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A Hybrid Neuro-Fuzzy Model to Forecast Inflation

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Abstract

One of the key issues in constructing monetary policy is accurate prediction of the inflation level. The complex behavior and non-linear nature of the financial markets makes it hard to forecast the inflation rate precisely. This paper introduces a hybrid model that attempts to forecast the inflation rate with a combination of a subtractive clustering technique and a fuzzy inference neural network to overcome the shortcomings of the individual methodologies. Selected macroeconomic factors were used to predict the historical CPI data from the US Markets. The results of the proposed hybrid model are measured in RMSE.

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Keywords: Consumer Price Index; Inflation, Fuzzy Inference Neural Networks; Regression Analysis

1. Introduction

There are a vast number of studies dealing with the analysis and forecasting of various macroeconomic and financial activities, such as stock market and interest rate forecasting, and exchange rate prediction. Recently, various stakeholders, including academic researchers, governments, and financial institutions have started to pay special attention to the prediction of real economic activity, particularly, inflation rates, after the significant influence of the global recession of 2008. The possibility to forecast the future level of inflation rates with suitable publicly available information, such as reports and data provided by central banks or financial institutions, is the main driver for this research. Inflation is one of the central terms in macroeconomics as "it 1) harms the stability of the acquisition power of the national currency, 2) affects the economic growth because investment projects become riskier, 3) distorts consuming and saving decisions, 4) causes an unequal income distribution and 5) causes

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difficulties in financial intervention" [1]. As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values [2]. To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability. The remainder of the paper is structured as follows: Section 2 provides a review of the literature in this area. Section 3 introduces the importance of the Consumer Price Index (CPI) and the purpose of the research. Section 4 provides a general description of the proposed methodology and shows the results for the various phases of the proposed model. Concluding remarks are discussed in Section 5.

2. Literature Review

The survey of the literature reveals that researchers apply various forecasting approaches to model the inflation prediction. Stock and Watson [3] categorize these inflation forecasting techniques into four groups: (1) forecasts based solely on past inflation; (2) forecasts based on activity measures ("Phillips curve forecasts"); (3) forecasts based on the forecasts of others; and (4) forecasts based on other predictors. The first group of forecasts based solely on past inflation includes the implementation of the ARIMA models and time-varying univariate models. Stock and Watson [3] examined the results of the three prototypes from this family of models: the first prototype model is the direct autoregressive (AR) forecast, computed using the direct autoregressive model; the second approach is random walk model suggested by Atkeson-Ohanian [5]; and the last model is the Stock-Watson [4] unobserved components-stochastic volatility (UC-SV) model. The second group of inflation prediction models that use Phillips curve forecasts include various approaches such the Gordon [6] model, where the inflation depends on lagged inflation, the unemployment rate and supply shock variables, and the direct version of Gordon [6] without the supply shock variables, specifically, the autoregressive distributed (ADL) lag model in which forecasts are computed using the direct regression. The third group refers to inflation predictions from the inflationary expectations of others. These forecasts include regressions based on implicit expectations derived from asset prices, such as forecasts extracted from the term structure of nominal Treasury debt (which by the Fisher relation should embody future inflation expectations) and forecasts extracted from the TIPS yield curve [3]. The fourth group, that include inflation forecasting approaches, includes prediction with fundamental variables such as money aggregates, industrial production variables, and other financial and macroeconomic variables. Ang et al. [7] examined also the prediction ability of further forecasting approach families such as non-linear models and the combination of the various forecasting techniques. They conducted a comprehensive analysis of different inflation forecasting methods using four inflation measures and two different out-of-sample periods (post-1985 and post-1995).

3. Research Purpose

The goal of this research is to seek a model or system that can predict the change in CPI level precisely with the use of a minimum number of input variables. A review of the literature in the area reveals that various techniques and methodologies have been implemented to predict financial and economic activities. This is particularly true of inflation rates. Due to the non-linear and complex nature of the inflation rate data, the non-linear models appear to provide more precise results [8]. One approach that can be used to deal with complex real-world problems is to integrate the use of artificial intelligence technologies with neuro-fuzzy techniques in order to combine their different strengths while overcoming a single technology's weakness. Such hybrid models often provide better results than the ones achieved with the use of each technique in isolation [9]. Considering the dynamic, non-stationary, and complex nature of the CPI data, along with its uncertain environment, innovations in forecasting methodologies and improvements in prediction accuracy performance, researchers may prefer soft computing techniques in general, and more recent neuro-fuzzy techniques in particular, over standard qualitative and linear quantitative models in order to achieve more accurate calculations. The purpose of this study is to forecast the change in Consumer Price Index of the next period by applying the use of a Fuzzy Inference Neural Network.

4. Methodology and Results

The following research introduces a hybrid fuzzy model to predict the future changes in Consumer Price Index using fundamental factors (see Figure 1). The first stage involves analysing the existing literature in this area to generate a list of candidate macroeconomic and financial variables, and then choosing the most widely used variables. Otherwise, using all candidate input variables leads to high computational costs, thereby negatively damaging the preciseness of the results. At the second stage of the proposed hybrid model, the subtractive clustering algorithm was used to identify rules. In the final stage of the model, the rules generated from the previous stage are provided as inputs to the Fuzzy Inference Neural Network with the goal of forecasting the change in CPI prices for the following period. In the next subsections, these individual steps are discussed in detail.

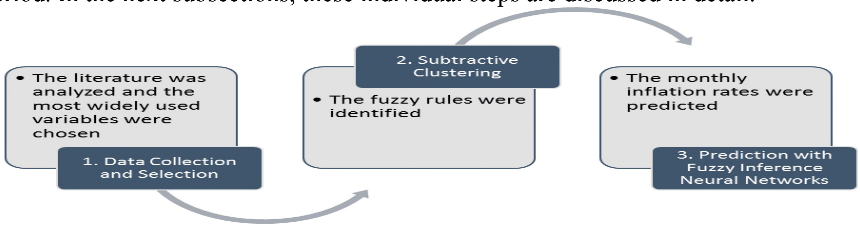

Fig. 1. The stages of the proposed model.

4.1. Data Collection

In this stage of the proposed hybrid model, relevant past research is analysed to determine possible variables for CPI prediction. Recent research suggest that various macroeconomic and financial variables have the ability to predict the future consumer price index, however, the empirical evidence is mixed and results are not robust with respect to model specification, sample choice, and forecast horizon [10].

Stock and Watson [11] investigate forecasts of the U.S. inflation rate at a 12-month horizon and suggest that these forecasts can be improved by using a generalized Phillips curve based on measures of real aggregate activity other than unemployment, especially when a new index of aggregate activity is based on 61 real economic indicators. Somaratna et al. [8] selected the Gross Domestic Product and the Money Supply Rate to represent supply-side factors, the Treasury Bill Rate value to represent demand-side factors, and the Foreign Exchange rate value to represent external factors for CPI prediction.

Kooths et al. [12] used the time series of oil price changes from the World Market Monitor (WMM), the ECU/US$ nominal exchange rate, and the change in energy prices, as well as the Bundesbank's inflation objective to forecast the future inflation rates. Forni et al. [13] used a large data set consisting of 447 monthly macroeconomic time series concerning the main countries of the Euro area to simulate out-of sample predictions of the euro area industrial production and the harmonized inflation index to evaluate the role of financial variables in forecasting. In our study, seven most widely used variable were chosen as input variables, including Industrial Production Index, Producer Price Index, M1 Money Stock, M2 Money Stock, 10-Year Treasury Constant Maturity Rate, Japan / U.S. Foreign Exchange Rate, and Moody's Seasoned Aaa Corporate Bond Yield for predicting the future U.S. CPI values. The data cover the period from January 2000 to January 2014, for a total of 169 data points.

4.2. Forecasting with Combination of Subtractive Clustering and Fuzzy Inference Neural Networks

4.2.1. Subtractive Clustering

The rules generated from this stage are provided as input to the fuzzy inference neural networks. As it is complicated in our case to determine the rules manually, a clustering technique can be implemented for this purpose. In this paper the subtractive clustering technique was chosen. Zhimin et al. [14] summarize the algorithm for subtractive clustering as follows:

"For the characteristic vector (X_1, X_2, ., X_n) belonging to the m dimensional input space, the mountain function referring its data density can be constructed as:

$$D_i = \sum_{j=1}^{n} \exp\left[-\frac{\|X_i - X_j\|^2}{\left(\frac{a}{2}\right)^2} \right] \quad (1)$$

where D is the density, a is the adjacent field next to this point and a >0.
Supposing that $X_{c,k}$ is the clustering center at the k_{th} time and its density is $D_{c,k}$, the mountain function of each vector can be revised as:

$$D_i' = D_i - D_{c,k} \sum_{i=1}^{N} \exp\left[-\frac{\|X_i - X_{c,k}\|^2}{\left(\frac{\beta}{2}\right)^2} \right] \quad (2)$$

where N is the vector quantity left after k clustering, b is defined as the adjacent field that its density is reduced greatly and usually is equal to 1.5a. The similar process mentioned above will not be stopped until the following is satisfied" [14].

$$D_{c,k+1}/D_{c,1} < \sigma \quad (3)$$

4.2.2. Fuzzy Inference Neural Networks

Forecasting inflation rates using neural networks is not new research. There are already different studies dealing with the prediction of CPI levels for different countries. Moshiri and Cameron [15] have conducted research to compare the performance of neural networks with econometric models in forecasting inflation. McNelis and McAdam [2] conducted research to forecast inflation with thick models and neural networks. In our study we combine artificial neural networks with neuro-fuzzy techniques, producing a Fuzzy Inference Neural Network with five layers between the inputs and the defuzzified output (see Figure 2). A 5-layered Fuzzy Inference Neural Network has the following stages: "The first layer of the model consists of membership functions that map inputs to the fuzzy terms used in the rules. The second layer comprises nodes representing these rules. Each rule node performs the Min operation on the outputs of the incoming links from the previous layer. The third layer consists of output membership functions. The fourth layer computes the fuzzy output signal for the output variables. Finally, the fifth layer realizes the defuzzification using the center-of-gravity (COG) defuzzification technique." [16]. The fuzzy inference process can be described using the following steps [16]:

1. For each rule level of validity, define the preconditions

$$\alpha_i = \min_{j=1}^{n}[\max_{X_j}(A_j'(x_j) \wedge A_{ij}(x_j)) \quad (4)$$

where $A_j'(x_j)$ are new independent values of input variables

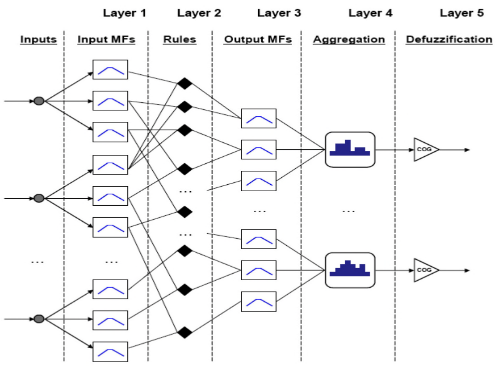

Fig. 2. The Structure of Fuzzy the Inference Neural Network

At this stage the degree of fulfilment (α_i) of the input for each rule is calculated (i) by considering the degree of membership (μ) [17].

2. For each rule calculate the individual outputs

$$B_i^{'}(y) = \min(\alpha_i, B_i(y)) \tag{5}$$

At this stage output fuzzy set B_i is derived for each rule using the minimum t-norm [17].

3. Calculate the aggregative output:

$$B^{'}(y) = \max(B_1^{'}(y), B_2^{'}(y), ..., B_m^{'}(y)) \tag{6}$$

Berkan and Trupbach [18] suggest that the result in the form of a fuzzy set is converted into a crisp result by the defuzzification process. In our case, the defuzzification was realized using center-of-gravity (COG) technique:

$$y = \int_s B(y) y dy \Big/ \int_s B(y) d(y), \tag{7}$$

where s is the support for the fuzzy set B(y) [17].

After selection of the input variables in the previous stage, the membership function for each variable is provided. Input fields of all variables have five fuzzy sets, including: "Very Low", "Low", "Medium", "High", and "Very High". All clusters of each input variable have Gaussian-type membership functions. The efficiency of the inference engine depends on the internal organization of the knowledge base. The fuzzy rules can express conclusions to be drawn by generalization from the qualitative information stored in the knowledge base with the natural language [19]. Mamdani implication was used to compute the individual output membership functions. Observing the relationship between the input and output clusters allows linguistic descriptions and production rules to be developed. The general form of the rule becomes:

IF x_1 is A_{11} and ….. x_n is A_{1n} THEN y is $B_{1;}$
…. …. ….
IF x_1 is A_{m1} and ….. x_n is Am_n THEN y is $B_{m;}$

where x_j=1…n are linguistic input variables, while A_{ij} and B_i are fuzzy sets. The graphical representation of the extracted fuzzy rules is given in Figure 3. The surface view of the relationship between the first two inputs and the output is shown in Figure 4. For the modeling, 70% of the data was used to train the Fuzzy Inference Neural Network, while the remaining 30% was used for testing purposes. A hybrid optimization method - the combination of least squares and the back propagation gradient descent method - was used for training. The number of training epochs was set at 10,000. The error was measured using the Root Mean Square Error (RMSE). The RMSE is defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - O_i)^2} \tag{8}$$

where S_i are the simulated values and O_i are the observed values. N is the number of testing samples.

An RMSE value of 0.837 was obtained when forecasting with the testing data. This result is compared with the average values of the inflation prediction models discussed in the paper by Stock and Watson [3]. The RMSE value for the post 2000 period was chosen in order to compare with our model. The results are introduced in the Table 1.

Table 1. The RMSEs of the inflation prediction model groups

Model	RMSE
Unobserved Components Stochastic Volatility	1.05
Univariate Forecasts (Mean of 16 Models)	1.37
Single-Predictor (Mean of 137 Models)	1.47
Triangle Model Forecasts (Mean of 4 Models)	1.34
Proposed Hybrid Model	0.829

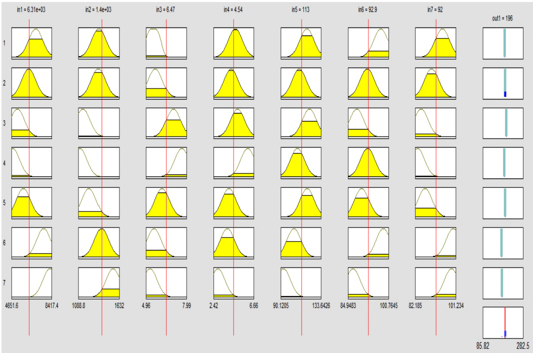

Fig. 3. Graphical Representation of the Extracted Fuzzy Rules for CPI Prediction

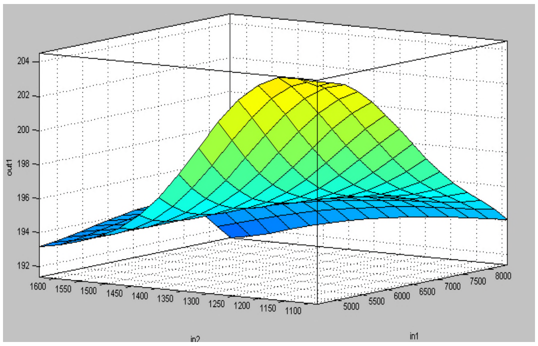

Fig.4. Example Surface View of Rule Relationship

For the selected period of time, the proposed hybrid fuzzy model outperforms other models. It is important to mention that these models yield different results for different periods. If we would compare the RMSE value of the proposed model for the post 2000 period with the performance of the unobserved components stochastic volatility model for period of 1993-2000, the later then outperforms significantly with RMSE=0.68.

5. Conclusion

In this paper, a hybrid neuro-fuzzy model with selected input variables has been developed for forecasting the U.S. inflation rate. Such a forecasting model is crucial for central banks and others that are influenced by inflation and other macroeconomic indicators. For the modeling, only the input variables with the strongest prediction ability were utilized. Extending the list of the candidate macroeconomic variables can be a subject of future research, possibly leading to more accurate results. The empirical experiments can also be repeated with other linear statistical or nonlinear methodologies in order to gauge the prediction ability of the proposed model. Prediction of the inflation rate in countries other than the United States can also be examined. Although the studies reveal that recently developed fuzzy techniques significantly outperform both traditional artificial neural networks and conventional statistical models, there are also some shortcomings with using individual fuzzy techniques. Lack of robustness in relation the topological changes of the system, which would demand alterations in the rule base and dependency on the existence of an expert to determine the inference logical rules, are typical disadvantages of neuro fuzzy systems [20]. In order to overcome the shortcomings and deal with the complex environment of the real economy, there appears to be promise in combining different artificial intelligence, fuzzy, and conventional statistical techniques with the goal of overcoming a single technology's weakness by relying on the combined strengths of the different models. Such combination of these techniques are called neuro-fuzzy systems. “A hybrid neuro-fuzzy system is a fuzzy system that uses a learning algorithm based on gradients or inspired by the neural networks theory (heuristic learning strategies) to determine its parameters (fuzzy sets and fuzzy rules) through the patterns processing (input and output)” [21]. In the proposed model the neuro-fuzzy model is supported with the data preprocessing technique, particularly regression analysis, in order to obtain more precise results by choosing appropriate input training data.

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