DOI: 10.26565/2311-2379-2025-108-05
УДК 620.91:332.87:330.131.7

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APPLICATION OF THE ARBITRAGE PRICING BASED ON GAUSSIAN TEMPORAL FACTOR ANALYSIS (TFA) FOR THE PREDICTION OF CRYPTOCURRENCY PRICES

The study demonstrates how the Gaussian TFA model can be applied for cryptocurrency price forecasting. The study considers four approaches of the Extended Normalized Radial Basis Function (ENRBF), namely, the N-Adaptive ENRBF, S-Adaptive ENRBF, ICA-ENRBF and APT-based TFA-ENRBF to make one-time-step predictions of the closing price of four different cryptocurrency prices (BTC, ETH, XRP and SOL) in the financial markets. We've evaluated and compared the performance of the proposed models with a conventional Root Mean Squared Error (RMSE) using daily series data from January 01, 2020 to December 31, 2024. The result indicates that the APT-based TFA-ENRBF consistently outperformed the other models by achieving the highest predictive performance for look-back and look-ahead periods in terms the least RMSE. This shows that the APT-based TFA-ENRBF approach shows consistently superior performance over three other conventional approaches. Moreover, we've found that the ICA-ENRBF approach comes second, whilst the N-ENRBF approach appears to be the worst compared to others. Because the paper ignores the influence of other factors that can likely influence price predictions, we suggest that future research may involve a more in-depth exploration of hybrid methods. which can help examine how other factors predict the cryptocurrency prices.

Keywords: **arbitrage pricing theory, Gaussian temporal factor analysis, cryptocurrency**.
JEL Classification: C10, G15, G17.

Problem statement. Cryptocurrency is an alternative payment method developed with encryption techniques. Since the launch of Bitcoin other digital currencies like Ethereum, XRP and Stellar have appeared incredibly quickly. The decentralized nature of cryptocurrencies makes them less vulnerable to manipulation by financial institutions than traditional currencies. Investors trying to precisely forecast price fluctuations and make profitable investments face problems due to the cryptocurrency market's extreme volatility and unpredictability (Pintelas et al., 2020). Bitcoin continues to hold the largest share of all cryptocurrencies and controls the digital economy (CoinDesk, 2021). Sporadic volatility of the cryptocurrency market has prompted attempts to forecast its daily future price (Munim et al., 2019; Chen et al., 2020). Various cryptocurrencies continue to exhibit patterns which are largely predictable upon their historical past. Figure 1 shows the price dynamics for four considered cryptocurrencies – Bitcoin (BTC), Ethereum" (ETH), Ripple (XRP) and Solari (SOL).

White (1988) noted that "volatility nature of assets pricing calls for their predictability". Since White's application of backpropagation networks in the prediction of stock, several applications of feedforward neural networks in stock price prediction have been made (Schoneburg, 1990; Refenes et al., 1993; Sagar & Lee, 1999). The better performance of neural networks as compared to conventional statistical approaches in financial forecasting can be attributed to neural networks' capability to learn, adapt and generalize (Gbadebo et al., 2022). Nonetheless, a typical weakness of feedforward neural networks is the inability to model existing temporal relations in financial time series. To overcome this limitation, recurrent neural networks with feedback were adopted (Giles et al., 1997; Sagar, & Lee, 1999; Pantazopoulos et al., 1998).

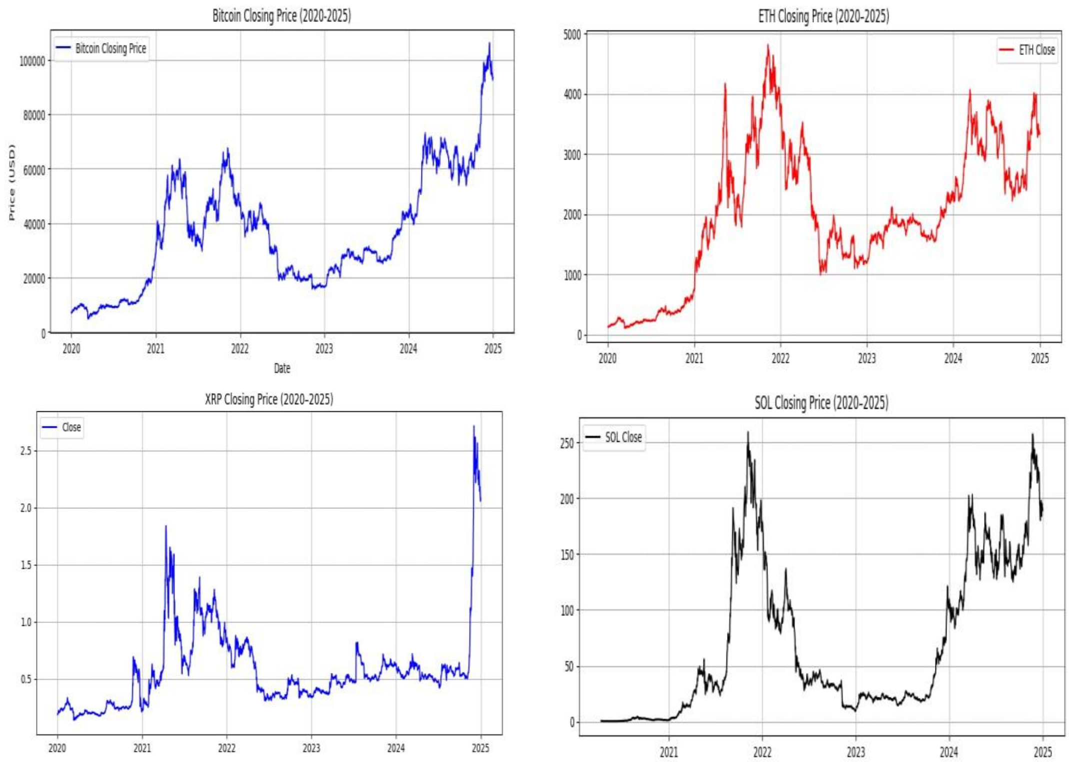

Fig. 1. Plots of Cryptocurrency Prices (Actual Series)

Source: Authors

From the perspective of statistical learning, stock price prediction was implemented via a special case of the alternative models for mixture of experts, called Extended Normalized Radial Basis Function (ENRBF), via the well-known Expectation-Maximization (EM) algorithm (Xu, 1998). Still, these efforts failed to consider some well-known finance models which not only have established their foundation in finance literature but have undergone rigorous statistical testing in relation to their explanatory power on certain empirically observed phenomena. Therefore, it would be desirable to use such learning algorithms designed for financial forecasting. In literature one could find forecasting of cryptocurrency prices within the framework of the Arbitrage Pricing Theory (APT) (Refenes et al., 1993). In our research we were interested in using machine learning algorithms that can predict prices. The algorithms are a collection of techniques for using data to adapt mathematical models without having to explicitly teach the computer to fulfill certain functions.

Developing a suitable machine learning and accurate forecast model for next-day price forecast may increase traders' returns and trading activities (Munim et al., 2019). Asymmetric information, dynamic behaviour of miners and uncertainties in the cryptocurrency markets make forecasting of Bitcoin price a challenging task (Kliber et al., 2019). The choice of the forecasting model can have a significant effect on the performance of Bitcoin and make the cryptocurrency market more efficient (Caporale, Gil-Alana, & Plastun, 2018). This research aims to find a model that enables accurate forecast of daily Bitcoin price.

Purpose and objectives. An accurate analysis of financial time series appears to be crucial for traders and institutional investors in an attempt to increase the chances to make profits (or minimize losses), i. e. to discover patterns or manipulation activities and to identify buy/sell signals. Although authoritative studies based on the Efficient Market Hypothesis (Fama, 1970) claim that financial markets follow a random walk and are unpredictable, the field of stock market analysis and prediction has attracted researchers in the Machine Learning field, whose obtained results suggest that stock (and cryptocurrency) trends can, at least partially, be predicted on the basis of historical data (Alvo et al., 2011, Caporale et al., 2018, Onali & Goddard, 2011). The cryptocurrency market, contrary to the traditional stock market, is also characterized by frequent, abrupt, sharp swings and falls, which make the predictive task even more difficult. Additional challenges come from the strong influence of external factors, such as global politics, market cycles, public opinion, or (also fake) news (Colon et al., 2021, Rognone et al., 2020, Wątorek et al., 2023).

Recently a new technique focused on the classical financial APT model was proposed by Xu (2000). There is a need for various models that can capture more intricate data representations for the cryptocurrency industry. The time-series challenge of cryptocurrency price prediction can be resolved by deep learning models, particularly recurrent neural networks. In recent years, several studies have been conducted by different authors to use machine learning and deep learning algorithms to forecast the value of stocks and securities (Hung et al., 2020). This paper considers four distinct machine learning models. The use of the APT-based Gaussian Temporal Factor Analysis (TFA) model for the prediction of cryptocurrency prices is shown in section 1; section 2 reviews the APT and the Gaussian TFA mode; section 3 provides information on the forecasting methods; section 4 offers the experimental comparisons of how Gaussian TFA can be applied to forecasting and section 5 contains conclusions.

Analysis of recent research. The literature on Bitcoin and other cryptocurrencies is quite huge. Some studies focus on Bitcoin price formation and clustering (Urquhart, 2018), some ones – on factors that explain and predict Bitcoin price (Jang & Lee, 2018; Guizani & Nafti, 2019; Hung et al., 2020; Kraaijeveld & De-Smedt, 2020; Gbadebo et al., 2021; Jaquart et al., 2021), or on time-of-day periodicities trading of Bitcoin (Baur et al., 2019; Gbadebo et al., 2023), on the estimation of price volatility (Troster et al., 2019; Hung et al., 2020; Adekunle et al., 2022), on the examination of Bitcoin exchange and crypto-finance (Goutte et al., 2019; Jeon et al., 2020).

Zhong and Enke (2017) used ANNs with dimensionality reductions, which only captures linear/planar intricacy within the data, in their dimensionality reduction strategies and principal component analysis, including market history, commodity prices and foreign currency rates. Kohli et al. (2019) have predicted the movements of the Bombay Stock currency (BSE) and have discovered that the BSE was most impacted by gold prices. Their investigation showed that the AdaBoost algorithm had outperformed the others. Zhang et al. (2019) developed an architecture for Generative Adversarial Networks (GAN) that uses Multi-Layer Perceptrons (MLP) as discriminators and Long Short-Term Memory (LSTM) as generators. Zhang and associates (2019) Multiple metrics have been used to evaluate the models, and the suggested GAN model has proven to be superior to another model based on all metrics used in this study. The GAN model has been compared with the LSTM, Artificial Neural Network (ANN), and Support Vector Regression (SVR).

Sin and Wang (2017) have compared the well-known time series forecasting ARIMA model with deep learning models; the highest classification of LSTM is 52%, and the RMSE is 8%. The non-deep learning approach fared better than the non-linear ARIMA estimator, as was expected. When deep learning was finally tested on both GPU and CPU, the GPU's learning time was 67.7% faster than the CPU's. In deep learning for time sequence forecasting LSTM connection is more contemporary. Less research has been done on economic forecasting, particularly regarding cryptocurrencies. To forecast the daily price of Bitcoin, we just provide a novel LSTM model prediction framework that makes use of two distinct LSTM models (the conventional LSTM model and the LSTM with ARIMA model). Daily variations of bitcoin data during the time frame from January 1, 2018 to July 28, 2018, comprising 208 data points, were used to assess the design's performance. Sin and Wang (2017) model shous that LSTM performs better than the conventional LSTM model when it comes to overcoming the difficulty of diverse input selection in LSTM models without requiring precise data, and that it might be applied to several commercial scenarios, including real-time financial data, medical data, and cryptocurrency prediction.

For non-linear feature extraction many kinds of autoencoders are employed. Deep stacked autoencoders have been employed in behaviour-based credit card fraud detection by Gradxs and Rao (2023). They have paired a deep balanced stacking autoencoder with Harris Grey Wolf Network.

Fanai and Abbasimehr (2023) have employed deep classifiers and hybridism LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), WLSTM (Weighted LSTM) and LSTM with attention. Two popular recurrent neural networks for processing sequential data are LSTM and with attention (LSTMA). Their testing demonstrates the autoencoder's advantage over PCA. Multiple feature consideration is also crucial for accurate prediction; in this case, hybridization is helpful. Numerous features of several techniques can be combined into a single model by hybridizing numerous DL models. This aids in capturing hidden intricacies that were previously overlooked.

Zhao et al. (2023) have integrated LSTM with k-nearest neighbours (KNNs). Performance of the combined approach was notable when compared to conventional ML models. In their experiments on the KOSPII market, Kwak and Lim (2021) have found that the AdaBoost and GRU ensemble model was more efficient than the LSTM, GRU and ARIMA models. For trading-signal prediction, Shen et al. (2018) previously experimented with GRU by substituting SVM for the final layer. Their research has revealed that hybridizing ML and DL models significantly improved performance. According to Hossain et al. (2018), LSTM-GRU hybridization improves pricing predictability. Song and Choi (2023) investigated DL model hybridizations and have found a significantly increased efficiency when compared to other conventional models. Adekunle et al. (2022) have applied 18 models to forecast the price of Bitcoin for daily time-series from 1/09/2014 to 28/12/2020 and have found that the Holt-Winters filter HWF ($\gamma\epsilon$[0,1]) with lower limit fitted on STL-Trend provides the best prediction on the first training-sample, while ARIMA(fix) fitted on actual data outperform in the second training-set with the smallest Mean Absolute Error (MAE). The training-set forecast performance of the ARIMA(fix) for the actual function provides better performance with the least MAE.

Awoke et al. (2021) used two recurrent neural networks (RNNs) for the daily forecast of the Bitcoin price. They used gated recurrent units (GRU) and long short-term memory (LSTM). The results have shown that GRU-based models were more effective in forecasting highly volatile time series. Nevertheless, the analysis has also revealed that LSTM exhibited superior performances when the measurements of only 7 previous days are used as descriptive features. Yiying and Yeze (2019) compared the performances of a simple fully connected neural network with an LSTM model when trying to forecast the price of three popular cryptocurrencies (Bitcoin, Ethereum, and Ripple). They highlighted the effectiveness of LSTM in exploiting information in historical memory.

Theoretical background and methods.

Theoretical foundations

a. Arbitrage Pricing Theory (APT)

The APT, from Ross (1976), begins with the assumption that the $n \times 1$ vector of asset returns, $\tilde{R}_t$, is generated by a linear stochastic process with k factors:

$$\tilde{R}_t = \bar{R} + Af_t + e_t \tag{1}$$

where f_t is the $k \times 1$ vector of realizations of k common factors, A is the $n \times k$ matrix of factors weights or loadings, and e_t is a $n \times 1$ vector of asset-specific risks. It is assumed that f_t and e_t have zero expected values so that $\bar{R}$ is the $n \times 1$ vector of mean returns.

b. Temporal Factor Analysis (TFA)

The Gaussian TFA model, see Xu (2001), supposes that the relationship between a state $y_t \in \mathbb{R}^k$ and an observation $x_t \in \mathbb{R}^d$ are described by the first-order state-space equations as:

$$y_t = By_{t-1} + \varepsilon_t \tag{2}$$

$$x_t = Ay_t + e_t,\ t = 1,2, \dots, N. \tag{3}$$

where ε_t (being Gaussian distributed) and e_t are mutually independent zero-mean white noises with $E(\varepsilon_i \varepsilon_j) = \Sigma_\varepsilon \delta_{ij}, E(e_i e_j) = \Sigma_e \delta_{ij}, E(\varepsilon_i e_j) = 0, \Sigma_\varepsilon$ and Σ_e are diagonal matrices; δ_{ij} is the Kronecker delta function. In the context of APT analysis, expression (1) can be obtained from (3) by substituting ($\tilde{R}_t - \bar{R}$) for x_t and f_t for y_t. The only difference between APT and TFA models is the added equation (2) for modelling temporal relation of each factor. The added equation represents a factor series $y = \{y_t\}_{t=1}^{T}$ in a multi-channel auto-regressive process, driven by an i.i.d. noise series $\{\varepsilon_t\}_{t=1}^{T}$ that are independent of both y_{t-1} and e_t.

Methods

The model presents a holistic strategy for forecasting cryptocurrency prices, utilizing methods to offer valuable perspectives for cryptocurrency traders and investors (Roth, 2015). The data is divided into subsets for training and tests. The test datasets are used to evaluate the trained model, and the predictive capability is measured using the Root Mean Squared Error (RMSE):

$$RMSE = \left(\frac{1}{m}\sum_{t=1}^{m}(e_t)^2\right)^{1/2} \qquad (4)$$

We use the Extended Normalized Radial Basis Function (ENRBF) approach to compare the relative performance of four selected cryptocurrency. The ENRBF method falls into two groups based on the input source. Category I approach refer to the time series method, denoted as the N-Adaptive ENRBF and S-Adaptive ENRBF, applies only the time series of the respective data. Category II approach refers as the market-based approach, defined as the Independent Component Analysis (ICA)-ENRBF and APT-based TFA-ENRBF, which use both the series price alongside the corresponding constituent stock.

The algorithm of N-ENRBF approach is defined as such that the input vector consists of nonstationary raw index prices and is set as $\mathbf{x_t} = [p_{t-1}, p_{t-2}, p_{t-3}]^T$ at time t (Xu, 1998). The S-ENRBF approach is like the N-ENRBF, for which the adaptive ENRBF algorithm is adopted. The input vector at time t is $\mathbf{x_t} = \left[\tilde{R}_{t-1}, \tilde{R}_{t-2}, \tilde{R}_{t-3}\right]^T$, where stationary returns $\hat{R}_t$ are used instead of nonstationary index prices p_t. The price at time t can be recovered by from the predicted returns via $p_t = p_{t-1}\left(1 + \tilde{R}_t + \bar{R}\right)$, where $\tilde{R}$ and $\bar{R}$ are as defined in (1). ICA-ENRBF approach involves two steps. First, the inverse mapping $\mathbf{y}_t = W\mathbf{x}_t$ is effected via the technique called ICA for higher-than-second order dependence reduction. For this step the stock returns of the corresponding index constituents at time $t - 1$ are used as input to recover independent components $\mathbf{y}_{t-1}$. Then, the adaptive ENRBF algorithm is adopted for establishing the relationship between $\mathbf{y}_{t-1}, x(t-1)$ and $x(t)$ (Xu et al., 1997). The APT-Based TFA-ENRBF Approach differs from the preceding approach only in the first step. Here, the Gaussian TFA algorithm is used instead of the LPM-ICA algorithm, to recover independent hidden factors $\mathbf{y}_{t-1}$ at time $t - 1$ from cross sectional stock returns $\mathbf{x_{t-1}}$. According to our previous work (Chiu & Xu, 2002), the number of factors determined via the model selection ability of TFA is found to be 4 for HSI constituents and 3 for HSCCI constituents.

Experimental investigation is based on the performance of prediction of the four cryptocurrencies – Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Solari (SOL). The study used the closing price series covering using daily series data from January 01, 2020, to December 31st, 2024. We log transform each series to ensure use of smoothen striation (Munim et al., 2019; Gbadebo et al., 2023). It is necessary to make the price forecasts in its logarithm of returns, hence, the cryptocurrency prices are converted to stationary returns (Adekunle et al., 2022; Hudson & Gregoriou, 2010) or other transformation forms (Meucci & Quant, 2010). Figure 2 shows the log transformation and log-difference of the series. We use the first 300 data for training and the remaining for test. The training and test procedures are implemented in an adaptive fashion. The number of optimum hidden units is chosen via automatic selection of Rival Penalized Competitive Learning algorithm (Xu et al., 1993) procedures areimplemented in an adaptive fashion. The number of optimum hidden units is chosen via automatic selection of Rival Penalized Competitive Learning algorithm (Xu et al., 1993).

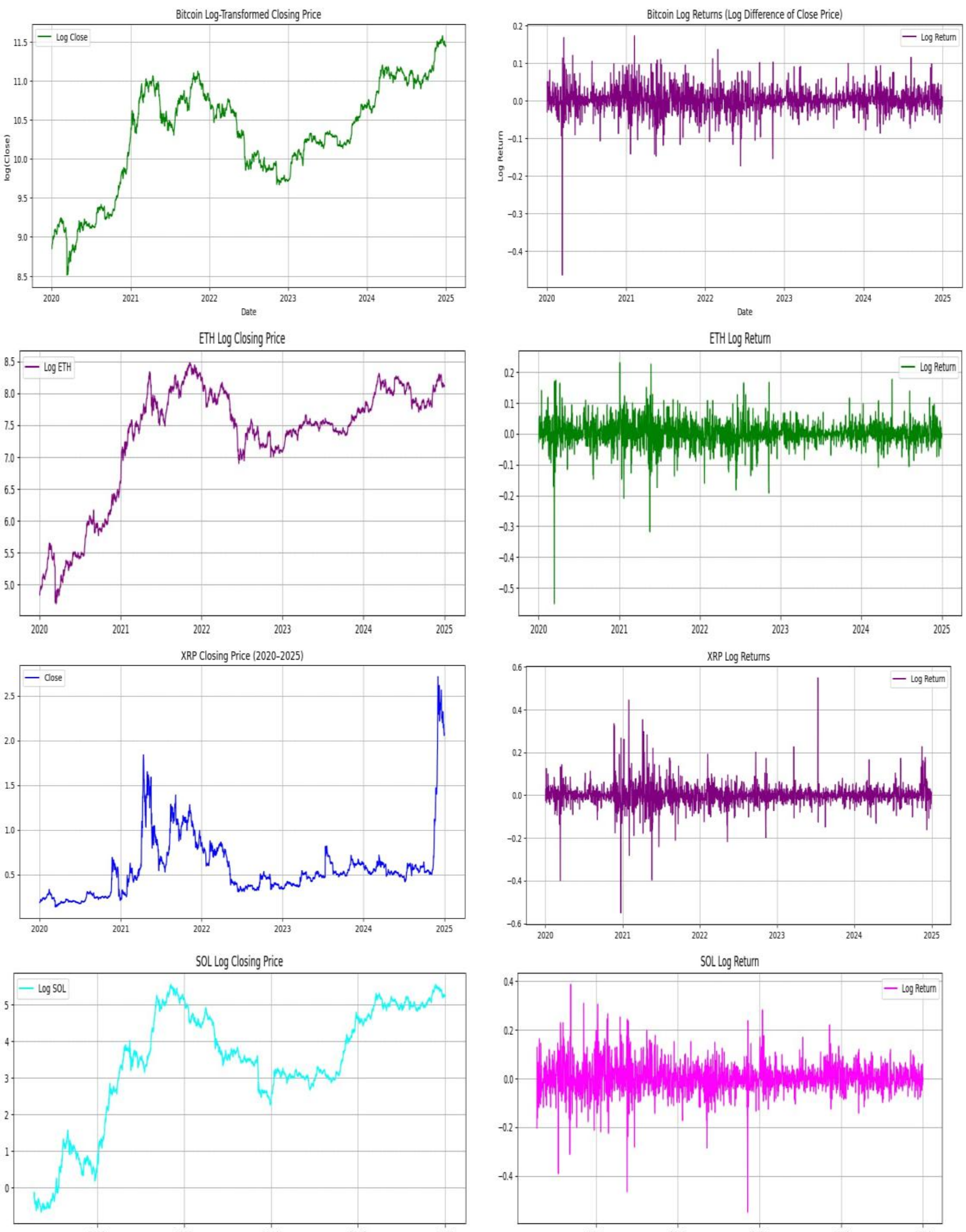

Fig. 2. Log and Log Difference Plots of Cryptocurrency prices

Source: Authors

Results. Typical results of BTC, ETH, XRP and SOL prices using the N-ENRBF, S-ENRBF, ICA-ENRBF and APT-based TFA-ENRBF as defined, are presented in Figure 2 and Table 1. The performance of each method can be compared quantitatively by their respective Root Mean Square Errors (RMSE) between the predicted prices $\hat{p}_t$ and the desired prices p_t. The APT-based TFA-ENRBF has the least RMSE for all three indices, thus, consistently outperforms the other three approaches. The ICA-ENRBF approach comes second, whilst the N-ENRBF approach appear worst relative to others.

Table 1 – **Model Accuracy by (RMSE for different approaches**

Approach	BTC	ETH	XRP	SOL
N-ENRBF	198.977	31.802	8.816	0.925
S-ENRBF	81.435	0.796	5.982	0.315
ICA-ENRBF	69.128	7.729	4.434	0.677
APT-based TFA-ENRBF	56.203	6.620	3.187	0.323

Source: *Authors*

This is unsurprising, as theoretically APT-based TFA-ENRBF approach is superior to the "ICA-ENRBF approach because it considers the observation noise e_t ignored by the LPMICA algorithm (the term e_t in equation (3) of the TFA model). As far as signals pre-processed by the ICA technique contain less redundancy, the ICA-ENRBF approach performs better than the duo N-ENRBF and S-ENRBF. From the information point of view both SENRBF and N-ENRBF approaches are lacking information because no constituent returns are provided during parameter learning, therefore, less precise parameters are computed. It should be noted that in the N-ENRBF approach nonstationary raw prices are used while in the other three approaches stationary cryptocurrency returns are used instead. Since difference stationary signals are in general more difficult to anticipate, this unfavourable condition makes the N-ENRBF approach the worst of all.

Conclusion. The study considered four approaches of the Extended Normalized Radial Basis Function (ENRBF), namely, the N-Adaptive ENRBF, S-Adaptive ENRBF, ICA-ENRBF and APT-based TFA-ENRBF to make one-time-step predictions of the closing price of four different cryptocurrency prices (BTC, ETH, XRP and SOL) in the financial markets. We've evaluated and compared the performance of the proposed models with conventional Root Mean Squared Error (RMSE). Clearly, the APT-based TFA-ENRBF model consistently outperformed the other models by achieving the high predictive performance for look-back and look-ahead periods in terms of the least RMSE. This shows that the APT-based TFA-ENRBF approach is consistently superior in performance over three other conventional approaches. Moreover, we've found that the ICA-ENRBF approach comes second, whilst the N-ENRBF approach appears to be the worst relative to others.

The research has some limitations: first of all, we focused only on four cryptocurrencies, ignoring others that can correlate with these predicted coins. More so, we've ignored the influence of other factors that could likely influence the price predictions. To increase the precision of the predictions we suggest that in future research we could increase the epoque size and apply alternative deep learning algorithms or hybrid DL models. Epoch size might be increased to enhance the accuracy rate, while deep learning or its hybrid methods can be utilized to examine how other factors predict the cryptocurrency price.

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The article was received by the editors 12.04.2025
The article is recommended for printing 26.05.2025

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ЗАСТОСУВАННЯ ТЕОРІЇ АРБІТРАЖНОГО ЦІНОУТВОРЕННЯ НА ОСНОВІ ГАУСІВСЬКОГО ЧАСОВО-ФАКТОРНОГО АНАЛІЗУ (TFA) ДЛЯ ПРОГНОЗУВАННЯ ЦІН НА КРИПТОВАЛЮТИ

У дослідженні продемонстровано, як модель Гаусівського TFA може бути застосована для прогнозування цін на криптовалюти. Розглянуто чотири підходи Розширеної Нормалізованої Радіальної Базисної Функції (ENRBF): N-адаптивна ENRBF, S-адаптивна ENRBF, ICA-ENRBF та ENRBF на основі APT-TFA, які використовуються для одночасового прогнозування ціни закриття чотирьох криптовалют (BTC, ETH, XRP і SOL) на фінансових ринках. Ми оцінили й порівняли ефективність запропонованих моделей, використовуючи звичайну середньоквадратичну помилку (RMSE) на щоденних даних за період з 1 січня 2020 року по 31 грудня 2024 року. Результати показали, що метод APT-TFA-ENRBF стабільно перевершував інші моделі, демонструючи найвищу точність прогнозування у зворотних і прямих інтервалах за найменшою RMSE. Це вказує на послідовну перевагу підходу APT-TFA-ENRBF над трьома іншими традиційними методами. Крім того, було встановлено, що метод ICA-ENRBF показав другий найкращий результат, тоді як N-ENRBF виявився найгіршим за ефективністю. Через те, що дослідження не враховує вплив інших чинників, які можуть суттєво впливати на прогнозування цін, ми рекомендуємо, аби майбутні дослідження зосередилися на глибшому вивченні гібридних методів, які дозволяють аналізувати ці чинники.

Ключові слова: **теорія арбітражного ціноутворення, Гаусівський часово-факторний аналіз, криптовалюта.**

JEL Classification: C10, G15, G17.

In cites: Gbadebo A.D., & Abdulrauf L.A. (2025). Application of the arbitrage pricing based on Gaussian temporal factor analysis (TFA) for the prediction of cryptocurrency prices. *Bulletin of V. N. Karazin Kharkiv National University Economic Series*, (108), 49–58. https://doi.org/10.26565/2311-2379-2025-108-05