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Predicción del Índice Nacional de Precios al Consumidor en México

Prediction of the National Consumer Price Index in Mexico

Previsão do Índice Nacional de Preços ao Consumidor no México

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Resumen

Los precios al consumidor integran el indicador fundamental para medir el cambio en el costo de una canasta representativa de bienes y servicios, ponderada conforme a su importancia económica, el cual se utiliza como referencia principal para estimar la inflación. La investigación tuvo como objetivo predecir el Índice Nacional de Precios al Consumidor (INPC) empleando dos enfoques de series de tiempo: componentes no observables (UCM) y el modelo estacional autorregresivo integrado de media móvil (SARIMA) para contrastar su desempeño. Se empleó una metodología cuantitativa de tipo descriptivo y explicativo, utilizando 288 observaciones mensuales comprendidas entre enero de 2002 y diciembre de 2025. Ambos modelos fueron ajustados mediante el software estadístico SAS® y su desempeño se comparó con base en la raíz del error cuadrático medio (RECM) fuera de muestra (enero 2023 a diciembre 2025), así como los criterios de información de Akaike (AIC) y Schwarz (SBC). En los resultados, el modelo SARIMA (2,1,0)(0,1,1)[12] presentó un menor RECM, coeficientes estadísticamente significativos y valores más bajos de AIC y SBC, superando al modelo UCM. El análisis se limita a una serie temporal específica del INPC mexicano, por lo que su aplicación a otros contextos requiere precaución. La sensibilidad de UCM ante cambios estructurales plantea una ventaja en escenarios con alta volatilidad. En conclusión, el modelo SARIMA demostró mejor capacidad predictiva y bondad de ajuste en comparación con el modelo UCM, lo que sugiere que es una herramienta eficaz para el análisis prospectivo del comportamiento inflacionario en México y para la toma de decisiones en políticas públicas.

Palabras clave: Box-Jenkins SARIMA, economía, inflación, modelos de series de tiempo.

Abstract

Consumer prices constitute the core indicator used to measure changes in the cost of a representative basket of goods and services, weighted according to their economic relevance, and serve as the main reference for estimating inflation. The objective of this study was to forecast the Mexican National Consumer Price Index (INPC) using two time series approaches: unobserved components models (UCM) and the seasonal autoregressive integrated moving average model (SARIMA), in order to compare their predictive performance. A quantitative descriptive and explanatory methodology was employed, using 288 monthly observations from january 2002 to december 2025. Both models were fitted using the SAS® statistical software, and their performance was evaluated based on out-of-sample Root Mean Squared Error (RMSE) for the period january 2023 to december 2025, as well as the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). In the results, the SARIMA (2,1,0)(0,1,1)[12] model showed a lower RMSE, statistically significant coefficients and lower AIC and SBC values, surpassing the UCM model. The analysis is limited to a specific time series of the Mexican INPC; therefore, caution should be exercised when extending the results to other contexts. The sensitivity of UCM to structural changes suggests potential advantages in scenarios with elevated volatility. In conclusion, the SARIMA model demonstrated better predictive capacity and goodness of fit compared to the UCM model, suggesting that it is an effective tool for prospective analysis of inflationary behavior in Mexico and for decision-making in public policies.

Keywords: Box-Jenkins SARIMA, economics, inflation, time series models.

Resumo

Os preços ao consumidor são o indicador fundamental para medir as variações no custo de uma cesta representativa de bens e serviços, ponderada de acordo com sua importância econômica, e são utilizados como principal referência para estimar a inflação. Esta pesquisa teve como objetivo prever o Índice Nacional de Preços ao Consumidor (INPC) utilizando duas abordagens de séries temporais: componentes não observáveis (UCM) e o modelo autorregressivo integrado de médias móveis sazonais (SARIMA), para comparar seu desempenho. Foi empregada uma metodologia quantitativa de natureza descritiva e explicativa, utilizando 288 observações mensais de janeiro de 2023 a dezembro de 2025. Ambos os modelos foram ajustados utilizando o software estatístico SAS®, e seu desempenho foi comparado com base no erro quadrático médio fora da amostra (RECM) (janeiro de 2023 a dezembro de 2025), bem como nos critérios de informação de Akaike (AIC) e de Schwarz (SBC). Nos resultados, o modelo SARIMA (2,1,0)(0,1,1)[12] apresentou um RECM menor, coeficientes estatisticamente significativos e valores de AIC e SBC menores, superando o modelo UCM. A análise se limita a uma série temporal específica do IPC mexicano, portanto, sua aplicação a outros contextos requer cautela. A sensibilidade do UCM a mudanças estruturais oferece uma vantagem em cenários com alta volatilidade. Em conclusão, o modelo SARIMA demonstrou melhor capacidade preditiva e ajuste aos dados em comparação ao modelo UCM, sugerindo que ele é uma ferramenta eficaz para a análise prospectiva do comportamento inflacionário no México e para a tomada de decisões de políticas públicas.

Palavras-chave: Box-Jenkins SARIMA, economia, inflação, modelos de séries temporais.

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Introduction

The National Consumer Price Index (INPC) is the benchmark for evaluating price changes in a basket of goods and services, weighted according to their economic importance, and is the main indicator for assessing inflation. Based on the period of July 2018=100, its calculation involves the bi-weekly collection of more than 159,000 prices in 55 cities across the country, covering 299 generic categories distributed across 91 sectors that make up the national economic structure. Data collection is carried out once or twice every two weeks, depending on the product (Heath, 2012; Salas, 2021; Alonso and Rivera, 2017; Bank of Mexico [BANXICO], 2025; National Institute of Statistics and Geography [INEGI], 2025a).

The classical time series approach decomposes a time series y_t into: trend, seasonality, cycle, and irregularity ($y_t = T_t + S_t + C_t + I$), where this choice of disaggregation lies in the fact that it facilitates separating the visible effects from those that remain hidden in the behavior of the analyzed variable. However, Harvey (1989) proposed a more complete model using unobservable components (UCM), where $y_t$it is the sum of structural elements (μ_t=trend, γ_t =seasonality, ψ_t=cycle, r_t= autoregressive, $\sum_{i=1}^{p} \phi_i y_{t-i}$= lagged variable, = $\sum_{j=1}^{m} \beta_j x_{jt}$ explanatory variable, and ε_t= random disturbance).

The Box-Jenkins structured method comprises four phases: identification, estimation, validation, and application of the model. It is based on past values of the series to construct models that combine autoregressive elements, differentiating terms, and moving average (ARIMA). These models require the series to be stationary, that is, with constant mean, variance, and covariance. To achieve this, transformations that stabilize the variance (Guerrero, 2009) and differences that stabilize the level are applied, guided by autocorrelation analysis (FAC) and partial autocorrelation analysis (FACP) (Gujarati and Porter, 2010).

The accuracy of a forecasting model is evaluated using metrics such as mean error (ME), mean absolute error (MAE), mean percentage error (MPE), mean absolute percentage error (MAPE), and mean squared error (MSE). Lower values for these measures indicate greater accuracy of the predictive model (Farrera, 2013).

To evaluate these models, several recent studies have applied time series models to forecast macroeconomic variables, particularly in inflationary contexts. SARIMA models have demonstrated high predictive capacity in emerging economies by capturing seasonal patterns and short-term dynamics, and are widely used for analyzing inflation, exchange rates, and economic growth (Hyndman & Athanasopoulos, 2021). In the case of Mexico, Flores (2017) shows that seasonal models significantly improve accuracy over short-term horizons.

Furthermore, structural models of unobservable components (UCMs) have been used to decompose economic series into trend, cycle, and seasonality, allowing for a deeper interpretation of macroeconomic behavior (Durbin & Koopman, 2012; Ercolani, 2023). Their application has been relevant in the analysis of core inflation and in the identification of structural shocks (Sujata, 2010; Brintha, 2010).

However, empirical evidence suggests a duality between predictive capacity and structural interpretation, where SARIMA models tend to optimize forecasting, while UCM models provide a greater understanding of underlying economic behavior. This gap justifies the methodological comparison proposed in this research. However, hybrid approaches (Makridakis *et al*., 2022) have shown significant improvements when employing machine learning techniques (Hewamalage *et al*., 2021).

Despite this, overestimation may persist, which can be attributed to recent structural shocks in the economy, particularly those associated with post-pandemic inflationary pressures, monetary policy adjustments, and supply chain disruptions (IMF, 2023). Since both approaches are univariate models, their capacity to incorporate abrupt changes in exogenous variables is limited, which can induce systematic biases in the projection horizon. In this sense, the observed overestimation does not represent a methodological deficiency, but rather empirical evidence of the inherent limitations of this type of model (Duran *et al.*, 2012).

The research aimed to predict the National Consumer Price Index using two time series approaches: unobservable components (UCM) and the seasonal autoregressive integrated moving average (SARIMA) model, to compare their performance. Based on the parsimony criterion, it was assumed that, when comparing both methods, the UCM structural model would present a component configuration equivalent to that of the SARIMA model, and that its decomposition would clearly reflect the periods of stability or variability present in the analyzed series.

Materials and methods

A historical series of accumulated data from the INPC was used, covering the period from January 2002 to December 2025 (INEGI, 2025b). A logarithmic transformation was applied to the series to avoid problems of units or magnitudes (Sabau, 2011) and to facilitate comparison between models.

UCM Model

The basic structural model (BSM) configuration was developed, in reference to Pelagatti (2016) where, with our own methodological adjustments, the estimated equation is:

$y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t (1)$

Where:

$$\mu_t = \mu_{t-1} + \beta_t + \eta_t \qquad (1.1)$$

$$\beta_t = \beta_{t-1} + \xi_t$$

In the structural model, y_t the temporal dataset being studied, for which projections are estimated, corresponds to μ_t the trend element ($\mu_0$level, $\beta_t$slope, $\eta_t$white noise with variance σ_η^2, $\xi_t$white noise with variance σ_ξ^2), $\gamma_t$seasonal element, $\psi_t$cycle element, and $\varepsilon_t$irregular element. According to Sabau (2011), cycles with periodicities other than seasonal are modeled using trigonometric ratios such as sine and cosine. Fomby (2008) proposed a formulation of the cyclic element, which is presented below:

$$\psi_t = cos\lambda\psi_{t-1} + sen\lambda\psi_{t-1}^* + v_t \qquad (1.2)$$

$$\psi_t = -sen\lambda\psi_{t-1} + cos\lambda\psi_{t-1}^* + v_t^* \text{z}$$

The basic trigonometric functions sine and cosine allow the representation of the cyclical element, in which $v_t$and $v_t^*$are random disturbances uncorrelated with each other or with other elements, and share the same variance σ_v^2. The frequency λ, expressed in radians, indicates how many times the cycle repeats in a period of 2π , so the cycle has a duration of $2\pi/\lambda$. According to Vidal and Fundora (2004), complementing Harvey (1989) and Fomby (2008), to capture typical spurious cycles that characterize economic series, a damping factor is incorporated ρ, which gives greater flexibility to the cyclical dynamics of the model:

$$\psi_t = \rho cos\lambda\psi_{t-1} + \rho sen\lambda\psi_{t-1}^* + v_t \qquad (1.3)$$

$$\psi_t = \rho sen\lambda\psi_{t-1} + \rho cos\lambda\psi_{t-1}^* + v_t^*$$

Based on the above analysis, the cycle is defined as stationary whenever $|\rho| < 1$.

For the seasonal element:

$$\sum_{i=0}^{s-1} \gamma_{t-i} = \omega_t \qquad (1.4)$$

The accumulation of impacts derived from seasonal effects (ω_t) assumes zero mean; however, its evolution depends on the variance σ_ω^2: if this is small, the seasonal effects change slowly; if it is large, they dissipate rapidly. When $\sigma_\omega^2 = 0$, the seasonal fluctuations remain constant and show no changes throughout the analyzed period (Fomby, 2008). According to Vidal and Fundora (2004), a deterministic approach is recommended when there are few years of data and a seasonal pattern cannot be established; conversely, if seasonality varies over time, it is modeled as stochastic, implying $\sigma_{\omega}^{2} \neq 0$.

SARIMA Model

The SARIMA model, derived from ARIMA, incorporates seasonal elements into the time series structure (Box *et al.*, 2008). This methodology predicts present and future values of a variable based on weighted averages of its own historical values. The model specification includes non-seasonal (p, d, q) and seasonal (P, D, Q) elements, allowing it to capture both short-term and long-term patterns in the series Y_t.

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)e_t \quad (2)$$

In the SARIMA model, the elements are divided into non-seasonal and seasonal components: $\phi(B)$and $\Phi(B^s)$represent the autoregressive operators of orders py and P, while $\theta(B)$and $\Theta(B^s)$correspond to the moving average operators of orders q and Q. The non-seasonal and seasonal differences of orders dy and D, respectively, are applied using operators $(1-B)^d$and $(1-B^s)^D$, where is $s$the seasonal periodicity. Meanwhile, the random disturbance $e_t$is usually referred to as white noise. Model selection is based on graphical analysis of the residuals (correlograms), looking for randomness and the absence of patterns. A parsimonious approach was adopted, evaluating the goodness of fit using the Akaike Information Criterion (AIC) and Schwarz Criterion (SBC), whose minimization guides the optimal model selection through different combinations of autoregressive and moving average orders. In ARIMA models, the stationarity of the series is essential and is verified using the Augmented Dickey -Fuller (ADF) test, which contrasts the null hypothesis of the presence of a unit root $H0: \varphi = 0$against the alternative of weak stationarity $H_a = \varphi < 0$. The test is strengthened by including additional differences up to a reasonable order. The formulation derives from the rewriting of an autoregressive model, where φit is defined as $\varphi = \alpha - 1$(Dickey & Fuller, 1981).

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Results

UCM Model

Six configurations of the UCM model were evaluated, with different fixed or random assumptions regarding level, slope, seasonality, and cycles. The optimal selection was based on Akaike Information Criteria (AIC) and Schwarz Criteria (SBC) (Table 1).

Table 1. Implementation of UCM models to adjust the elements of the INPC.

Model	Description	Variance elements	AIC [Þ]	SBC [¶]
UCM 1	Random level	σ_n^2>0	-1888	-1874
	Random slope	σ_ξ^2>0		
	Random seasonality	σ_ω^2>0		
UCM 2	Random level	σ_n^2>0	-1890	-1880
	Fixed slope	σ_ξ^2=0		
	Random seasonality	σ_ω^2>0		
UCM 3	Fixed level	σ_n^2=0	-1836	-1829
	Random slope	σ_ξ^2>0		
	Fixed seasonality	σ_ω^2=0		
UCM 4	Fixed level	σ_n^2=0	-1901	-1885
	Random slope	σ_ξ^2>0		
	Fixed seasonality	σ_ω^2=0		
	A random cycle	σ_v^2>0		
UCM 5	Fixed level	σ_n^2=0	-1895	-1869
	Random slope	σ_ξ^2>0		
	Fixed seasonality	σ_ω^2=0		
	Two random cycles	σ_v^2>0, σ_v^2>0		
UCM 6	Fixed level	σ_n^2=0	-1832	-1818
	Random slope	σ_ξ^2>0		
	Fixed seasonality	σ_ω^2=0		
	Fixed cycle	σ_v^2=0		

[¶] SBC = Schwartz information criterion, [Þ] AIC: Akaike information criterion.

Model four proved to be the most suitable for evaluating the corresponding hypothesis, as well as analyzing the parameter estimates, values, and significance levels, based on the null hypothesis (H_0): the element is not random, versus the alternative (H_a): the element is random. From these results (Table 2), it is possible to determine whether the model exhibits deterministic or stochastic behavior.

Table 2. Estimated values of the criteria.

Element	Parameter	Estimator	Standard Error	t-value	Approx. Pr > |t|
Irregular	Error variance	2.11E-12	1.87E-13	11.26	<.0001
Slope	Error variance	0.0000054	2.21E-06	2.45	0.0145
Cycle	Damping factor	0.82097	0.03007	27.3	<.0001
Cycle	Period	10.45319	1.02806	10.17	<.0001
Cycle	Error variance	0.00000204	3.85E-07	5.3	<.0001

Source: Self-construction using data processed in SAS® software.

The parameter estimates (Table 2), based on individual significance tests, allow us to determine the relevance of each element in the model. The analysis showed that all elements are relevant, except for the irregular element, which was initially not significant (Table 3). However, this element was retained in the specification because it is an inherent part of the model's random process and absorbs unsystematic fluctuations.

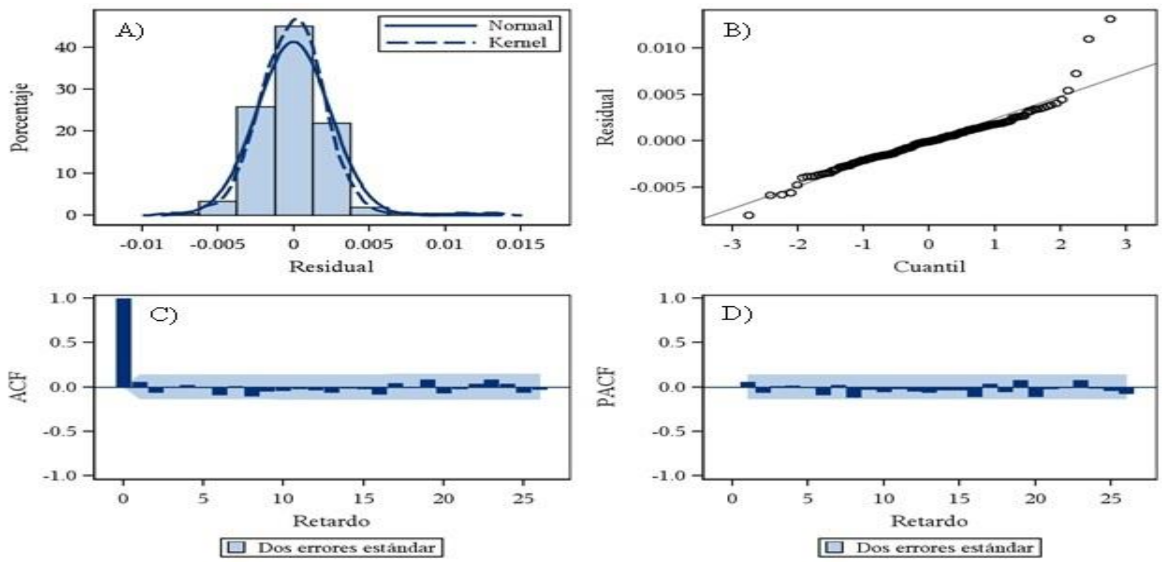
Table 3. Individual significance of each element.

Element	DF	Chi-square	Pr > ChiSq
Irregular	1	0.01	0.9996
Level	1	202535	<.0001
Angular coefficient	1	14.87	0.0001
Cycle	2	6.44	0.04
Seasonality	11	365.36	<.0001

Source: Self-construction using data processed in SAS® software.

The evaluation of the residuals confirms that they respect the assumptions of white noise, showing no correlation or systematic patterns and exhibiting an approximately normal distribution, validated through graphical analysis (histogram, QQ plot) and ACF and PACF functions. Similarly, the model did not show autocorrelation in the ACF and PACF plots, with different lags (Figure 1).

Figure 1. Assessment of the fit in relation to the model.



Note: UCM: A) histogram of residuals, B) quantile (QQ) scheme of residuals, C) ACF of residuals and D) PACF of residuals. Source: own construction.

The estimated model incorporated a trend composed of a deterministic level and a stochastic slope, deterministic seasonality, a stochastic cycle, and a stochastic irregular element. The general equation was $y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t$, where the trend ($\mu_t$) consisted of a constant level and a random slope. Given the stochastic slope $\sigma_\eta^2 > 0$and non-stochastic level $\sigma_\xi^2 = 0$, the model was classified as trend-smoothed, meaning that the variability arose from changes in the long-term growth rate dynamics, not from the level itself. This configuration reflected that the CPI exhibited trend growth that evolves continuously over time. The cyclical element displayed random and irregular behavior, implying that the CPI's economic cycles do not follow a fixed periodicity and manifest as recurrent, non-systematic oscillations.

SARIMA Model

In this investigation, modeling methods corresponding to temporal processes were implemented, considering different orders. To validate their applicability, the stationarity (constant mean and variance) of the series was evaluated using the Augmented Dickey -Fuller (ADF) test, contrasting the null hypothesis of the presence of a unit root against the alternative of stationarity. The null hypothesis was rejected when the tau statistic was less than or equal to the critical value (calculated tau ≤or tau from tables). Upon detecting non-stationarity, differentiations were applied: one of ordinary type (d=1) and another of seasonal type (D=1), due to the existence of recurring patterns every 6, 12, and 24 observations. After these transformations, the tau value allowed the rejection of the null hypothesis, concluding that the INPC series became stationary, that is, with stable behavior over time (Table 4).

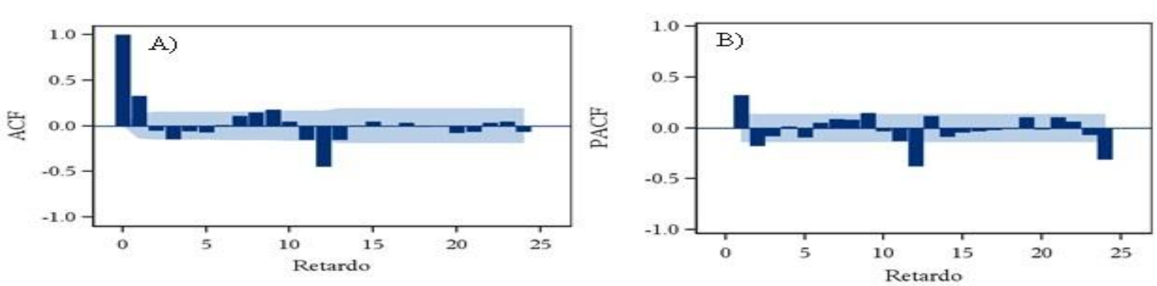
Table 4. Augmented Dickey Fuller Test (ADF), INPC series.

Type	Delays	Tau	Pr < Tau	F	Pr > F
Intercept	0	-11.77	<.0001	69.27	0.001
	1	-10.97	<.0001	60.19	0.001
	2	-9.39	<.0001	44.12	0.001
Trend	0	-11.95	<.0001	69.02	0.001
	1	-10.95	<.0001	59.98	0.001
	2	-9.38	<.0001	43.96	0.001

Source: own work

The indicators that allowed the identification of the temporal structure, through simple and partial autocorrelations (ACF and PACF) of the differentiated series (d=12, D=12), revealed a recurring seasonal pattern every 12 periods (s=12). The ADF analysis in lags 1, 3, and 12 confirmed this behavior, identifying an autoregressive (AR) and moving average (MA) structure in lags 12 and 24. This procedure supported the choice of a SARIMA model to describe the dynamics of the INPC economic indicator (Figure 2).

Figure 2. Simple and partial $Y_t = (1-B)^d(1-B^s)^D$autocorrelogram for INPC



Note: A) ACF, B) PACF. Source: own elaboration.

In the model specification procedure, the ACF and PACF functions were analyzed to obtain a graphical diagnosis of the series' behavior, identifying only three statistically significant lags according to the white noise tests. Various combinations of AR and MA (p, q) terms, as well as their seasonal elements SAR and SMA (P, Q), were estimated, evaluating the fit using selection and information criteria AIC and SBC. The best-performing model was SARIMA(2,1,0)(0,1,1) $_{s=12}$, as shown in Table 5.

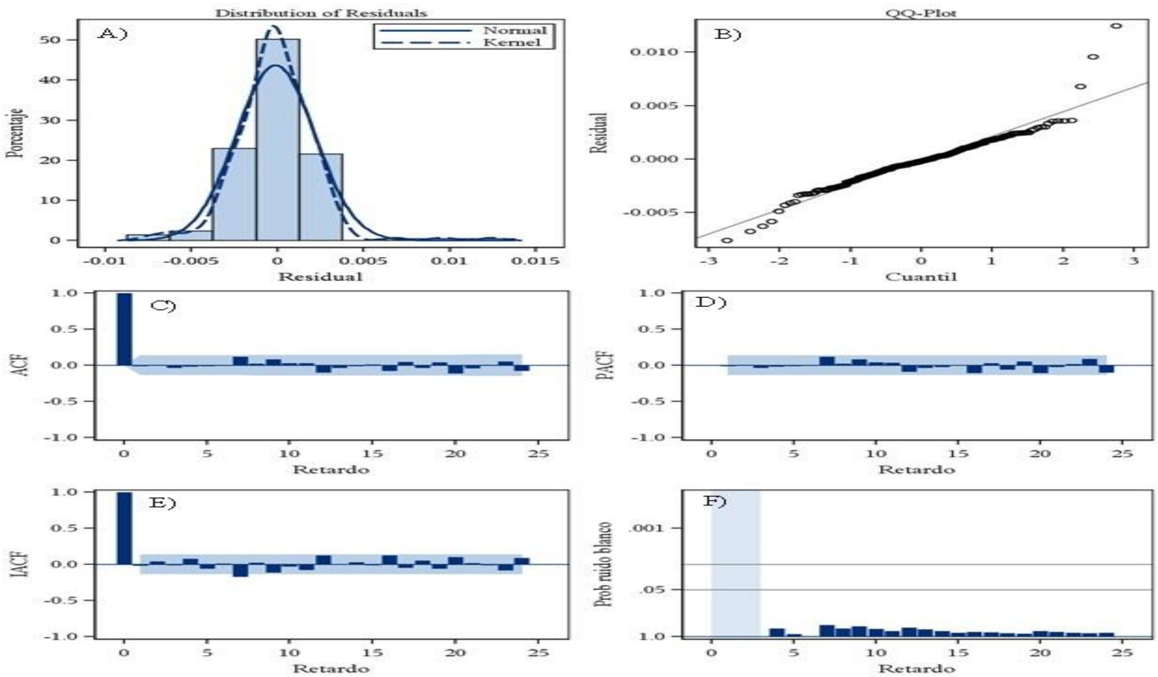
Table 5. Calculation of the best SARIMA models identified.

SARIMA †	Ordinal part			Seasonal part			SBC ¶	AIC Þ
	AR § (p)	MA ¤ (q)		AR §§ (P)	MA ¤¤ (Q)			
(2,1, 0)X (0,1,1) $_{s=12}$	0.40245	.		.	0.85100		-2510.8	-2521.7
(1,1, 0)X (2,0,0) $_{s=12}$	0.44757	.		0.36204	.		-2556.1	-2567.1
(1,1, 0)X (0,1,1) $_{s=12}$	0.36676	.		.	0.85187		-2513.9	-2521.1

† SARIMA: seasonal autoregressive integrated moving average, § AR: autoregressive of order (p), ¤ MA: moving average of order (q), §§ AR: seasonal autoregressive of order (P), ¤¤ MA: seasonal moving average of order (Q), ¶ SBC = Schwartz information criterion, Þ AIC: Akaike information criterion. Source: own construction with data processed in the SAS® software.

With the parameter values already estimated, the SARIMA (2,1, 0)X (0,1,1) $_{s=12}$ model was accepted through residual analysis. The results confirmed that these are white noise, meaning they lack correlation, follow an approximately normal distribution, and do not exhibit detectable patterns (they are completely random and do not maintain temporal dependence between observations). Normality was evidenced in the histogram and QQ plots, while the absence of autocorrelation was verified with the ACF and PACF functions within the confidence band (Figure 3).

Figure 3. Residual analysis, calibration of the SARIMA model (2,1, 0)X (0,1,1) $_{s=12}$.



Note: A) histogram B) quantile scheme (QQ), C) ACF, D) PACF, E) inverse error autocorrelogram, F) white noise in residuals. Source: own elaboration.

According to the Box-Jenkins methodology and the criteria for statistical significance, coefficients whose t-statistic, in absolute value, exceeded the threshold of two and whose *p-values* were less than 0.05 were considered relevant. Thus, the SARIMA(2,1,0)(0,1,1)$_{s=12}$ approach was identified as the most suitable compared to the other alternatives evaluated (Table 6).

Table 6. Model estimation using maximum likelihood, for the INPC series

Parameter	Estimator	Standard error	t-value	Approx. Pr > |t|	Lag
MA1,1	0.85100	0.04261	19.97	<.0001	12
AR1,1	0.40245	0.05890	6.83	<.0001	1
AR1,2	-0.09636	0.05876	-1.64	0.0215	2

Source: Self-construction using data processed in SAS® software.

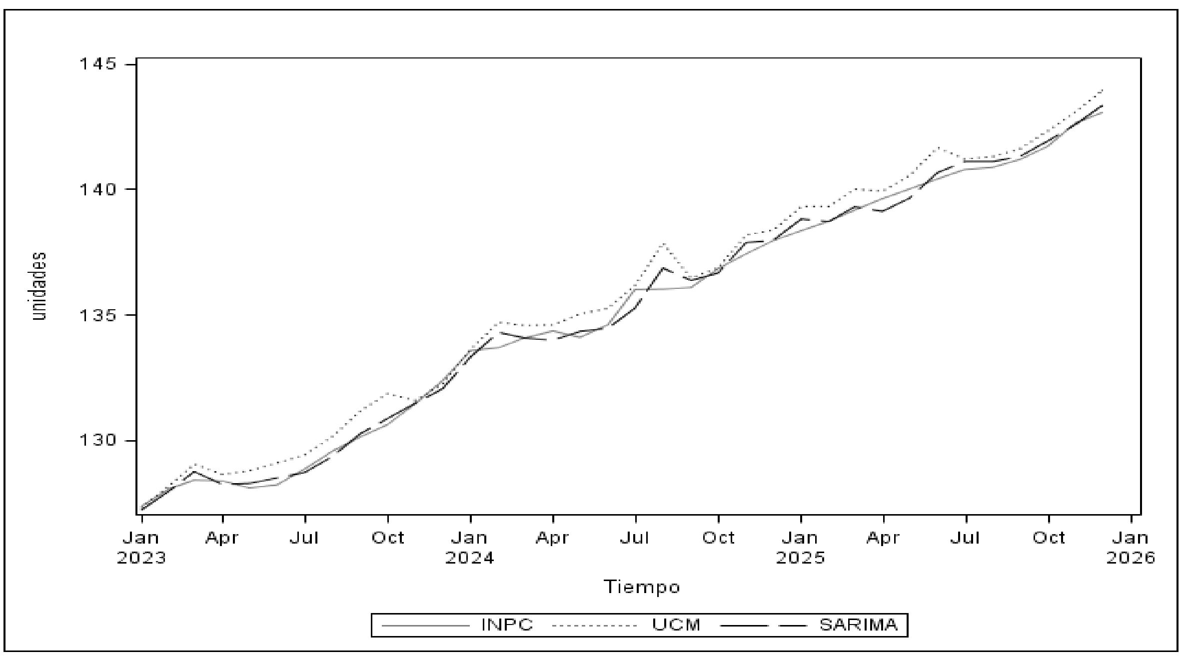
To evaluate the model's implementation stage, the Mean Squared Error (MSE) estimator was used, considered a key criterion for optimality. However, predictive quality depended heavily on the persistence of past observed behaviors, such that sudden changes negatively affected the significance of the results.

Predictive evaluation of the out-of-sample model

The predictive performance of the UCM and SARIMA models was compared using 36 out-of-sample observations (January 2023–December 2025). SARIMA showed the lowest mean squared error (MSE=0.2951), surpassing the UCM (MSE=0.3207). Despite this, both models tended to overestimate the CPI towards the end of the projected horizon, especially from the third quarter of 2024 and throughout 2025, in response to variations not captured by the univariate specification (Figure 4).

Both models adequately reproduced the trajectory of the CPI and allowed for the characterization of its behavior during the analyzed period. However, the differences observed in in-sample and out-of-sample performance demonstrated that predictive capacity and structural interpretation do not necessarily converge on the same approach, since SARIMA optimized predictive accuracy while UCM provided elements for decomposing the index's dynamics. In short, the results confirm that the compared models fulfill different functions: one optimizes prediction and the other the understanding of the structure. This duality is key to interpreting their scope and limitations.

Figure 4. Predictive performance of the CPI out of sample: January 2023-December 2025.



Source: own elaboration.

The results showed that the structure of the CPI exhibited a well-defined and stable seasonality throughout the analyzed period, which favored the parsimony of the SARIMA model and demonstrated greater predictive accuracy. Although both approaches adequately captured the variability of the series, SARIMA showed smaller discrepancies between observed and forecasted values, suggesting that, under deterministic seasonality conditions, Box-Jenkins processes constitute an efficient alternative for short-term forecasting. Meanwhile, the UCM proved useful for decomposing inflationary behavior and identifying the transitory nature of certain cyclical movements, providing a structural interpretation that complements the analysis, but with less capacity to anticipate the future evolution of the index.

Discussion

The SARIMA(2,1,0)×(0,1,1) $_{s=12}$ $_{\text{model}}$ showed better predictive performance than the UCM, which coincides with recent studies highlighting the effectiveness of seasonal approaches for forecasting inflation in emerging economies. In Mexico, several studies have documented that SARIMA models adequately capture short-term inflationary dynamics, competing with structural or multivariate methodologies (Ayllon *et al*., 2024). These results are consistent with previous evidence indicating that Box-Jenkins processes tend to improve their accuracy when seasonality is deterministic and stable. This also occurs when the series meets stationarity criteria assessed using ADF tests (Pankratz, 1983; Enders, 2014).

For its part, the UCM allowed the INPC to be decomposed into permanent and transitory elements, which is consistent with the literature that uses this approach to analyze cyclical shocks and seasonal effects (Ercolani, 2023; Sujata, 2010). The inclusion of the irregular component is methodologically appropriate, given that it absorbs random fluctuations without systematic direction, so its exclusion could bias the model's structure (Brintha *et al*., 2014). The presence of irregular cycles in the CPI is consistent with the economic understanding of cycles as recurrent, though not necessarily periodic, oscillations, a result widely discussed in macroeconomic theory (Mankiw, 2012).

While the UCM provided a better structural characterization of the series by identifying transient and permanent elements, its lower predictive accuracy suggests that structural decomposition does not necessarily optimize the forecast when the goal is prediction. This finding is consistent with studies that have indicated that the stability of the historical pattern is a key determinant of performance in time series models (Luis *et al.*, 2019). Mexican literature has also documented that deterministic seasonal schemes tend to improve mean squared errors in out-of-sample horizons, reinforcing the results of the present study (Flores, 2017).

Both models showed overestimation toward the end of the analyzed horizon, a phenomenon associated with external shocks, monetary policy adjustments, and post-pandemic volatility in emerging countries (BANXICO, 2022; OECD, 2023). Among the study's limitations is the use of a univariate approach without incorporating key variables such as exchange rates, energy prices, or economic activity—variables recognized as relevant for explaining Mexican and Latin American inflation (De Gregorio, 2019; Bonizzi *et al.*, 2022). However, the results contribute methodologically to the analysis applied at the national and international levels.

Recent studies have begun to explore hybrid approaches that combine SARIMA models with machine learning techniques, achieving significant improvements in predictive accuracy in complex inflationary contexts (Peirano *et al.*, 2021). These advances suggest that integrating traditional and modern methodologies represents a promising avenue for applied economic analysis.

Conclusions

Within the unobservable elements approach, the variations associated with the trend pattern are explained primarily by changes in the slope rather than changes in the level, reflecting sustained and constant growth throughout the analyzed period. Meanwhile, the integrated moving average autoregressive seasonal model allowed for adequate adjustment of the dynamics of a time series, whether stable or fluctuating, using simple differentiating and autoregressive terms to capture deterministic or stochastic trends. The SARIMA(2,1,0)×(0,1,1) $_{s=12}$ process provided the most suitable representation within the evaluated models. Its predictive performance was satisfactory, with an out-of-sample error margin of less than 30%. Overall, the parameter estimation and the forecasts obtained following the principle of simplicity or parsimony and considering the historical evolution of the series provide useful information for strategic economic decision-makers, based on data that efficiently and statistically explains the complexity of a phenomenon that monitors changes in the level of spending necessary for households to maintain their well-being in a country. This study contributes to the empirical literature by comparing two widely used methodological approaches in time series analysis, providing applied evidence for the

Mexican case with recent data. The distinction between predictive capacity and structural decomposition is a relevant contribution to economic policy decision-making.

Future lines of research

Based on the findings and limitations of this study, several avenues for future research are proposed to strengthen the analysis and predictive capacity of inflation models. First, incorporating exogenous variables through the development of multivariate models that integrate key determinants of Mexican inflation, such as the exchange rate, interest rates, energy prices, and economic activity, is relevant to improving accuracy over medium- and long-term horizons. Likewise, exploring hybrid and nonlinear models that combine SARIMA approaches with machine learning techniques, such as neural networks or regime-switching models, is suggested. These models are capable of capturing complex patterns and structural changes in inflationary dynamics. Similarly, disaggregated analyses of the CPI, differentiating between underlying and non-underlying components, are recommended to identify specific sources of inflationary pressure and refine forecasts. The need to validate the models over longer time horizons, including complete economic cycles and periods of high volatility such as financial crises or pandemics, is also raised in order to assess their robustness in uncertain contexts. Finally, the incorporation of monetary policy scenarios through simulations is proposed, allowing for the analysis of the sensitivity of the forecasts to different central bank regimes and strategies.

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