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Pronóstico del Índice Nacional de Precios al Consumidor

Forecast of the National Index of Consumer Prices

Previsão do Índice Nacional de Preços ao Consumidor

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Resumen

En la economía y las finanzas los pronósticos de indicadores macroeconómicos se han convertido en una herramienta indispensable para la planeación de políticas económicas, decisiones de inversión, de ahorro y consumo para los diversos agentes económicos. El futuro es incierto pero los pronósticos permiten anticipar situaciones de riesgo. El objetivo de este trabajo tuvo como eje temático realizar el pronóstico de Índice Nacional de Precios al Consumidor. En la metodología se utilizó un enfoque cuantitativo y descriptivo sobre tres metodologías de pronóstico, el modelo autorregresivo integrado de media móvil (ARIMA), la técnica Holt-Winters y redes neuronales artificiales. Los resultados mostraron la precisión de cada uno de los modelos de pronóstico al evaluar cada predicción respecto al error cuadrático medio. De acuerdo a los resultados obtenidos se concluye que la metodología de redes neuronales artificiales presenta menor poder predictivo para este caso en particular.

Palabras Clave: Modelos de series de tiempo, redes neuronales artificiales, modelo ARIMA, técnica metodología y aplicaciones.

Abstract

In economics and finance, forecasts of macroeconomic indicators have become an indispensable tool in the planning of economic policies, investment decisions, savings and consumption for the various economic agents. The future is uncertain but the forecasts allow us to anticipate risk situations. The purpose of this paper was to make the forecast of the National Consumer Price Index. The methodology used a quantitative and descriptive approach on three prognostic methodologies, the integrated autoregressive moving average model (ARIMA), the Holt-Winters technique and artificial neural networks. The results showed the accuracy of each forecast model when evaluating each prediction using the mean square error. According to the results obtained it is concluded that the artificial neural network methodology presents a lower predictive power for this particular case.

Key words: Models of time series, artificial neural networks, ARIMA model, technical methodology and applications.

Resumo

Nas previsões econômicas e financeiras, os indicadores macroeconômicos se tornaram uma ferramenta indispensável para o planejamento de políticas econômicas, decisões de investimento, poupança e consumo para os vários agentes econômicos. O futuro é incerto, mas as previsões nos permitem antecipar situações de risco. O objetivo deste trabalho foi fazer a previsão do Índice Nacional de Preços ao Consumidor. A metodologia utilizou uma abordagem quantitativa e descritiva em três metodologias de previsão, modelo de média móvel autoregressiva integrada (ARIMA), técnica de Holt-Winters e redes neurais artificiais. Os resultados mostraram a precisão de cada um dos modelos de previsão ao avaliar cada previsão em relação ao erro quadrático médio. De acordo com os resultados obtidos, conclui-se que a metodologia da rede neural artificial apresenta menor poder preditivo para esse caso particular.

Palavras-chave: modelos de séries temporais, redes neurais artificiais, modelo ARIMA, metodologia técnica e aplicações.

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1.- Introduction

The National Consumer Price Index (INPC) is an economic indicator that facilitates economic decision-making inherent in price behavior. This is because it provides information to the government, companies and families on the changes that the cost of living in the country has.

The INPC is a statistical instrument that allows measuring inflation, that is, its primary objective is to measure over time the variation in the prices of a basket of goods and services representative of household consumption.

All countries need to know their inflation levels, in order to know the purchasing power of the various social strata; The INPC provides information for decision-making to the various economic agents: in the case of households, based on it are the consumption and savings budgets; In the case of companies inflation allows for better investment and production decisions; And in the case of the government the INPC has an essential relevance in the design of the monetary policy of a country, which is in the hands of the Central Bank, BANXICO for the case of Mexico. The behavior of the INPC is the starting point for the design of policies aimed at the search for stability of the purchasing power of the national currency. Nowadays, every country whose economy allows it to show macroeconomic stability must necessarily show a stable level of general prices.

Currently the responsibility for collecting, processing and disclosing the INPC is the INEGI and this attribute is established in the Fiscal Code of the Federation in the second paragraph of article 20. The applications of the INPC have evolved over time, nowadays Its main uses, are indicated by INEGI (2013) and are as follows:

1. Factor for updating tax credits.
2. Determining the value of the Investment Unit (UDI).
3. Referring to various contractual negotiations.
4. Factor of updating of nominal values and as deflator in the System of National Accounts of Mexico.
5. Assist in the determination of salary increases, retirement amounts and social security benefits.
6. Auxiliary in the calculation of interest payments, rental amounts, private contracts and bond prices are usually indexed to the NCPI.
7. Assist the financial and fiscal authorities of the country in the design of monetary policies, purchasing of the national currency and sound public finances.
8. Statistical tool for companies and researchers.

In Mexico, price control through monetary policy is based mainly on the inflation targeting model, which seeks to obtain stable and controlled inflation rates. Angeriz and Arestis (2009) conducted an analysis that includes developed and emerging economies that operate under the inflation targeting regime in a study that seeks to assess the empirical evidence of the results of applying the inflation targeting model. They affirm that this strategy commits countries to adopt price stability as the main objective of monetary policy, the results obtained show that so far none of the countries that have adopted this regime have discarded it, although working under this approach has Given good results.

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Now, why make a prediction of the NCPI? Daily economic agents are faced with economic decisions, mainly: consumption, saving, investment, keeping cash, and buying and selling financial assets. A rational individual bases his decision-making on information obtained from the very behavior of the economy. Since the general price level is a determinant variable of general economic activity, it is normal for individuals to know their past, present and future trajectory; In order to achieve a well-informed and rational decision-making.

The objective of the research is to perform and evaluate the forecast of the NCPI from the results obtained from the implementation of three alternative forecasting methods, such as the RNA model, the ARIMA model and the Holt-Winters technique. For the forecast, a historical sample composed of 133 observations was used with monthly frequency of the NCPI, which covers the period from January 2005 to January 2016. In order to achieve the stated objective, this document is made up of five sections: the first is the Present introduction; The second, the description of the methodology used to meet the objective of the work; The third, fourth and fifth show the results, discussion and conclusions.

2. Method

In this paper we adopted a type of descriptive research with a quantitative approach and longitudinal-retrospective design where direct information of the INPC values is collected and its tendency identified with the purpose of performing and evaluating the prognosis.

For the forecast, a historical sample composed of 113 observations with monthly frequency of the INPC was used. The sample was divided into two periods, with the objective of evaluating the prognosis inside and outside the sample. Includes the period from January 2005 to May 2014, for the test within the sample; And from June 2014 to January 2016 for the evaluation of the out-of-sample forecast.

The tools to perform the forecast are three different techniques implemented by artificial neural networks, the integrated autoregressive model of moving average (ARIMA) and the Holt-Winters technique:

a) Artificial neural networks

The theory of neural networks goes back to 1960, when the first neural network, known as perceptron, was introduced, and the learning techniques to train it; From this new advance in knowledge a large number of contributions to the subject emerged and several applications were found for this tool.

Artificial neural networks are a model of information processing, which can be expressed by mathematical methods that seek to emulate the functioning of the human brain. They are nonlinear, non-parametric statistical models mainly used for classification, data prediction and variables; In finance the implementation of a neural network is focused as support for the forecast and management of portfolios.

An artificial neural network (RNA) can be useful for non-linear processes that have an unknown functional relationship and as a consequence are difficult to adjust. RAD implementation in the prediction of behavior of several variables [Jonson and Padilla (2005), Fadlalla and Lin (2001), Swales and Young (1992), Villada, Cadavier and Molina (2008), Villamil and Delgado (2007)] , Assert that the RNA model is significantly superior and has advantages over the results obtained through traditional linear models.

As for the structure of an artificial neural network, it can be designed based on a multi-layer perceptron structure, which can be made up of three layers of neurons with different functions. The first layer is the input layer, through which inputs are fed to the network. The second layer is called the hidden layer, which has associated a propagation rule and an activation function. The third layer is linear and calculates a response as a linear combination of the response of the hidden layer, obtaining the output of the network.

According to Martin and Sanz (2007), the basic elements of an RNA are the following:

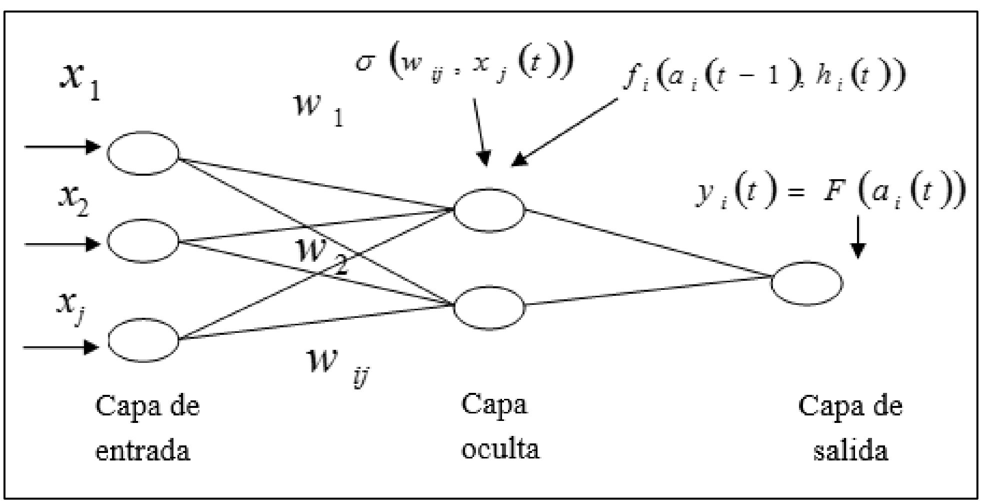
- Set of inputs, x_j (t).
- Synaptic weights of the neuron *i*, w_{ij} Which represent the intensity of interaction between each pre-synaptic neuron *j* and the postsynaptic neuron *i*.
- Rule of propagation $\sigma(w_{ij},x_j(t))$, which provides the value of the postsynaptic potential $h_i(t)= \sigma(w_{ij},x_j(t))$ of neuron i in terms of their weights and inputs.
- Function of activation of neuron i in function of its previous state $a_i(t-1)$ and its current pos-synaptic potential, which simultaneously represents the output of the neuron and its activation state.
- Output function $f_i(a_i(t))$, which provides the current output of the neuron i in its activation state.

The operation of a neuron i can be expressed as:

$Y_i(t)=F_i(f_i[a_i(t-1), \sigma(w_{ij},x_j(t))])$ (1)

In Figure 1 the basic elements of an artificial neural network mentioned above can be observed.

Figure 1. Elementos básicos de una Red Neuronal Artificial



Source: Elaboración propia.

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Training phase:

During the training phase the weights of the connections are modified and the learning rule is followed that tries to optimize its response by minimizing the adjustment error. The simplest learning mode consists of presenting a set of desired input and output patterns for each input pattern.

The problem to characterize the model of the neural network is to determine the vector of weights that associates the input vector with the output value to obtain precisely the desired value; The learning process corresponds to minimizing the differences between the desired outputs and the actual output for all the input vectors to determine the weights that minimize the set of errors (w_1*, w_{2*}).

The assessment of the functioning of the neural network is performed once the training phase has been completed. It is usual to have a set of data different from those used for training for which the correct answer is known and used as a test to evaluate the learning of the network, it is observed if it responds adequately to the known set of inputs and outputs.

b) Model ARIMA

In the late 1970s Box and Jenkins (1970) developed a new prediction tool, the so-called integrated autoregressive moving average model (ARIMA (p, d, q)), by which one can predict values in a series Which depends on time with a linear combination of your own past values and past mistakes (also called shocks or innovations).

The general expression of the ARIMA model (p, d, q), where p represents the order of the autoregressive process, d is the order of the stationary data and q is the order of the moving average process, given by:

$$\Delta^d y_t = \phi_1 \Delta^d y_{t-1} + \ldots \quad \phi_p \Delta^d y_{t-p} + a_t + \phi_1 a_{t-1} + \ldots \quad \phi_p a_{t-q} \qquad (2)$$

Where $\Delta^d y_t$, expresses that on the original series y_t they have been applied d differences. The Box-Jenkins method considers four steps:

1. Identification: determine the appropriate values of p, d, q.
2. Estimation: estimate the parameters of the autoregressive and moving average terms included in the model.
3. Diagnostic check: Check if the selected model adjusts the data properly.
4. Prediction.

The identification process can be determined as one of the following:

a) Self-regression process AR(p)

$$y_t=\phi_{0+}\ \phi_1 y_{t-1}+\ \phi_2 y_{t-2+}\ldots.+\ \phi_p y_{t-p+}+a_t+\varepsilon_t \quad (3)$$

b) Moving average process MA(q)

$$y_t=\mu_+\ \varepsilon_t\ -\Theta\varepsilon_{t-1}-\ \Theta\varepsilon_{t-2}-\ldots.-\ \Theta\varepsilon_{t-q} \quad (4)$$

c) Self-regression and moving average process ARIMA

$$y_t=\phi_{0+}\ \phi_1 y_{t-1}+\ \phi_2 y_{t-2+}\ldots.+\ \phi_p y_{t-p+}\ \varepsilon_t\ -\Theta\varepsilon_{t-1}-\ \Theta\varepsilon_{t-2}-\ldots.-\ \Theta\varepsilon_{t-q} \quad (5)$$

The major problem in estimating the ARIMA model is to determine the most appropriate values for p, d, q.

c) Holt-Winters Technique

The basic structure of the Holt-Winters technique was developed by Holt in 1957, and expanded to include a seasonal adjustment parameter by his student Winters in 1960. In this paper we consider the multi-seasonal seasonal Winters smoothing, which is a method of Smoothing of time series that show trend and seasonality, which according to González:

> Consists of three equations, each smoothing a factor associated with each of the components of the series: randomness, trend and seasonality so you have to use three smoothing constants, all of them between 0 and 1 (2009).

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The smoothing equations are as follows:

$$a_t = \alpha(y_{t/St-p}) + (1-\alpha)(a_{t-1} + T_{t-1}) \quad (6)$$

$$T_t = \beta(a_t - a_{t-1}) + (1-\beta)T_{t-1} \quad (7)$$

$$S_t = \gamma(y_t / a_t) + (1-\gamma) S_{t-p} \quad (8)$$

The prediction equation defined in this model is as follows:

$$y_{t+n} = (a_t + KT_t) S_{t+k-1} \quad (9)$$

Where:

a_t: Constant component, smoothed estimate for period t.

y_t: With the current values of the variable

ε: Uncontrollable randomness

α: Exponential smoothing constant of the data series

γ: Constant for seasonal factors

β: Constant for the trend

T_t: Tenancy component

S_t: Seasonal component

p: Means the seasonal period (eg 4 for quarterly data and 12 for monthly data).

n: Number of periods to forecast forward

k: Observations it predicts

Briefly described the three methodologies that are considered to perform the prognosis. Regarding the procedure that was followed in the investigation, this consisted of: 1) to collect the monthly data of INPC, in the page of National Institute of Statistics and Geography; B) give treatment to the historical series according to each of the models; C) follow the procedure of forecast that establishes each model; D) evaluate the prognosis with the mean square error and determine which model minimizes the error.

3. Results

When considering the methodological aspects raised in this research, the empirical evidence is observed when performing the INPC prognosis with each of the models exposed RNA, ARIMA and Holt-Winters technique.

Forecast of the INPC using artificial neural networks

The INPC forecast is estimated by designing an autoregressive non-linear network with exogenous inputs (NARX); This network has the properties of efficiency in memory and speed. These characteristics reduce the time in which the network is trained, an advantage that allows the forecasting process to be faster; The network uses the past values of the series and lags in the information to predict future values:

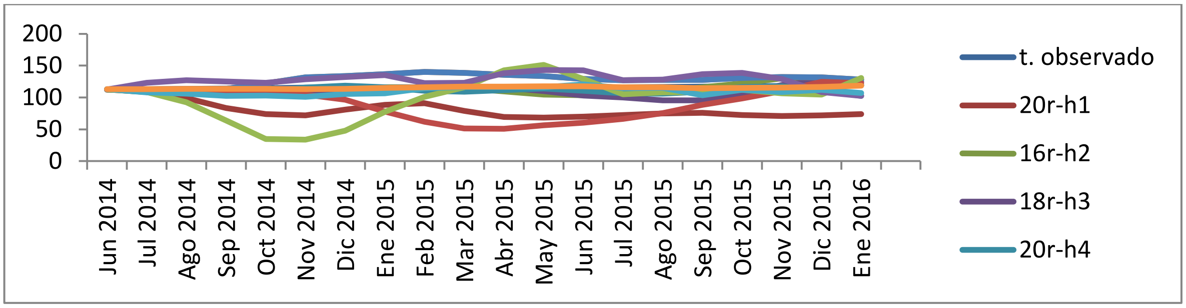
$$Y(t)=f(y(t-1), y(t-2)\ldots.y(t-n)) \qquad (10)$$

The objective data representing the entry of the network correspond to the monthly observations of the NCPI; Are randomly divided into three subsamples, 70% is used in the training phase, 15% in the validation and measurement of the generalization of the behavior of the neural network and 15% for test effects in the determination of the trained neural network.

```
targetSeries = tonndata(INPC, false, false)
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'time'; % Divide up every value
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
```

The training of the network is generated by the Levenberg-Marquardt training algorithm of backpropagation, an optimization algorithm that allows to reach a global minimum faster, by minimizing the error in the training phase. From an iterative trial-error process, different values are considered for the number of neurons in the hidden layer and the number of lags included in the network structure. The forecast obtained by each of the structures is shown in Graph 1.

Graph 1. Pronóstico del INPC con diferentes estructuras de una red



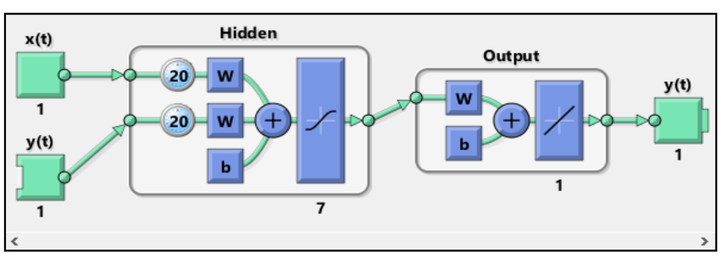
Nota: *r* se refiere al número de rezagos y *h* al número de neuronas incluidas en el diseño de la red.

Source: Elaboración propia con datos del INPC.

According to the mean square error, the network structure that minimizes the error is the one that considers 20 lags and 7 neurons in the hidden layer with a performance level of 91.5%. This indicates a better predictive capacity in relation to the other designed network structures.

Figure 2 shows the network design with the structure that was selected following the NARX model. The input data are represented by the vector x and the objective data is represented by the vector y; It is observed that the network considers the 20 lags in the input data and 7 neurons in the hidden layer. The output of the network indicates the values that the network forecasts.

Figure 2. Diseño de la RNA



Source: Elaboración propia con datos del INPC y la caja herramientas de RNA de Matlab

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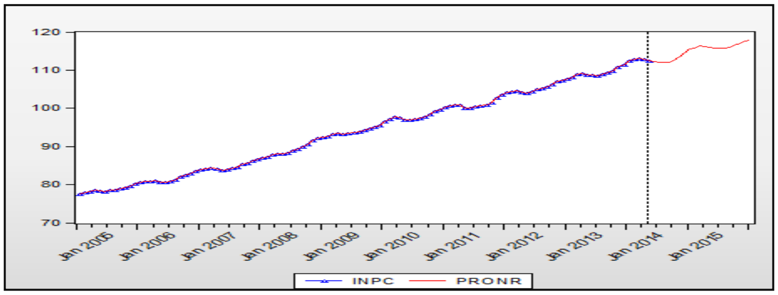
In Graph 2, the values obtained from the INPC are shown as a result of the RNA prognosis. It is observed that the forecast obtained (represented by the solid red line) is very well adjusted to the real INPC values within the sample.

Graph 2. Tendencia del pronóstico



Source: Elaboración propia con datos del INPC y la caja herramientas de RNA de Matlab

Table 1 indicates that when comparing the observed values with those predicted, a certain margin of error is registered.

Table 1. Pronóstico con RNA

Fecha	INPC Observado (1)	RNA *t+20* (2)
Jun 2014	112.722	112.25796
Jul 2014	113.032	112.04706
Ago 2014	113.438	111.9772
Sep 2014	113.939	111.98278
Oct 2014	114.569	112.5899
Nov 2014	115.493	113.55201
Dic 2014	116.059	114.46047
Ene 2015	115.954	115.4663
Feb 2015	116.174	115.86738
Mar 2015	116.647	116.30212
Abr 2015	116.345	116.12019
May 2015	115.764	115.96856
Jun 2015	115.958	115.75109
Jul 2015	116.128	115.67797
Ago 2015	116.373	115.77701
Sep 2015	116.809	115.97621
Oct 2015	117.41	116.53766
Nov 2015	118.051	117.08103
Dic 2015	118.532	117.53644
Ene 2016	118.984	117.84547

Source: Elaboración propia con datos del INPC

In this paper we will select the methodology that minimizes the mean square error. The forecast of the INPC with the ARIMA model is then estimated.

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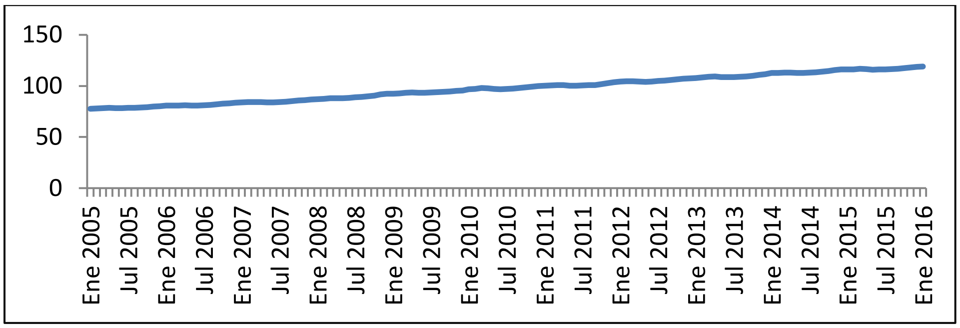
Forecast of the INPC using the ARIMA model

The first step to obtain the forecast using the integrated autoregressive moving average model (ARIMA) is to verify if the series is stationary. In Graph 3, a systematic change in mean and variance over time is observed.

Graph 3. Tendencia del INPC



Source: Elaboración propia con datos del INPC

A formal criterion to detect the stationarity of the series is the unit root test, which is obtained by the increased Dickey-Fuller test (ADF). The null hypothesis in this test considers the presence of unit root in the INPC series.

The results of the test are shown in Table 2. Since the probability is greater than 0.05 and the lowest t-statistic in absolute values relative to the critical values (see Table 2), the null hypothesis is accepted: the series has a root Unitary It has a mean and a variance that changes with time and therefore is not stationary, only the behavior of the series during the period under consideration can be studied without generalizing for other periods. For the purpose of making a forecast on any variable, a non-stationary series has little value, it is advisable to make it stationary.

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Table 2. Prueba de Dickey-Fuller aumentada

	t-estadístico	Prob*
Prueba estadística Dickey-Fuller aumentada	0.998479	0.9964
Valores críticos de la prueba		
1%	-3.493129	
5%	-2.888932	
10%	-2.581453	

Source: Elaboración propia con datos del INPC

Due to the non-stationarity of the series a transformation is made applying logarithms and a first differentiation to the values of the original series $\Delta Y = Y - Y_{t-1}$, After this transformation the Dickey-Fuller test is increased.

Table 3 shows the results of the increased Dickey-Fuller test, which indicates a probability of 0.00 and a t-statistic value of -8.200339 in absolute value, higher than the critical values. The null hypothesis is rejected, and therefore it is confirmed that the series is stationary.

Table 3. Prueba de Dickey-Fuller aumentada

	t-estadístico	Prob*
Prueba estadística Dickey- Fuller aumentada	-8.200339	0.000
Valores críticos de la prueba		
1%	-3.493129	
5%	-2.888932	
10%	-2.581453	

Source: Elaboración propia con datos del INPC

Since the INPC is a monthly series, in Figure 4 a seasonal component is observed; Which is also observed in the correlogram shown in Figure 3.

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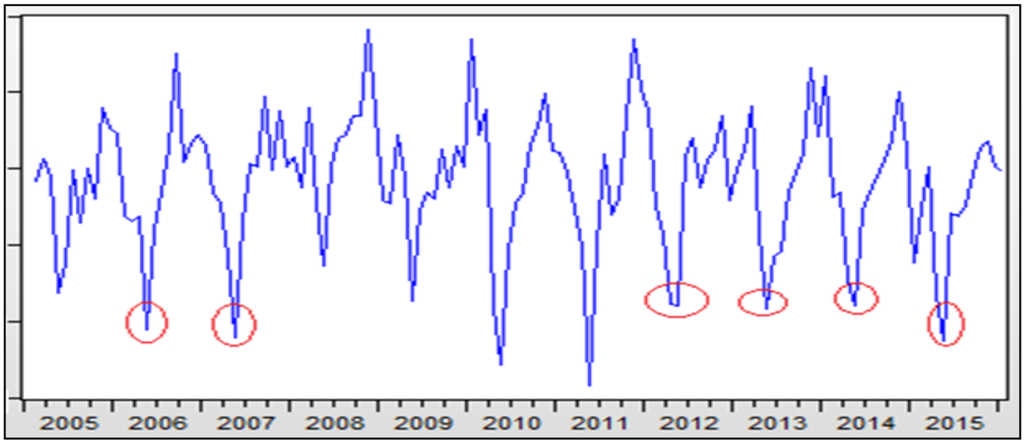
Graph 4. Serie estacionaria del INPC



Source: Elaboración propia con datos del INPC

From the fac and facp functions presented graphically through the correlogram shown in Figure 3 of the INPC time series, the ARIMA model was identified.

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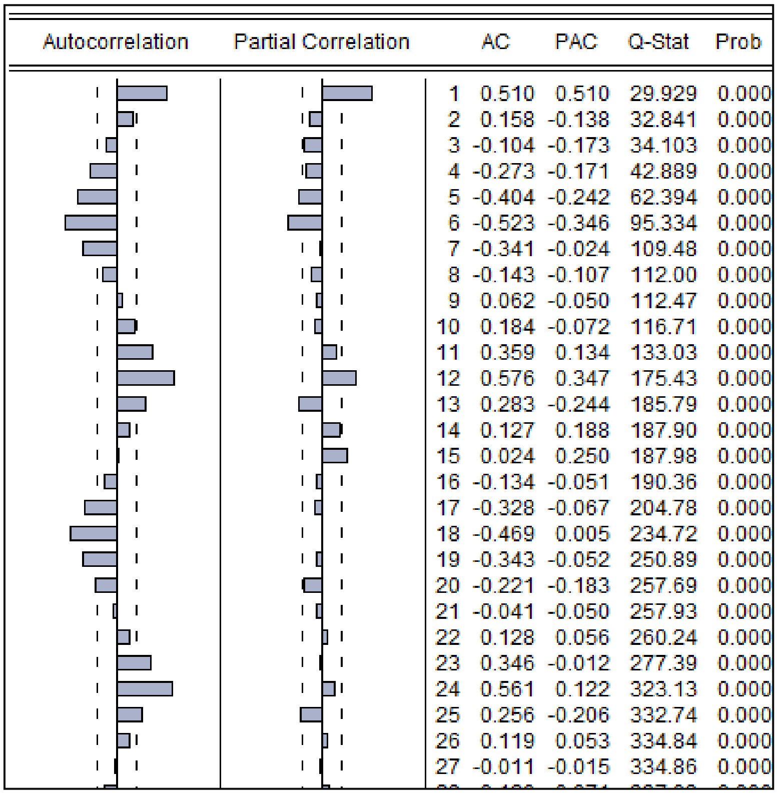
Figure 3. Correlograma del INPC



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.510	0.510	29.929	0.000
		2	0.158	-0.138	32.841	0.000
		3	-0.104	-0.173	34.103	0.000
		4	-0.273	-0.171	42.889	0.000
		5	-0.404	-0.242	62.394	0.000
		6	-0.523	-0.346	95.334	0.000
		7	-0.341	-0.024	109.48	0.000
		8	-0.143	-0.107	112.00	0.000
		9	0.062	-0.050	112.47	0.000
		10	0.184	-0.072	116.71	0.000
		11	0.359	0.134	133.03	0.000
		12	0.576	0.347	175.43	0.000
		13	0.283	-0.244	185.79	0.000
		14	0.127	0.188	187.90	0.000
		15	0.024	0.250	187.98	0.000
		16	-0.134	-0.051	190.36	0.000
		17	-0.328	-0.067	204.78	0.000
		18	-0.469	0.005	234.72	0.000
		19	-0.343	-0.052	250.89	0.000
		20	-0.221	-0.183	257.69	0.000
		21	-0.041	-0.050	257.93	0.000
		22	0.128	0.056	260.24	0.000
		23	0.346	-0.012	277.39	0.000
		24	0.561	0.122	323.13	0.000
		25	0.256	-0.206	332.74	0.000
		26	0.119	0.053	334.84	0.000
		27	-0.011	-0.015	334.86	0.000

Source: Elaboración propia con datos del INPC

Table 4 shows the model that was identified to make the forecast; Is a seasonal ARIMA model (SARIMA model). Table 4 shows that all parameters are significant according to the t-statistic and the probability level.

Table 4. Model SARIMA

	Coeficiente	Std. error	t-estadístico	Prob.
AR(1)	0.39941	0.090053	4.435291	0.0000
AR(3)	-0.280538	0.088632	-3.1652	0.0021
SAR(12)	1.0055558	0.020794	48.35871	0.0000
MA(12)	-0.883766	0.029001	-30.47336	0.0000

Source: Elaboración propia con datos del INPC

Once the model has been determined, it is possible to perform the forecast of the NCPI, which is shown in Table 5.

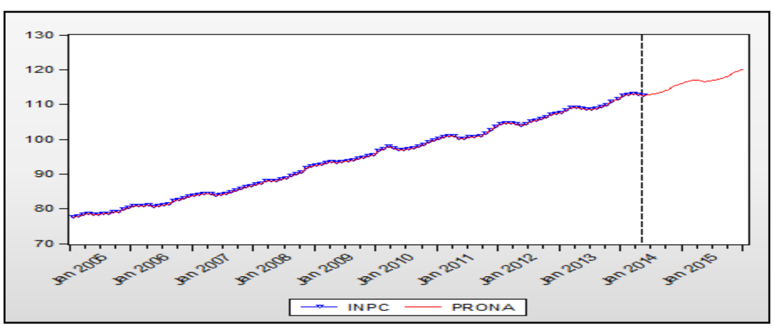
Table 5. Pronóstico con modelo SARIMA

Fecha	INPC	*t+20*	Fecha	INPC	*t+20*
Jun 2014	112.72	112.68	Abr 2015	116.35	116.99
Jul 2014	113.03	113.05	May 2015	115.76	116.59
Ago 2014	113.44	113.37	Jun 2015	115.96	116.70
Sep 2014	113.94	113.86	Jul 2015	116.13	117.01
Oct 2014	114.57	114.32	Ago 2015	116.37	117.33
Nov 2014	115.49	115.13	Sep 2015	116.81	117.82
Dic 2014	116.06	115.66	Oct 2015	117.41	118.31
Ene 2015	115.95	116.32	Nov 2015	118.05	119.13
Feb 2015	116.17	116.65	Dic 2015	118.53	119.67
Mar 2015	116.65	117.05	Ene 2016	118.98	120.33

Source: Elaboración propia con datos del INPC

Graph 5 shows the trend of the INPC forecast, and it is observed that the fit within the sample is well defined.

Graph 5. Tendencia del pronóstico



Source: Elaboración propia con datos del INPC

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Forecast of the INPC using the Holt-Winters technique

In consideration of the INPC forecast using the Holt-Winters technique, the first step is to determine the number of seasonal factors in the series. In the case of the INPC and considering the monthly periodicity of the data, Table 6 indicates the values for the alpha, beta and gamma parameters, and 12 seasonal factors are determined.

Table 6. Componente estacional

Parámetros:	Alfa			1
	Beta			0
	Gamma			0
Suma cuadrada del error				3.997093
Error cuadrático medio				0.188076
		Media		112.9439
		Tendencia		0.318115
		Estacional:	2013M06	0.994049
			2013M07	0.994091
			2013M08	0.993848
			2013M09	0.995908
			2013M10	0.997293
			2013M11	1.001753
			2013M12	1.00373
			2014M01	1.006347
			2014M02	1.006091
			2014M03	1.006793
			2014M04	1.003788
			2014M05	0.996309

Source: Elaboración propia con datos del INPC

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Once the alpha parameter value is obtained, it is possible to estimate the value of the constant for the softening of the data $a_t = \alpha(y_{t/St-p})+(1- \alpha)(a_{t-1}+T_{t-1})$. When obtaining the value of beta can obtain the component of the slope of the trend $T_t=\beta(a_t - a_{t-1})+(1- \beta)T_{t-1}$, And when obtaining gamma is determined the value of the seasonal component $S_t=\gamma(y_t/ a_t)+(1- \gamma) S_{t-p}$ So that the forecast can be obtained for $n+20$ by the following equation: $y_{t+n} = (a_t + kT_t)S_{t+k-1}$. $y_{t+n}=(a_t+KT_t) S_{t+k-1}$

The Eviews estimate shown in Table 6 shows the values of α, β *y* γ which minimize the mean squared errors in obtaining the forecast. The forecast of the series can be seen in table 7.

Table 7. Pronóstico con técnica Holt-Winters

Fecha	INPC	*t+20*	Fecha	INPC	*t+20*
Jun 2014	112.72	112.59	Abr 2015	116.35	116.88
Jul 2014	113.03	112.91	May 2015	115.76	116.33
Ago 2014	113.44	113.20	Jun 2015	115.96	116.38
Sep 2014	113.94	113.75	Jul 2015	116.13	116.70
Oct 2014	114.57	114.22	Ago 2015	116.37	116.99
Nov 2014	115.49	115.05	Sep 2015	116.81	117.55
Dic 2014	116.06	115.60	Oct 2015	117.41	118.03
Ene 2015	115.95	116.22	Nov 2015	118.05	118.88
Feb 2015	116.17	116.51	Dic 2015	118.53	119.43
Mar 2015	116.65	116.91	Ene 2016	118.98	120.06

Source: Elaboración propia con datos del INPC

Graph 6 shows the trend of the forecast obtained by the Holt-Winters technique within the sample and outside the sample.

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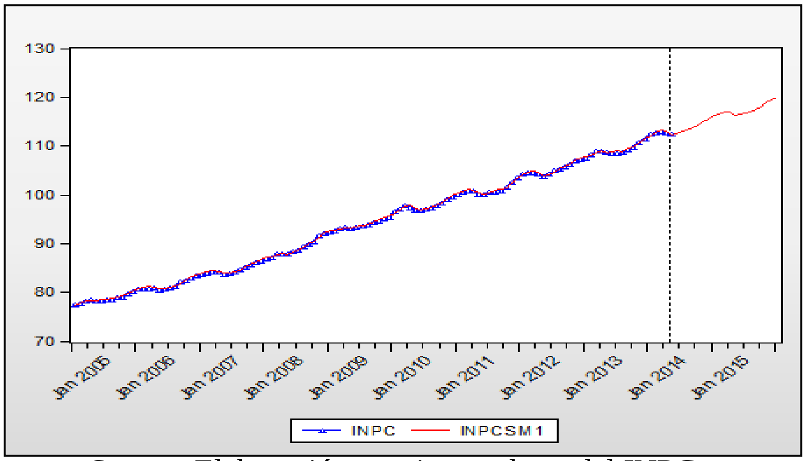
Graph 6. Tendencia del pronóstico.



Source: Elaboración propia con datos del INPC

Assessment of predictive capacity

The prognostic capacity of each of the models was carried out from the mean square error. The formula for obtaining it is expressed in equation 11.

$$ECM = \left[\frac{1}{N} \sum_{n=1}^{N} \left(f_n - O_n \right)^2 \right]^{1/2} \tag{11}$$

The mean square error for each of the forecasts obtained by the various models is shown in the Table 8.

Table 8. Error cuadrático medio

	ECM
SARIMA	0.258700984
HOLT-WINTERS	0.037260577
RNA	0.759556223

Source: Elaboración propia con datos del INPC

According to the mean square error, the Holt-Winters technique has a smaller error in the INPC prognosis, followed by the seasonal ARIMA model, while the artificial neural network presents the biggest error.

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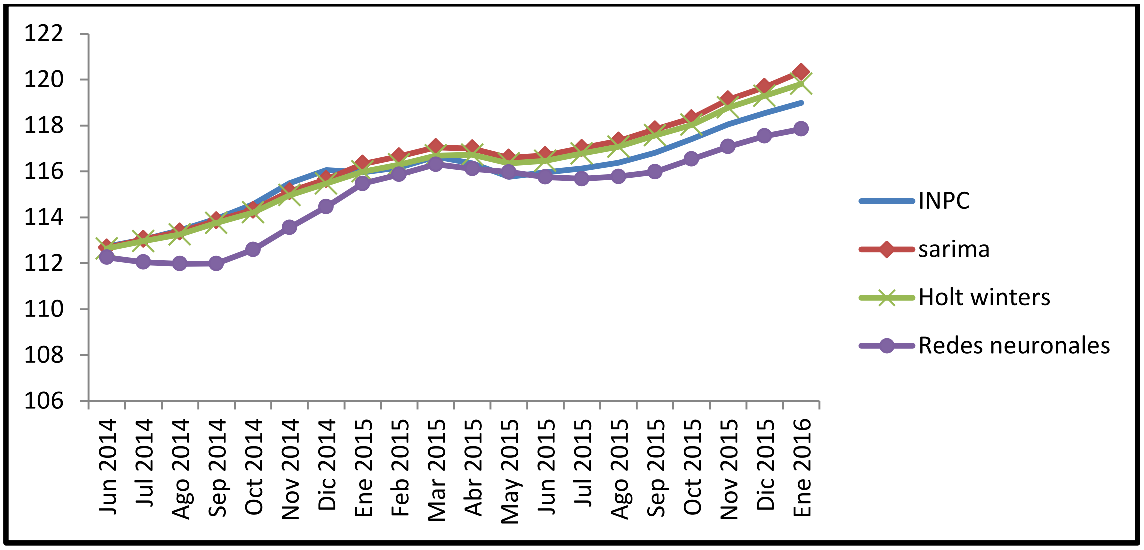
Graph 7. Pronóstico del INPC



Source: Elaboración propia con datos del INPC

The forecast of the NCPI obtained outside the sample analyzed by each of the methodologies can be visually contrasted in Figure 7. Clearly, a time horizon is observed that starts from June 2014 to January 2016, that is, it has A forecast of 20 observations compared to the observed real value of the NCPI. The ARIMA model and the Holt-Winters technique allow a better fit in the first ten predicted data; Starting from number 11, the error begins to grow and an overestimated forecast is generated. In this exercise, the forecast obtained by the neural network shows that the trend of the series follows, but generates an underestimated prognosis.

4. Discussion

A limitation within the work lies in the fact that the NCPI is predicted as a time series, without considering independent variables. Therefore an area of weakness could be presented with respect to economic theory, since it does not include variables that can influence inflation. These variables could be the interest rate, fixed exchange rate and overall index of economic activity, among others; The methodology to be used would be that indicated by an autoregressive vector model (VAR).

The main strength of the work is the comparison of the forecasts obtained with each of the proposed methodologies and identify those that minimize the mean square error and therefore have greater predictive power.

5. Conclusions

In economics and finance forecasts of macroeconomic indicators have become an indispensable tool in the planning of economic policies and investment decisions, savings and consumption for the various economic agents. The future is uncertain but the forecasts allow us to anticipate risk situations. Throughout this paper, three forecasting methodologies of the NCPI are described; This indicator is chosen because of its importance at the macroeconomic level and its influence in the financial and real sectors; Once the theoretical bases of the three methodologies were exposed, the corresponding prognosis was made and in the end a comparison of the results achieved.

The results obtained allow to compare the prognoses from a nonlinear model (neural network) with those of a traditional linear ARIMA model and the Holt-Winters technique of smoothing with seasonal component. The empirical results of the test, when performing the predictive capacity contrast, show greater predictive power of the linear models for forecasts with a horizon of less than ten days, while the nonlinear model projects values underestimated.

A disadvantage that became evident in the case of the neural network is that the training of the network is long and time-consuming, which slows the process of obtaining the prognosis.

It is interesting to compare the same three methodologies with different economic and financial variables in order to identify behaviors to expand the conclusions.

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