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COMPARATIVE ANALYSIS OF ARIMA AND LSTM MODELS IN FORECASTING THE CONSUMER PRICE INDEX UNDER CONDITIONS OF HIGH INFLATIONARY VOLATILITY

ПОРІВНЯЛЬНИЙ АНАЛІЗ МОДЕЛЕЙ ARIMA ТА LSTM У ПРОГНОЗУВАННІ ІНДЕКСУ СПОЖИВЧИХ ЦІН В УМОВАХ ВИСОКОЇ ІНФЛЯЦІЙНОЇ ВОЛАТИЛЬНОСТІ

This study focuses on improving forecasting models for Ukraine's macroeconomic indicators under conditions of volatility and exogenous shocks. The scientific novelty lies in the integration of neural network theory with the principles of dynamic system identification. The LSTM architecture effectively models significant time lags and resolves the vanishing gradient problem. Model parameters are determined using iterative optimization algorithms to minimize the loss function. Computational experiments on statistical data confirm the superiority of deep learning methods over linear approaches. The results justify the use of non-linear models to account for economic inertia and enhance the accuracy of long-term forecasting.

Keywords: *CPI, LSTM, system identification, volatility, econometric modeling, iterative algorithms, macroeconomic forecasting, inertial lag.*

У статті розглянуто проблему підвищення якості прогнозних моделей макроекономічних показників України в умовах зростаючої ринкової волатильності та впливу екзогенних факторів. Індекс споживчих цін (ІСЦ) є ключовим індикатором макроекономічної стабільності та орієнтиром для формування монетарної політики. Проте динаміка інфляційних процесів у сучасних умовах характеризується високим рівнем нелінійності та нестаціонарністю, що суттєво обмежує ефективність класичних статистичних методів. Необхідність впровадження адаптивних інструментів аналізу, здатних ідентифікувати складні довготривалі залежності в часових рядах, визначає доцільність даного дослідження. Науковий пошук базується на інтеграції теорії нейронних мереж та принципів ідентифікації динамічних систем. Основною архітектурою моделі обрано рекурентну нейронну мережу LSTM, що розроблена для моделювання процесів із тривалими часовими лагами. Математичний апарат спирається на систему рекурентних співвідношень, що описують процеси селективного оновлення інформації про стан системи, що дозволяє нівелювати проблему затухання градієнта при тривалих інтервалах прогнозування. Процедура визначення параметрів моделі реалізована через ітераційні алгоритми мінімізації цільової функції втрат. Проведені обчислювальні експерименти на основі статистичних даних ІСЦ України дозволили встановити переваги методів глибокого навчання над лінійними підходами. У роботі удосконалено методичний підхід до прогнозування динаміки інфляційних процесів шляхом поєднання ітераційних процедур ідентифікації систем із рекурентними архітектурами нейронних мереж. Обґрунтовано ефективність застосування нелінійних методів глибокого навчання для моделювання волатильних макроекономічних показників, що дозволяє враховувати інерційність економічних процесів без втрати точності на довгих горизонтах прогнозування. Водночас застосування *класичного методу ARIMA залишається доцільним для малих вибірок та прогнозування стаціонарних процесів із низькою волатильністю.*

Ключові слова: *ІСЦ, рекурентна LSTM, ідентифікація систем, волатильність, економетричне моделювання, ітераційні алгоритми, макроекономічне прогнозування, інерційний лаг.*

Formulation of the problem. The dynamics of the Consumer Price Index (CPI) serve as a fundamental indicator of a nation's macroeconomic stability. Amidst global instability, armed conflicts, and the disruption of logistics chains, the Ukrainian economy exhibits high inflationary volatility. Accurate CPI forecasting is essential for informed decision-making in monetary policy, fiscal planning, and strategic corporate management. Existing inflation forecasting models for Ukraine are frequently based on the assumptions of linearity and stationarity in economic processes. However, the presence of sharp structural shifts in the CPI time series (in particular, the 2015 and 2022–2024 periods) leads to a significant increase in forecast errors in classical models. In this context, a critical scientific challenge emerges: determining the performance limits of statistical models and machine learning methods under conditions of high volatility, and identifying algorithms that exhibit the greatest resilience to structural breaks in time series dynamics.

Analysis of recent research and publications. Classical approaches based on the iterative cycle of identification, estimation and diagnosis (ARIMA) have long been considered the benchmark in short-term forecasting. [1, 2]. In contrast to classical methods, modern researchers focus on the ability of neural networks to approximate nonlinear functions of any complexity. A key breakthrough in forecasting time series with unstable structures was the implementation of Recurrent Neural Networks (RNNs), specifically the Long Short-Term Memory (LSTM) architecture. S. Hochreiter and J. Schmidhuber [3] demonstrated that traditional recurrent networks suffer from the 'vanishing gradient' problem, which causes them to lose connection with data over long time intervals. The LSTM architecture they developed overcomes this barrier through a system of internal gates, allowing the model to selectively “remember” long-term trends and “ignore” random market fluctuations. In particular, the forget gate determines which information from the previous state should be discarded, which is critically important for handling structural breaks within the Ukrainian economy.

In the Ukrainian scientific space, forecasting methods based on time series models are the subject of research: V. Heitsia, B. Kvasniuka, O.O. Rud, H.S. Ivashchenka, D.O. Tymoshenka, O.V. Blyzniuk, O.M. Kononenka, [4, 5]. The classification of the main time series forecasting models is given in the work Yu. O. Andrusenka, S. Boiarchuka, I. Tyshchenko [6,7]. However, a comparative analysis of classical econometrics and deep learning methods on current data from 2024–2025 remains insufficiently covered.

Formulation of the purpose of the article. The purpose of the article is to conduct a comparative analysis of the effectiveness of the classical statistical model ARIMA and the recurrent model LSTM for short-term forecasting of the consumer price index in Ukraine. Particular attention is paid to assessing the ability of these methods to adapt to high inflationary volatility and structural shifts in time series observed during the 2022–2025 period, in order to justify the selection of the most accurate tool for macroeconomic modeling under conditions of instability.

Presentation of the main material. The process of modeling and forecasting the CPI of Ukraine was divided into three sequential stages: data preparation, model parameterization, and final testing.

The analysis utilizes monthly Consumer Price Index (CPI) data for Ukraine for the 2014–2025 period, sourced from the Federal Reserve Bank of St. Louis database (Federal Reserve Bank of St. Louis, 2025) [8]. The use of the FRED platform ensures the verifiability and reproducibility of the study's empirical base. For modeling purposes, the CPI indicator is represented as a percentage change with a one-month step.

At the first stage, an analysis of the initial time series was conducted (Fig. 1). Data visualization through a line chart allowed for the identification of key trends and structural shifts in the economy. The plot clearly demonstrates the presence of significant breaks, specifically a sharp increase in inflation during 2022–2023, which confirms the complexity and nonlinearity of the analyzed process. High inflationary volatility and unstable dynamics of the indicator point to the evident non-stationarity of the series.

As illustrated in Fig. 1, the time series is characterized by extended periods of relative stability followed by abrupt exogenous shocks. It is this specific data structure that determines the potential advantage of the LSTM architecture, which is capable of adapting to such spikes through long-term memory mechanisms, unlike the classical ARIMA class of models.

To eliminate the identified non-stationarity and prepare the data for identifying the ARIMA model parameters, a first-difference operator was applied:

$$\Delta y_t = y_t - y_{t-1} \tag{1}$$

The resulting transformed series (Fig. 2) demonstrates a stabilization of the mean value around the zero mark, which is a visual indication of the transition to a stationary state. The trend line on this plot is nearly horizontal, confirming stationarity in the broad sense. Under such conditions, the mathematical expectation of the series becomes a constant, allowing for the correct application of the ARIMA model.

Despite the visual stabilization of the CPI dynamics, the first-difference plot (Fig. 2) clearly exhibits a volatility clustering effect (particularly after the 85th observation), where the amplitude of fluctuations increases significantly. This confirms the complex nature of inflationary processes in Ukraine, driven by exogenous shocks—sharp spikes in the indicator's values (consequent to military actions, the energy crisis, etc.)—as reflected in the difference plot.

To statistically confirm the stationarity of the time series, an Augmented Dickey-Fuller (ADF) test was conducted [2, 9]. The test was performed by estimating a regression equation for the first differences, incorporating a constant, a time trend, and lagged values:

$$\Delta y_t = \alpha + \beta \cdot t + \gamma \cdot y_{t-1} + \sum_{i=1}^{p} \delta_i \cdot \Delta y_{t-1} + \varepsilon_t , \tag{2}$$

where: $\Delta y_t = y_t - y_{t-1}$ – first difference of the series (Fig. 2);

α – constant (drift);

β – deterministic time trend;

γ – the coefficient that we test for the presence of a unit root;

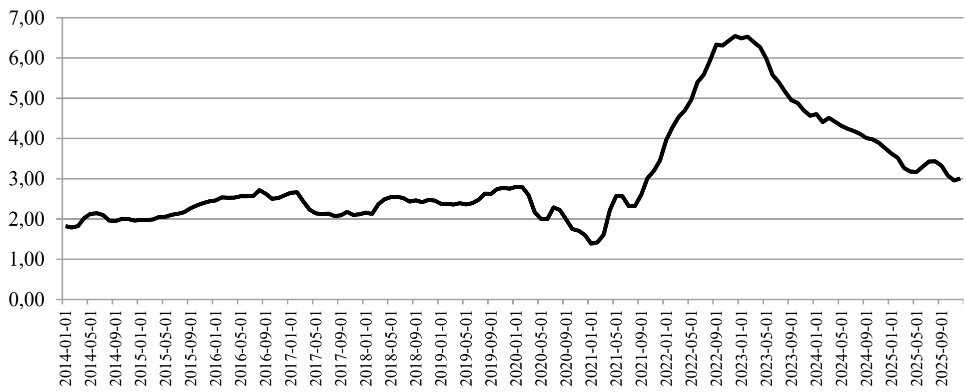

Figure 1. Consumer Price Index (CPI) dynamics in Ukraine (January 2014 – December 2025)

Source: calculated and constructed by the author based on FRED data [8]

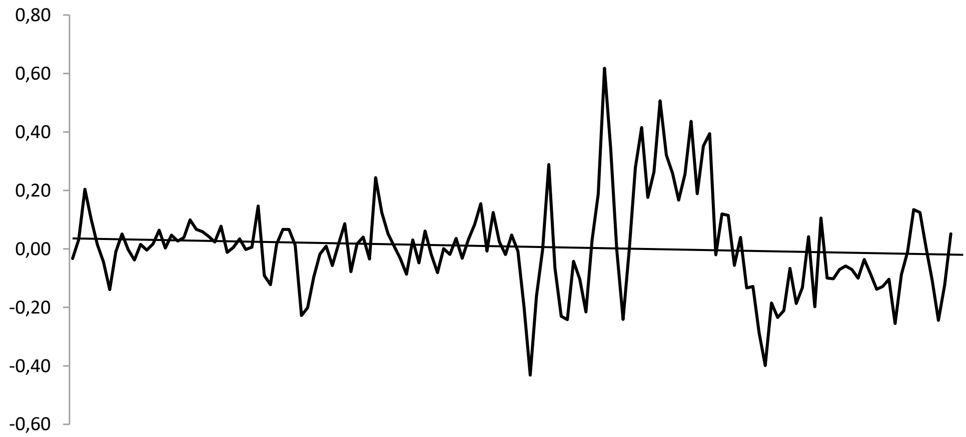

Figure 2. First-differenced CPI time series of Ukraine with a linear trend line
Source: Calculated and constructed by the author

$\sum_{i=1}^{p}\delta_i \cdot \Delta y_{t-1}$ – first difference lags (removing autocorrelation of data);
ε_t – error ("white noise").

The parameter α in model (2) is interpreted as the average inertial rate of inflationary processes. Incorporating this parameter accounts for the fact that CPI dynamics in Ukraine during the 2014–2025 period exhibit a steady upward trend (positive drift), driven by fundamental monetary and structural factors independent of short-term fluctuations. The component βt in equation (2) represents a deterministic time trend. Its inclusion in the model is necessitated by the need to account for the long-term direction of CPI dynamics, which may be driven by gradual structural transformations of the national economy. The statistical inference was based on a comparison of the calculated t-statistic with MacKinnon critical values [10], which account for the sample size (N=144) and the presence of deterministic components (constant and trend). The ADF test statistics for the first differences are presented in Table 1. The regression analysis results for equation (2) showed that for the differenced CPI series, the obtained t-statistic is -5,281, which is significantly lower than the critical values at the 1% significance level (-3,99) and the 5% level (-3,43). Thus, the null hypothesis of a unit root is confidently rejected. The calculated p-value of 0,0001 further confirms the high statistical significance of the obtained result.

Thus, it has been demonstrated that the first-differencing operation successfully eliminated the stochastic trend, transforming the initial series into a stationary one in the broad sense. This provides the necessary methodological foundation for proceeding to the identification of ARIMA model parameters and the subsequent training of the LSTM recurrent model.

Table 1

Augmented Dickey-Fuller (ADF) test results for first differences

Statistical criterion	**Numerical value of the criterion**
ADF Statistic	-5,281
p-value	0,0001
Critical Value (1%)	-3,99
Critical Value (5%)	-3,43
Critical Value (10%)	-3,13

Source: compiled by the author

To identify the optimal orders of autoregression (p) and moving average (q), the correlograms of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were analyzed. Visual inspection of the correlograms for the stationary first-differenced CPI series allowed for the tentative identification of the model as ARIMA (2, 1, 0). Based on the results of the regression analysis, the empirical ARIMA (2, 1, 0) model describing the dynamics of inflationary processes was specified as follows (3):

$$\Delta y_t = 0,003 - 0,893 \cdot \Delta y_{t-1} + 1,516 \cdot y_{t-2} + \varepsilon_t \tag{3}$$

The obtained value of the coefficient of determination (R^2 = 0,388) indicates that the linear model explains only 38,8% of the indicator's variation. This suggests that a significant portion of the inflation dynamics is driven by non-linear dependencies that classical ARIMA models fail to capture.

Despite the overall statistical significance of the model (F_{stat} = 44,4; p < 0,001), the share of unexplained variance remains substantial at 61,2%.

This indicates that the dominant portion of consumer price dynamics in Ukraine is driven by complex non-linear factors or exogenous shocks, which the linear specification of the ARIMA model is unable to adequately identify. This circumstance justifies the necessity of employing the LSTM architecture, which specializes in modeling complex non-linear dependencies in time series. The low statistical significance of individual lag coefficients and the high level of residual variance confirm the hypothesis regarding the non-linear and stochastic nature of inflationary processes in Ukraine.

To identify hidden long-term patterns, the LSTM architecture was applied. Unlike classical econometric methods, it effectively addresses the vanishing gradient problem and allows for modeling long-term time dependencies without loss of informativeness. The mathematical foundation of the utilized LSTM architecture is based on the system of recurrent relations described in [3].

The software implementation of the proposed model was carried out in the Python environment using specialized machine learning libraries, TensorFlow and Keras. The Mean Squared Error (MSE) was selected as the target loss function for this study. During the training process, the algorithm aims to minimize the MSE value by iteratively adjusting the weight coefficients. The choice of an iterative approach for training the LSTM network is driven by the principles of dynamic system identification set forth in the work of B. I. Mokin, V.B. Mokin, and B. B. Mokin [11]. Their research demonstrates that multi-step parameter refinement procedures allow for minimizing the error of autoregressive models when dealing with volatile CPI indicators.

The network architecture was based on the following layer specifications:

– Input Layer: configured to work with a 12-month look-back period (sliding window), which is critical for identifying seasonal lags in CPI dynamics.

– LSTM Hidden Layer: consists of 50 computational units (neurons).

– Dropout Layer: a coefficient of 0,2 was implemented as a regularization measure to prevent overfitting and to enhance the model's generalization capability.

– Output Layer (Dense): designed to generate the final point forecast of the target indicator.

Figure 3 presents the learning curve of the neural network, reflecting the change in Mean Squared Error (MSE) on the training set. Analysis of the graph shows a rapid decrease in error during the first 30 epochs, indicating the model's swift identification of the main patterns in CPI dynamics. After the 45th epoch, the loss function value stabilizes at a low level (reaching a plateau), confirming the algorithm's convergence and the completion of the main training phase without signs of overfitting.

The absence of signs of overfitting allows for the use of the proposed model for subsequent forecasting of Ukraine's CPI.

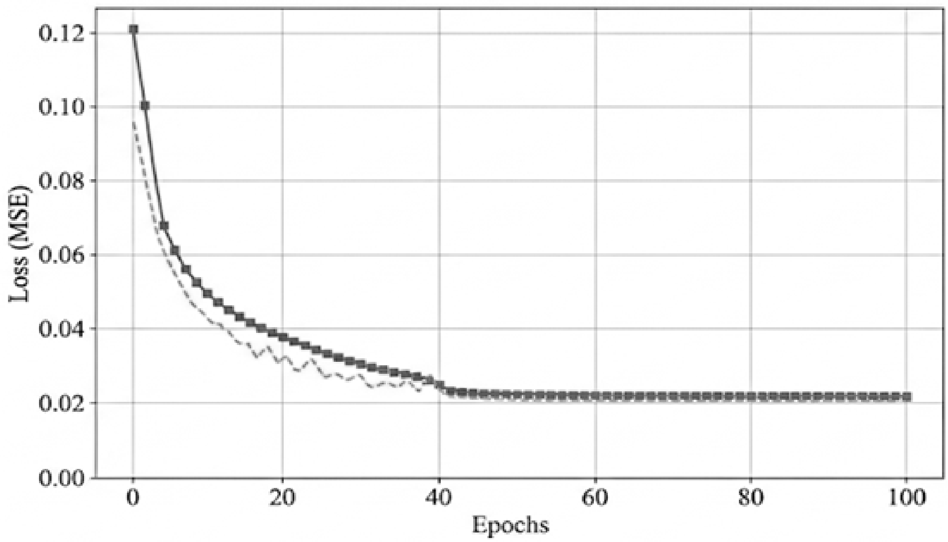

Figure 3. Learning curve of the LSTM model (MSE) over 100 epochs (solid blue line represents the training set, dashed orange line represents the validation set)

Source: calculated and constructed by the author based on FRED data [8]

For the final validation of the hypothesis regarding the superior accuracy of non-linear models, a comparative analysis of the forecasting performance of the identified ARIMA (2, 1, 0) model and the developed LSTM recurrent model was conducted (Table 2). The data in Table 2 demonstrate a significant advantage of neural network modeling.

The coefficient of determination (R2) for the LSTM model is 0,842, indicating the network's ability to explain over 84% of the variance in inflationary processes, whereas the linear ARIMA model accounts for only 38,8%. Most notably, the Mean Absolute Percentage Error (MAPE) decreased from 7,42% to 2,38%.

The obtained results empirically validate the hypothesis regarding the non-linear nature of inflationary processes in Ukraine and demonstrate the feasibility of employing deep learning algorithms to enhance the accuracy of macroeconomic forecasting.

Conclusions. The comparative analysis of classical econometric methods and deep learning algorithms for forecasting the CPI in Ukraine has established the following:

1. Insufficient adequacy of ARIMA (2, 1, 0). The coefficient of determination ($R^2 = 0{,}388$) and the high residual variance (61,2%) confirmed the inability of linear models to fully capture the dynamics of inflationary processes driven by exogenous shocks.

Table 2

Comparative characteristics of the accuracy of CPI forecasting models

Performance indicator	**Модель ARIMA (2, 1, 0)**	**Модель LSTM**
Coefficient of determination (R2)	0,388	0,842
The Mean Absolute Error (MAE)	0,642	0,184
Mean Absolute Percentage Error (MAPE), %	7,42%	2,38%
Predictive validity	Satisfactory	High

Source: compiled by the author

2. Superiority of the LSTM architecture. It has been empirically proven that recurrent networks identify non-linear inertial dependencies more accurately. The application of LSTM has led to a threefold increase in forecasting accuracy, reducing the MAPE from 7,42% to 2,38% (R^2 = 0,842).

3. Scopes of application for classical methods. Despite the efficiency of LSTM, the use of ARIMA remains appropriate in the following cases:

– Small sample size: with a data volume of fewer than 36–50 points, classical models are more stable and carry a lower risk of overfitting.

– Trend stationarity: in the absence of sharp structural shifts, the complexity of neural networks is redundant.

– Interpretability requirements: classical regressions are «transparent» for regulatory purposes, whereas neural networks operate on the "black box" principle.

– Low volatility: in stable systems, classical methods provide sufficient accuracy without the need for complex hyperparameter tuning.

Thus, the choice between recurrent architectures and classical statistical methods should be based on a comprehensive analysis of sample size, volatility levels, and interpretability requirements. A promising direction for further research lies in the development of hybrid models that integrate the ability of ARIMA to identify linear trends with the power of LSTM to model non-linear shocks. Such an approach will ensure maximum adaptability of forecasting systems within the dynamic macroeconomic environment of Ukraine.

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