation occurs when aggregate demand grows faster than the economy's potential productive capacity. Prices will rise so that aggregate demand and aggregate supply are in balance. If the quantity of money increases, the aggregate demand will increase but will not lead to an increase in prices; when the economy reaches a state of full employment, if the quantity of money increases, the aggregate social demand will increase, which will lead to an increase in prices.

3.3. IMF Test Results. The EEMD method has been widely used in various fields for its excellent performance in solving model uncertainty problems. The typical practice of people analyzing data is to select the optimal model among many models and then make statistical inferences under the optimal model. Choosing the optimal model means abandoning the "suboptimal" model. The problem of information loss caused by abandoning the "suboptimal" model is called the model uncertainty problem, which makes the statistical inferences made under the optimal model credible. The reduction of its degree cannot be ignored.

There are many factors that affect inflation, but because many factors overlap each other, and in order to reflect the main economic factors that affect inflation, it is necessary to select several representative ones from many factors. Taking all factors into consideration, this paper selects the index, broad money, the total investment in fixed assets of the whole society, the average salary of employees, and foreign exchange reserves as the main variables that affect inflation, and many other factors that affect inflation will be treated as random factors. The data are derived from the ten-year change of a certain database. According to the test principle, the software is used to test the stationarity of each logarithmic value and the difference series, respectively. The Akaike information criterion is used to determine the lag order in the test process, and the results are shown in Figure 2.

The test results in Figure 2 show that in the sample period, using the unit root test method, the EEMD series cannot reject the unit root process at the 10% significance level, that is, they are all nonstationary time series; in its first-order difference series, the unit root process can be rejected at the 10% significance level, the unit root process can be rejected at the 5% significance level, and the unit root process cannot be rejected at the 10% significance level. The series is stationary at the 1% significance level, while A can reject the unit root process at the 5% significance level.

When testing each variable IMF, the modified lag window uses the Bartleet window. The test results are shown in Figure 3.

The test results in Figure 3 show that in the sample period, using the IMF unit root test method, the sequence cannot reject the unit root process at the 10% significance level, that is, it is a nonstationary time series; in its first-order difference sequence, the unit root process cannot be rejected even at the 10% significance level, the unit root process can only be rejected at the 10% significance level, and the sequence can reject the unit root process at the 5% significance level: in its second-order difference, the series is stationary at the 1% significance level, while the unit root process can be rejected at the 5% significance level.

4. Construction of Inflation Forecasting Model

4.1. Data Indicator Processing. EEMD is a sequence generated by displaying a certain parameter value in historical order. The

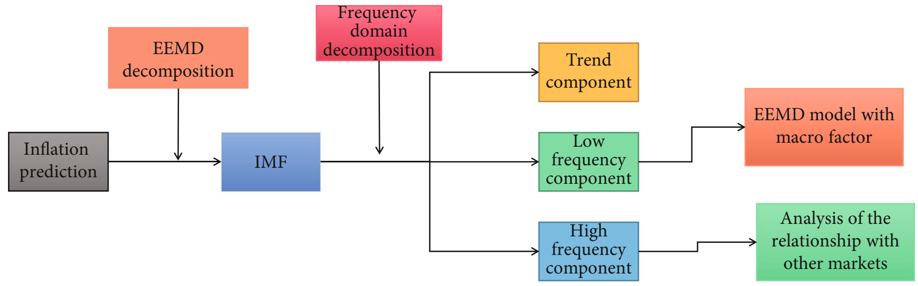

Figure 1: EEMD decomposition of inflation.

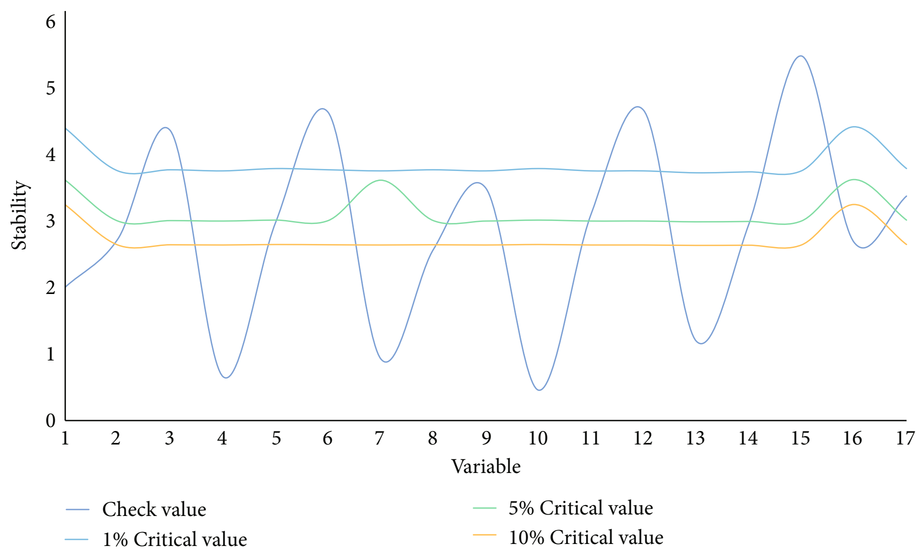

Figure 2: EEMD unit stationarity test.

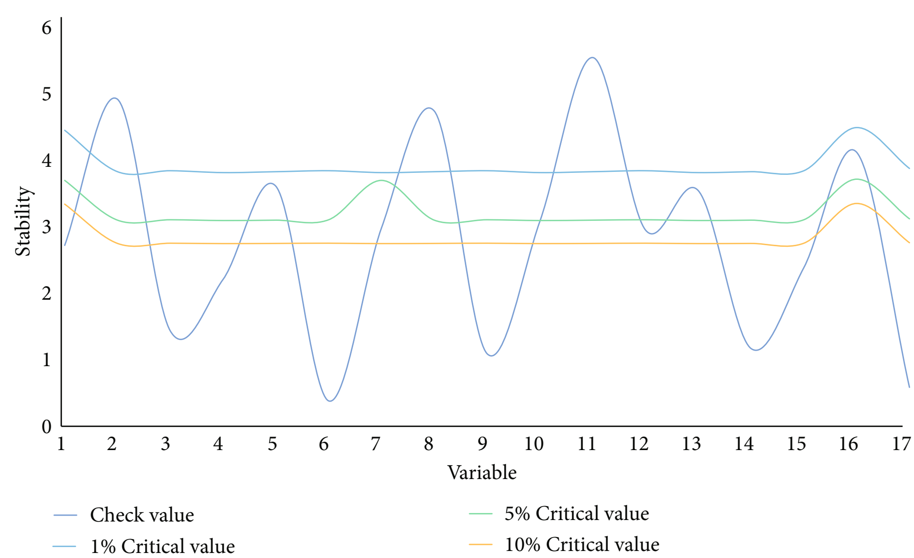

Figure 3: IMF unit stationarity test.

time series estimation method refers to constructing and studying the series and then inferring or expanding the evolution process and trend of the series to estimate the level that can be reached in the next time period or the next few years.

Exponential smoothing is usually used for time series with no significant trend changes or time series with long-term trends but frequently changing short-term trends. EEMD automatically tracks changes in the data and continually adjusts its

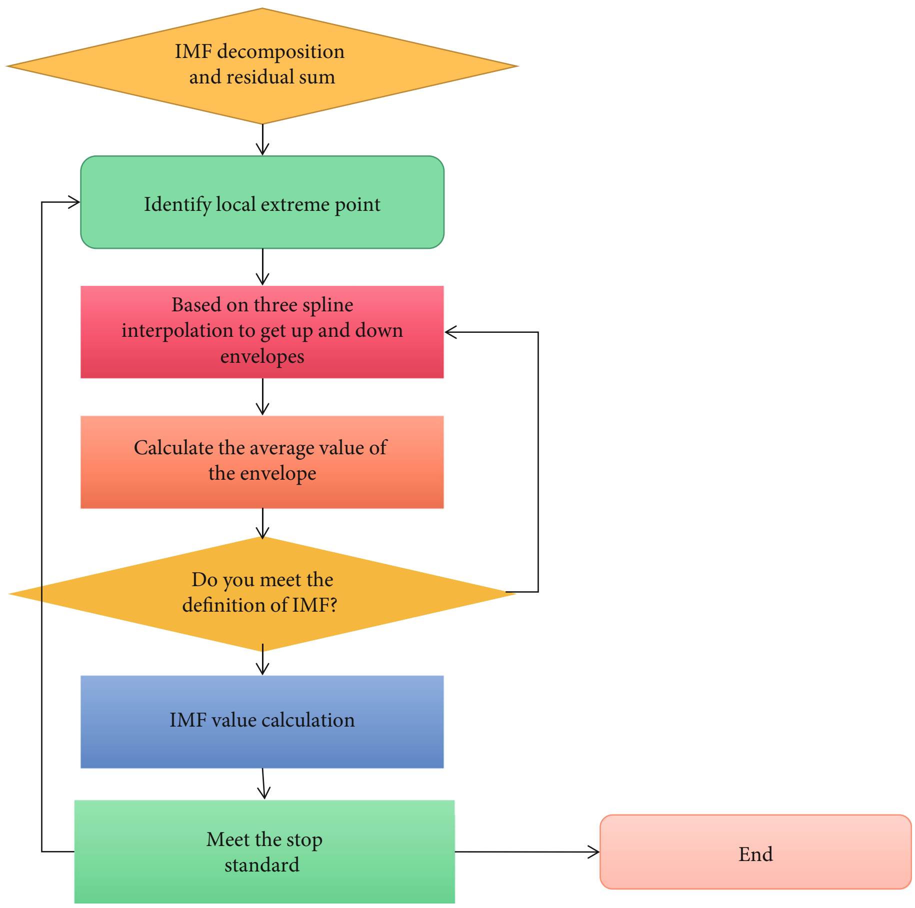

FIGURE 4: Data indicator processing flow.

approach to estimating short-term trends contained in the series. The data flow is shown in Figure 4.

The premise of using EEMD is that the trend of time series is stable and regular, so it can accurately predict the future situation. The most recent data can better reflect the regularity of the time series trend than the old data, so a larger weight should be set on the recent data. This method has more advantages than the simple average method and the moving average method. It not only considers the past data but also assigns different weights according to the time distance of the data, and the prediction accuracy is very high.

4.2. Stationarity Test. The EEMD stability is the basis for building the model. If the EEMD is unstable, the model must be built to meet the requirements of stationarity through differential operation. Therefore, we must first check the stationarity of the series. This paper adopts the method of combining the autocorrelation function test method and the unit root test method to test the stationarity of the time series. Since we selected monthly data, we chose a lag of 12. The sequence available through software operation is shown in Figure 5.

From the autocorrelation function diagram of the time series, it can be seen that the histogram does not change to 0 quickly with the increase of the lag order, and the following conclusions can be drawn: EEMD is not a stationary series, and the model construction cannot be started. If the original sequence is not stable, but the sequence obtained after the difference operation of different orders is stable, so do a difference operation on the sequence and check the autocorrelation function after the difference operation again; the result is shown in Figure 6.

From the ADF test results of the time series in Figure 6, it can be concluded that in the null hypothesis, the time series has a unit root, that is, the series is not stationary. The significance test result of its unit root is 0, and the absolute value of AC is greater than the absolute value of 1%, 5%, and 10% level, indicating that the null hypothesis is rejected at 1%, 5%, and 10%. Therefore, the time series is a stationary series, and an EEMD model can be established.

4.3. EEMD Model Prediction. The above has verified that the model EEMD is reasonable, so it can be used to estimate short-term inflation. Since we want to predict the inflation level of a certain place for one year, we must first expand the sample interval, use the EEMD function to obtain the prediction result, and obtain the comparative analysis of the predicted value and the actual value at the same time as shown in Figure 7.

By comparing the predicted value and the actual value, it can be seen that the prediction effect of the EEMD model is

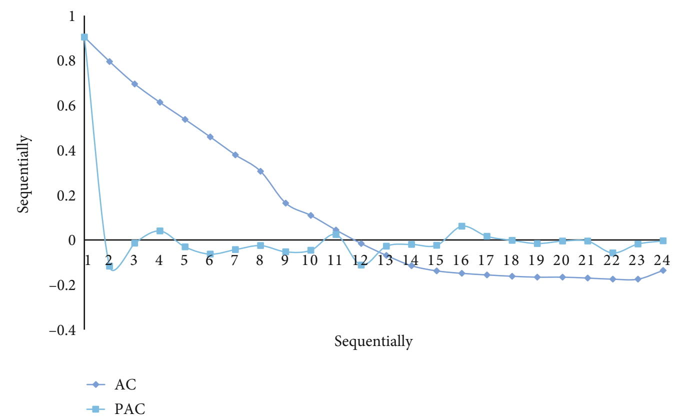

Figure 5: Time series autocorrelation function.

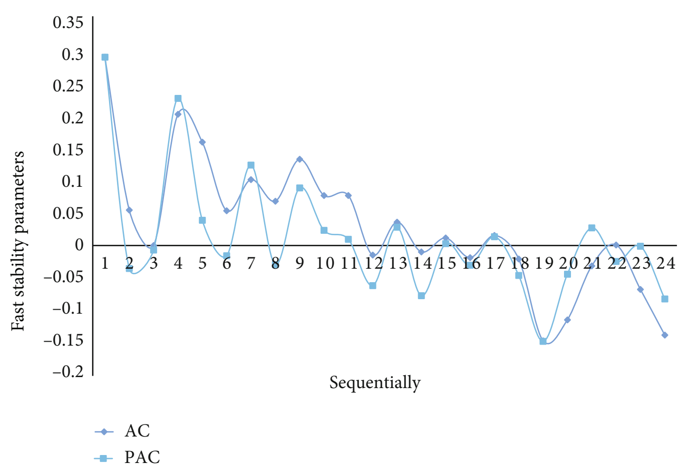

Figure 6: Autocorrelation function after the first-order difference of the sequence.

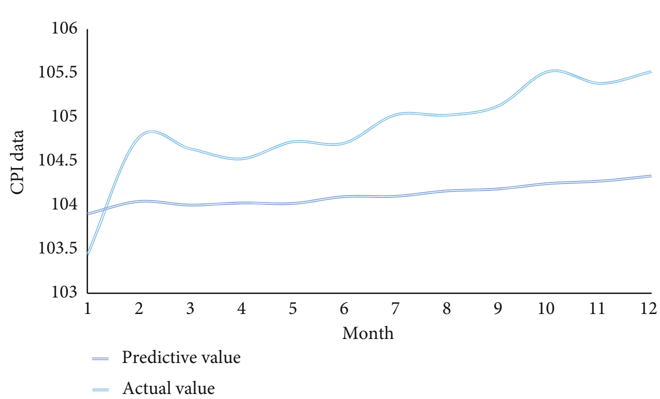

Figure 7: Comparison of prediction results.

better, and the predicted value is relatively close to the actual value, which has theoretical and practical significance.

4.4. Model Comparison. According to the steps of sample interval modeling, models are established for different time sample intervals. In the real model construction, it is generally desirable that the lag period is very large, so that the fluctuation of the model can be fully represented. However, if the lag period is relatively long, the variables that need to be estimated in the model will increase, and the degrees of freedom will decrease. Therefore, it is necessary to find a balance between hysteresis and degrees of

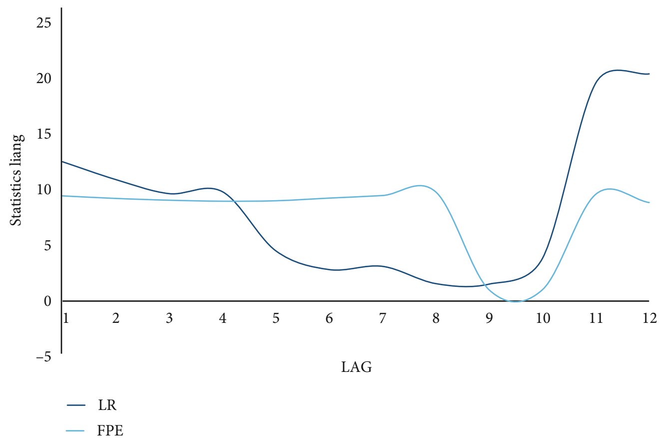

Figure 8: Judgment result of lag order.

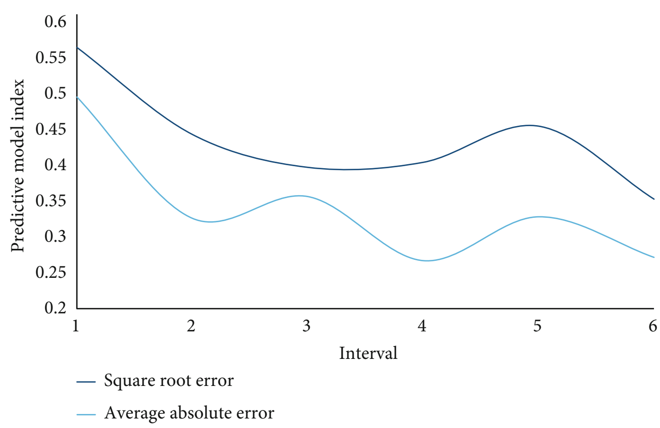

Figure 9: Prediction model index comparison chart.

freedom. In the EEMD model, the LR test statistic, the final prediction error FPE information criterion, and the results are provided, and the maximum lag order of the model can be obtained. Since we select monthly data, the maximum lag order of the input model to be investigated is 12, and the comparison results of the actual inflation value and the predicted value in each sample interval are shown in Figures 8 and 9.

It can be seen from Figures 8 and 9 that the prediction results obtained by EEMD prediction for sample intervals of the same length and different time starting points have no obvious regularity, but the root mean square error can be kept within 60%. The prediction results obtained by EEMD prediction are better as the length of the sample interval increases.

5. Conclusions

Inflation is the most important research topic in monetary economics. It is necessary for economists to study inflation in depth. It is also an important economic indicator closely related to people's livelihood. It is related to the vital interests of the people. This paper uses the Bayesian model method EEMD model to study inflation for forecasting. The study finds that the first-order lag of inflation, the growth rate of industrial added value, and currency can significantly affect the inflation rate, which can undoubtedly provide theoretical support for policy-making departments to manage inflation expectations. The advantages of Bayesian models and methods in forecasting can provide certain reference for decision-making departments. In order to take advantage of the theoretical advantages of Bayesian model method, improve the accuracy of out-of-sample inflation forecast, and reduce the forecast error, it is necessary to synthesize more complex models such as nonlinear models in future research. The uncertainty of the model and parameters and the comprehensive and effective use of information are the main factors that affect the prediction accuracy of macro variables. Use the EEMD model method to model and forecast out-of-sample inflation, integrate information from alternative models and variables to control model uncertainty, and effectively utilize abundant macro data information. The sample interval it targets is January to December, which is the longest sample interval obtained by the iterative method. While proving the previous conclusion, it can also be seen that the LR value has a large lag order, which means that inflation has a long lag period. This echoes the lag of monetary policy, and it will take a long period of time for macroeconomic policy adjustment and control to achieve the goal of adjustment in response to the current inflation situation. If the forecast accuracy of inflation can be improved and the relevant monetary policy can be formulated according to it, the current situation of monetary policy time lag can be improved. At the same time, it also helps to accurately guide the market operation and the public's expectation of inflation and achieve the ideal result of improving the effectiveness of monetary policy.

The standard for comparing the pros and cons of prediction models is relatively simple. Only the FPE of the EEMD model was compared, and other statistical-based model prediction comparison methods were not considered. Only the EEMD model including the variable LR fixed-base price index and broad money supply is aligned with the nominal effective exchange rate including the variable LR fixed-base price index and broad money supply. The number of variables involved is relatively small, and the comparison method has certain limitations.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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