Forecasting Mexican Inflation using Neural Networks

Chávez-Hurtado, José Luis
Department of Quantitative Methods
CUCEA , University of Guadalajara
Guadalajara, Mexico

Cortés-Fregoso, José Héctor
Department of Quantitative Methods
CUCEA, University of Guadalajara
Guadalajara, Mexico

***Abstract*—In this work we use a Neural Network model to forecast Mexican inflation. Related works forecast inflation in countries where this economic variable has a stable behavior while Mexican inflation has been characterized to be very volatile during certain periods. There were implemented different Neural Network models by varying the number of hidden layers (1 and 2) and the number of neurons in the hidden layer (from 1 to 100). The forecasting model results were divided into 3 categories: a volatile inflation phase, where the mean difference was 0.64% between real inflation and forecasted inflation; a transition phase, where the mean difference was 5.44%; and a stability phase, where the mean difference was 0.28%. By doing a comparison between model forecasting results and Bank of Mexico's predictions, Neural Networks model results are clearly more accurate to the real inflation behavior, a critical point during inflationary crisis periods.**

Keywords—Inflation forecasting; Neural Networks.

I. INTRODUCTION

According to [1], the relative prices of goods and services are constantly changing: when a product becomes plentiful its relative value decreases but when the product's availability is insufficient its relative value increases. However, when the price of all goods and services increases and continues increasing it means that the economy is suffering inflation. To Bank of Mexico [2] inflation is considered an undesired effect because it: a) harms the stability of the acquisition power of the national currency, b) affects the economic growth because investment projects become riskier, c) distorts consuming and saving decisions, d) cause an unequal income distribution and e) causes difficulties in financial intervention. To avoid these effects one function of Bank of Mexico is to control inflation by using monetary policies. In order to design efficient policies it is important to have good forecasting tools whose purpose is to reduce the range of uncertainty when a decision is taken [3].

According to [4], the most common method to forecast inflation is the Auto Regressive model (AR), a linear model that reaches its limitations when working with non-linear time series like inflation. There are three works ([4], [5] and [6]) that made a comparison between Neural Network models (NN) and AR models and they found that NN models have a better accuracy in forecasting performance. Authors highlight the NN capability to identify and capture non-linear behavior of the macroeconomic series. However, these reviewed works have implemented NN models to forecast inflation in countries with a strong economic power where this variable never has had many variations (see fig. 1). Then, following the reviewed literature, the objective of this article is to implement a NN model to forecast and anticipate abrupt changes in the Mexican inflation.

This paper is organized as follows: in section 2 there is a quick revision about different NN models and their functionality; in section 3 we explain the methodology adopted to select the best NN model to forecast inflation. Section 4 shows the results obtained from the forecasting procedure and Section 5 mentions some conclusions made by the authors.

II. NEURAL NETWORKS

There are some tasks for which algorithms do not exist or for which is virtually impossible to write a number of logical steps to find the answer [7]. These kinds of tasks are far from the conventional computer programming capability; as an alternative neurocomputing is an increasingly popular new discipline where NNs are the main units. In [8] NNs are defined as a massively parallel distributed processor made up of simple processing units called neurons, which has a natural propensity for storing experiential knowledge and making it available for use. The neuron is divided into three basic elements:

- Synapses or connecting links, each one characterized by a weight (w) of its own.

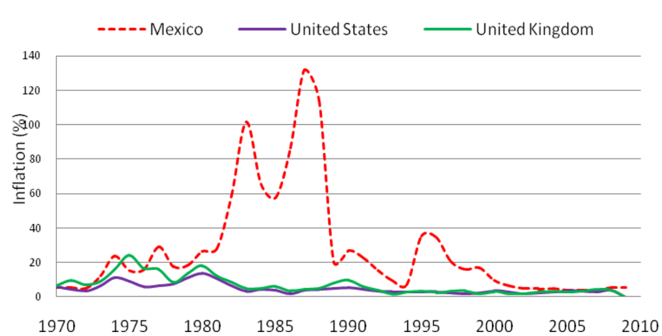

Figure 1. Annual inflation comparisson for three different countries. Most of the works made to forecast inflation have been done in countries where inflation has a stable behaviour (like United States and United Kingdom) while in Mexico inflation has been characterized to be a volatile variable.

- An adder, which sums the input weighted signals and a bias (b).
- An activation function (φ), which defines the NN behavior: a linear NN model is implemented by using a linear activation function while a non linear NN model is implemented by using a non-linear activation function.

The output value (y) for the neuron can be written like eq. 1, where *j* represents the number of inputs, *w* the synaptic connections, *x* the input variables, *φ* the activation functionand *b* the bias.

$$y = \varphi\left(W_j X_j + b\right) \tag{1}$$

The NN resembles the brain in two aspects [8]: the knowledge is acquired by the network from its environment through a learning process and the synaptic weights are used to store the acquired knowledge. [9] identifies two different general phases in the NN operation:

- Learning phase. Where the NN learns how to solve the desired problem by modifying its synaptic weights until a stop criterion is reached (commonly a minimum error value).
- Memory phase. During this phase the synaptic weights remain static and the NN can be used to determine the corresponding output to a new set of inputs (forecast).

The NN model is divided into layers: the simplest model (single layer model) has only two layers, the input layer and the output layer. More complex models (multilayer models) contain at least one hidden layer between the input and the output layer where the hidden layer contains at least one neuron. There is also a recurrent NN model which is designed with at least one feedback loop and can be, or not, designed with hidden layers. According to [4] and [7], a multilayer NN model with one or two hidden layers can approximate any kind of function by using the correct amount of data for its training.

Because there is no specification about the number of hidden layers and hidden neurons to use, the appropriate NN model must be found by modifying iteratively the number of neurons and layers and selecting the model with the best performance (least error during the learning phase). Based on [4], [5] and [6] a Multilayer Feedforward NN model will be implemented using the NN Toolbox from Matlab. The next section describes the methodology followed to design and select the NN model.

III. Methodology

The NN model design follows certain steps until the final model can be used to forecast inflation. The first step is to build the database which contains the input vectors and the target vectors. This database is used to train the NN. To determine the best NN model an algorithm is developed to vary the number of hidden layers from 1 to 2 and the number of neurons in the hidden layer from 1 to 100. The NN model with the least error during the training phase is selected to forecast inflation.

A. Database

One of the most important parts in NN implementation is the database, the larger the amount of data, the better the learning process will be. However, there are some variables where the amount of data is inherently limited. This is the case for the Mexican inflation which has been registered since 1970; it means that until 2010 there are only 40 annual observations. This small amount of data can affect the NN performance if it does not recognize a new pattern when forecasting inflation. In order to train the NN we used a database provided by the Bank of Mexico which contains monthly inflation, annual inflation and annual inflation expected according to inflation measured each month. January inflation is used as the input vector and annual inflation as the target vector. Expected inflation is used to compare NN results with the Bank of Mexico expectations.

B. NN model selection

As we mentioned before there is no standard NN model for each application; the number of hidden layers and hidden neurons in the NN model varies from one application to another, and even these specifications can vary for the same application when new data is added to the learning process. To test the ability of NN to forecast non – linear variables, the best NN model will be used to forecast annual inflation since the last inflationary crisis in Mexico which began in 1994. So database will contain annual inflation values from 1970 to 1993 and the selected NN model will be used to forecast inflation from 1994 to 2010. From the database, 70% of data will be used to train the NN and the remain 30% will be used to measure its performance according to the mean square error (MSE). The NN model with the least MSE will be selected to forecast inflation. The activation function used in the hidden layers was the hyperbolic tangent and the rest of the specifications were set to default Matlab values.

A simple algorithm was implemented to search the best NN model. It varies the number of hidden layers from 1 to 2, and the number of neurons on each layer from 1 to 50. Each implemented model was simulated 20 times to avoid local minima (a methodology proposed by [4]). It means that 2550 different models were implemented and 51,000 models were simulated. Simulation time was about 2 hours using a core i7 processor and 8 GB memory RAM. The model with the best MSE was a NN model with 1 hidden layer and 49 hidden neurons. This NN model was selected to forecast annual inflation.

C. Forecasting inflation

Once the best model was selected we used it in its memory phase to forecast inflation from 1994 to 2010. For the forecasting process we use the inflation measured in January, 1994, as the input vector. The simulated output is saved into a database to compare it later with Bank of Mexico's expectations. Once simulation is done we added to the database January inflation and real annual inflation for year 1994 and we trained again the selected NN model. When simulation is done we used inflation measured in January, 1995 as the new input vector to obtain the forecasting value for year 1995. This process was repeated until annual inflation for year 2010 was reached.

IV. Results

NN forecasting results can be seen on fig. 2 where we can distinguish three different phases on the NN forecasting performance:

A. Volatile inflation phase

Volatile inflation phase covers a period from 1994 to 1998 where Mexican inflation underwent an abrupt index change from 7.05% in 1994 to 51.97% in 1995, causing a new inflationary crisis. For this period the mean difference between real and forecasted inflation was 0.64%. This good forecasting performance can be a consequence of the NN learning process from previous inflationary crisis in Mexico.

B. Transition phase

Transition phase covers a period from 1998 o 2001 and is characterized by a steady reduction in the annual inflation value until it stabilizes. During this period the mean difference between real annual inflation and annual inflation forecasted by the NN model was 5.44%. This change in forecasting performance can be attributed also to the NN learning process: until 1998 we can considered that inflation in Mexico was always volatile (see fig. 1) and this could explain the inability of the NN to recognize a new set of patterns for an inflationary stable period.

C. Stability phase

Stability phase covers a period from 2001 to 2010 and is characterized by certain inflation stability. The mean difference between real annual inflation and inflation forecasted by the NN model was 0.28%. This mean difference is least than the obtained during volatile phase and could be a consequence of a bigger amount of data available for the simulation process. We also can conclude that the learning capability of the NN model allowed it to improve its forecasting performance once it learns a new set of patterns from the transition phase.

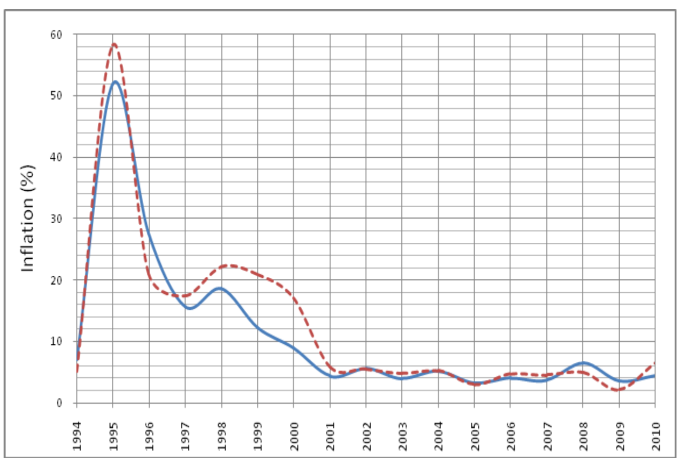

Figure 2. Annual inflation forecasted by the NN model implemented (dotted line) and real annual inflation in Mexico (solid line). From the results the NN performance can be divided into 3 phases: a volatile phase, from 1994 to 1998; a transition phase, from 1998 to 2001; and a stabiliy phase, from 2001 to 2010.

Bank of Mexico is the responsible to attenuate inflation effects in Mexico. Every month this institute estimates the possible value for the inflation at the end of the year. By using this information we compared the annual inflation value estimated by the NN model with the annual inflation estimated by Bank of Mexico for the same period. Results can be seen in fig. 3 and are explained according to the three phases described before.

A. Volatile inflation phase

The mean difference for the NN model was 0.64% while the mean difference for Bank of Mexico estimations was 198%. If we had the mean absolute error (MAE) the NN model error is 4.02% while the Bank of Mexico error is 16.05%. During this period there is the largest difference between the NN model forecasting results and the Bank of Mexico estimations, and also this was the most critical period due to the high inflation values.

B. Transition phase

The mean difference for the NN model was 5.44% while the mean difference for Bank of Mexico was -2.28%. When used the mean absolute error, the NN error was 5.45% and the Bank of Mexico error was 3.95%. Just in this phase the Bank of Mexico delivered a better estimation than the NN forecasting results, but as we say before, the performance of the NN during this phase was the worst.

C. Stability phase

The mean difference for the NN model was 0.96% while the mean difference for the Bank of Mexico estimations was -0.43%. When using the mean absolute error, the NN error is 0.96% and the Bank of Mexico error is 1.39%. Both errors are very similar but can be seen from fig. 3 that NN model follows the inflation behavior while the Bank of Mexico estimations follows an opposite one.

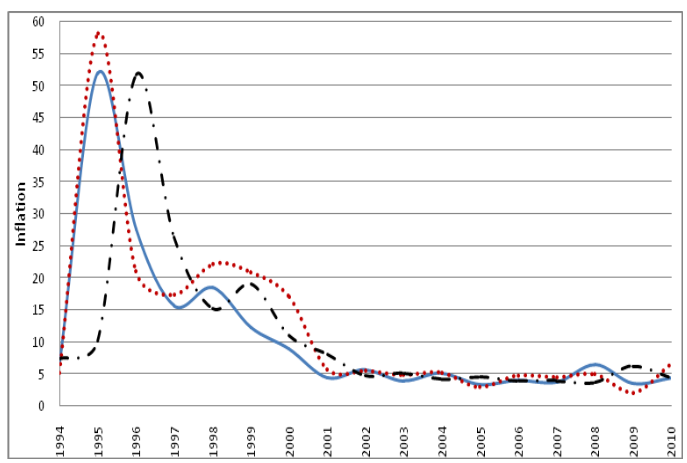

Figure 3. Annual inflation forecasted by the NN model implemented (dotted line), real annual inflation in Mexico (solid line) and annual inflation estimated by Bank of Mexico (dashed line). The NN model forecasting follows the behavior of the real annual inflation with more accuraccy than the Bank of Mexico estimations.

V. Conclusion

In this work we proposed a NN model to forecast annual inflation and to anticipate inflationary crisis. The implemented model was selected from 2550 different models according to the best MSE. The final model was a NN with one hidden layer and 49 hidden neurons.

For the learning process we used the inflation on January as the input vector and the annual inflation as the target vector. Database from 1970 to 1993 was used for the learning process and data from 1994 to 2010 was used to test the NN model performance. Forecast results were compared with the real annual inflation and with the Bank of Mexico estimations for each simulated year.

From the forecasting results, the NN performance can be described in three phases: a first phase (from 1994 to 1998) characterized for the volatility of the annual inflation, a second phase (from 1998 to 2001) described as a transition period from a volatile inflation to a stable inflation and a third phase (from 2001 to 2010) where inflation is stable. For the first phase the NN model had a MAE value of 4.02% versus a MAE of 16.05% from the Bank of Mexico estimation. For the transition period the MAE for the NN model was 5.45% while for the Bank of Mexico estimation was 3.95%. Finally, for the stability period, the MAE for the NN model was 0.96% and for the Bank of Mexico estimation was 1.39%.

The NN performance on the three different phases can be explained with its learning capacity, for the volatility period the NN model had a better performance than the Bank of Mexico because the inflation behavior from 1970 to 1993 was not stable. This performance was affected when the Mexican economy enters in a completely new stability phase and it was reflected in a better performance of the Bank of Mexico compared to the NN forecasting. Finally, once the NN model learns from the updated database its performance was again better than the Bank of Mexico prediction.

These results show the NN capability to forecast annual inflation in Mexico which can also be used to anticipate an inflationary crisis almost a year before it happens. This model can be used for the National Government as a very good alternative to forecast annual inflation and modify their policies to achieve the specified economic goals. The same process could be extended to other countries to anticipate inflationary crisis.

During the learning phase we vary the input set by using the inflation measured from February to November, but the best inflation forecasting results were achieved by using January as the input vector. It corroborates the conclusions of base literature ([4], [5] and [6]) where they conclude that NN models perform better when forecasting for long terms.

References

[1] O. Blanchard and D. H. Johnson, Macroeconomics, 6th ed., United States: Prentice Hall, 2012.

[2] Banco de Mexico, El índice nacional de precios al consumidor: características y actualización de base al año 2002. Mexico: Banco de Mexico, 2002.

[3] J. Hanke and D. Wichern, Business Forecasting, 9th ed., United States: Prentice Hall, 2009.

[4] J. Binner, R. Bissoondeeal and T. Elger, “A comparison of linear forecasting models and neural networks: an application to Euro inflation and Euro divisia”, Applied Economics, vol. 37, No. 6, pp. 665-680, 2005.

[5] E. Nakamura, “Inflation forecasting using neural network”, Economics Letters, vol. 86, pp. 373-378, 2005.

[6] A. Choudhary and A. Haider, “NN models for inflation forecasting: An appraisal”, discussion paper, 2008. Available from http://econpapers.repec.org/paper/sursurrec/0808.htm

[7] M. García, R. Bello and A. Reynoso, Redes neuronales artificiales, México: Universidad de Guadalajara, 2003.

[8] S. Haykin, Neural Networks. A comprehensive foundation, United States: Prentice Hall, 1999.