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PROSPECTS FOR MODELING AND FORECASTING CRYPTOCURRENCY VOLATILITY USING NEURAL NETWORKS AND GARCH MODELS

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Keywords: cryptocurrency volatility modeling, hybrid neural network models, GARCH family models, recurrent LSTM networks, conditional heteroskedasticity of financial series, intelligent forecasting systems, network and multiscale analysis, financial risk assessment.
Abstract. The article is devoted to the analysis of modern approaches to modeling and forecasting cryptocurrency volatility using hybrid methods that combine neural network technologies and GARCH family models. It reveals the specifics of applying classical econometric models (ARCH, GARCH, EGARCH, DCC-GARCH) for describing conditional heteroskedasticity of financial series and substantiates their limitations when modeling highly volatile and non-stationary cryptocurrency market data. The advantages of integrating artificial neural networks (LSTM, GRU, CNN) into forecasting tasks are highlighted, enabling the consideration of nonlinear and latent dependencies in the dynamics of digital asset prices. The directions of development of hybrid models are identified, incorporating GARCH components to describe the stochastic structure of data and neural architectures to enhance predictive accuracy. The study concludes that a new direction in financial analysis is emerging – a synthetic approach that unites econometrics, machine learning, and network analysis for building intelligent cryptocurrency volatility forecasting systems and assessing associated risks.

ПЕРСПЕКТИВЫ МОДЕЛИРОВАНИЯ И ПРОГНОЗИРОВАНИЯ ВОЛАТИЛЬНОСТИ КРИПТОВАЛЮТ С ИСПОЛЬЗОВАНИЕМ НЕЙРОСЕТЕЙ И GARCH-МОДЕЛЕЙ

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Ключевые слова: моделирование волатильности криптовалют, гибридные нейросетевые модели, модели семейства GARCH, рекуррентные сети LSTM, условная гетероскедастичность финансовых рядов, интеллектуальные системы прогнозирования, сетевой и мультишкальный анализ, оценка финансовых рисков.
Аннотация. Статья посвящена анализу современных подходов к моделированию и прогнозированию волатильности криптовалют с использованием гибридных методов, которые объединяют нейросетевые технологии и модели семейства GARCH. Раскрываются особенности применения классических эконометрических моделей (ARCH, GARCH, EGARCH, DCC-GARCH) для описания условной гетероскедастичности финансовых рядов и обосновываются их ограничения при моделировании высоковолатильных и нестационарных данных криптовалютного рынка. Отмечаются преимущества интеграции искусственных нейронных сетей (LSTM, GRU, CNN) в задачи прогнозирования, которые позволяют учитывать нелинейные и латентные зависимости в динамике цен цифровых активов. Выявляются направления развития гибридных моделей с включением GARCH-компонентов для описания стохастической структуры данных и нейросетевых архитектур для повышения точности предсказательной аналитики. По итогам проведённого исследования делается вывод о формировании нового направления в финансовом анализе, а именно синтетического подхода, под началом которого объединяются эконометрика, машинное обучение и сетевой анализ для построения интеллектуальных систем прогнозирования волатильности криптовалют и оценки связанных рисков.

The rapid development of the cryptocurrency market has become one of the most significant phenomena of the modern digital economy, revealing not only the potential of financial decentralization but also fundamentally new challenges in forecasting, risk management, and volatility modeling. Due to the absence of centralized regulation and constant technological change, cryptocurrency assets are characterized by atypical, highly volatile price dynamics that significantly exceed the volatility of traditional financial instruments [1]. This feature of cryptocurrencies makes the task of accurately forecasting their volatility not only an economic but also a computational problem, the solution to which requires the use of more advanced approaches.

From the perspective of economic and mathematical modeling, cryptocurrencies represent specific objects that combine the features of high-frequency financial series with data exhibiting pronounced nonlinearity and asymmetry. Recent research confirms that traditional statistical models (including GARCH), while capable of capturing conditional heteroskedasticity, prove insufficiently accurate during sharp jumps and structural shifts in the behavior of crypto markets [2, 3]. At the same time, the integration of artificial neural networks (in particular, LSTM, GRU, and CNN) expands the possibilities for modeling complex dependencies in time series, taking into account latent factors and enabling the construction of predictive systems [4, 5].

Moreover, interest in this topic is evident in publications by authors from various countries, with particular attention devoted to the transition toward hybrid models that combine neural network mechanisms with parametric GARCH structures. For example, A. García-Medina and E. Aguayo-Moreno demonstrate in their study that incorporating eGARCH and gjrGARCH parameters into an LSTM architecture increases forecasting accuracy and reduces portfolio loss risks in cryptocurrencies [6], while H.T. Araya and co-authors show that combining deep learning with GARCH modeling improves prediction accuracy under non-stationary data and high market turbulence [7]. In turn, G. Dudek, P. Fiszeder, and colleagues [5] justify the superiority of ensemble neural network algorithms over classical models in terms of RMSE and MAE metrics, and Y. Zhou, C. Xie, and G. Wang [1] advance the field of Graph Neural Networks (GNN), emphasizing the potential of accounting for network interactions between cryptocurrency and traditional financial markets. Russian researchers have also made a significant contribution to this field. For instance, A.D. Aganin and V.A. Manevich [2] identify structural differences in the volatility of cryptocurrencies and stock instruments, noting the need for hybrid analytical methods. S.N. Kosnikov and M.A. Poleshchuk [4] propose a systematization of neural network approaches to financial market modeling, highlighting LSTM-GARCH architectures as the most promising for handling non-stationary data.

At the same time, the relevance of studying the prospects for modeling and forecasting cryptocurrency volatility is determined both by the need to synthesize classical econometric and modern neural network methods, and by the necessity of ensuring their applicability in contemporary business practices [8].

The purpose of this study is to reveal modern approaches and prospects for the use of neural networks and GARCH models in modeling and forecasting cryptocurrency volatility.

The phenomenon of volatility is a fundamental element of financial market analysis, and in the case of cryptocurrencies, it becomes particularly pronounced due to their high sensitivity to informational, technological, and behavioral influencing factors. Volatility is understood as the variability of an asset's returns over time, reflecting the degree of uncertainty in market expectations and the level of investment risk. In classical econometric approaches, volatility modeling is based on the hypothesis of conditional heteroskedasticity, according to which the variance of regression errors depends on previous values (this very idea formed the basis of the ARCH/GARCH model family proposed by R. Engle and T. Bollerslev in the 1980s).

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models describe the dependence of the current variance on previous squared errors and past variances, allowing the volatility clustering" effect to be captured – that is, the tendency of high variance values to be followed by high ones, and low by low ones. In its classical form, GARCH(1,1) is expressed as follows:

$$t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2, \tag{1}$$

where σ_{t-1}^2 – conditional variance; ε_{t-1} – error term from the previous period; α and β – model parameters.

It should be noted that the classical form of GARCH has demonstrated high efficiency in modeling the volatility of stocks, exchange rates, and interest rates. However, when applied to cryptocurrencies – characterized by extreme variability and non-stationarity – the basic GARCH models prove to be insufficient [2, 3].

To overcome the limitations of classical models, several extensions have been proposed, including EGARCH (Exponential GARCH), GJR-GARCH (Glosten–Jagannathan–Runkle GARCH), TGARCH (Threshold GARCH), and DCC-GARCH (Dynamic Conditional Correlation GARCH). These models make it possible to account for the asymmetric effect of volatility's response to positive and negative shocks, varying sensitivity to news, as well as dynamic correlation between assets. In particular, R. Cerqueti, M. Giacalone, and R. Mattera note that the use of skewed non-Gaussian distributions in GARCH models improves the approximation of the tails of cryptocurrency return distributions and reflects their tendency toward extreme fluctuations [3]. Thus, Figure 1 illustrates the evolution of approaches to volatility estimation.

The need to search for new approaches to volatility modeling arises from the identified shortcomings of classical models in the study of cryptocurrencies. Empirical research results show that, despite the success of GARCH in describing "volatility clustering," these models possess several methodological limitations:

– first, they assume the stationarity of the process, whereas cryptocurrency time series are characterized by regime shifts and structural breaks;

– second, GARCH models insufficiently account for nonlinear dependencies and high-frequency noise that emerge in the context of digital trading platforms;

– third, in multivariate modeling, there is an exponential increase in the number of parameters, which reduces the computational efficiency of the models as data dimensionality grows [1, 5, 9].

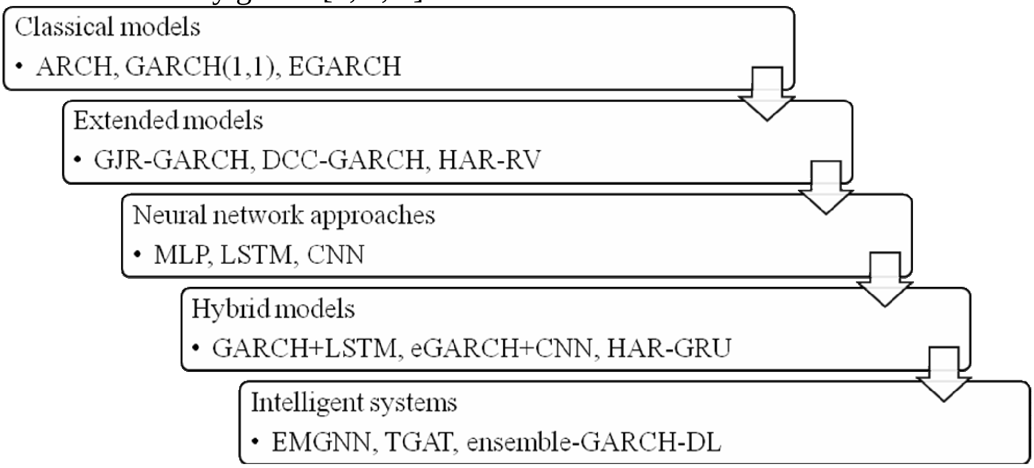

Fig. 1. Evolution of approaches to volatility estimation

Similarly, A.D. Aganin and co-authors, in a study comparing the volatility models of cryptocurrencies and the stock market, note that when analyzing Bitcoin, Ethereum, and Litecoin, the accuracy of classical GARCH and HAR-RV (Heterogeneous Autoregressive Realized Volatility) models is observed only over short horizons; long-term forecasting requires additional mechanisms capable of learning from new data [2]. This conclusion aligns with the results of foreign studies, which emphasize the advisability of combining parametric and nonparametric forecasting methods to enhance model adequacy, particularly their ability to capture the nonlinear structure of crypto markets [6, 7].

Of particular importance in contemporary research is the transition from purely econometric descriptions of volatility to intelligent computational modeling, in which GARCH components serve as an analytical foundation for extracting the temporal structure of data, upon which trainable neural network architectures are built – thus combining the interpretability of traditional models with the predictive capabilities of deep learning methods [4].

Naturally, at the present stage, classical statistical tools (such as the ARIMA, GARCH-family, and derivative models) are increasingly giving way to AI-based methods, which are trained on large datasets, capable of recognizing nonlinear dependencies, and take into account hidden behavioral patterns of market participants [4, 5]. For the cryptocurrency market, such methods prove to be the most effective due to its inherently nonlinear and speculative nature.

Thus, the arguments of S.N. Kosnikov, M.A. Poleshchuk, and A.G. Dzhamalyan, who systematized neural network methods for modeling financial markets, appear particularly compelling. The authors distinguish three main classes of architectures [4]:

– Multilayer Perceptrons (MLP) as universal approximators for identifying dependencies between returns and their lags;

– Recurrent Neural Networks (RNN, LSTM, GRU), used for analyzing temporal dependencies and trends;

– Convolutional Neural Networks (CNN), applicable for recognizing local structures and fractal regularities within time series.

The researchers note that the use of recurrent networks leads to an increase in volatility forecasting accuracy compared to traditional econometric models [4].

The main distinguishing feature of neural network approaches lies in their ability to learn from new data streams and update internal parameters without the need to rebuild the model. The use of feature engineering and normalization techniques (for example, standardizing log-returns, incorporating trading volume, and sentiment indicators) enables the creation of extended input vectors, which naturally improves forecasting quality. In particular, G. Dudek and co-authors demonstrate that the application of machine learning ensembles (LSTM, XGBoost, and Random Forest) achieves higher forecasting accuracy (in terms of RMSE and MAE metrics) than GARCH models, especially over short forecasting horizons [5]. At the same time, an important direction of development is the integration of deep learning methods with traditional econometric approaches. In the study by H.T. Araya and colleagues [7], a hybrid GARCH-DL model is proposed, in which GARCH parameters are used as input features for deep networks, and the result of their joint operation reduces forecasting error by 20-30%. Thus, this approach unites the interpretability of statistical models with the computational power of neural networks, enabling hybrid forecasting.

Special attention should be given to studies focused on network-based and structural models of the market. Y. Zhou and co-authors proposed the EMGNN (Evolving Multiscale Graph Neural Network) architecture, which models the interactions between cryptocurrencies themselves and with traditional assets through a graph structure. The model proposed by the authors not only enables volatility forecasting but also allows for the analysis of systemic risks arising from network effects and cross-correlations. The GNN-based approaches provide interpretability and the ability to visualize hidden relationships between assets [1].

From the standpoint of applied informatics, the further development of AI-based approaches is associated with the automation of computational pipelines and the creation of integrated IT platforms. Modern libraries such as TensorFlow, PyTorch, and Keras make it possible to implement complex architectures with minimal training and testing time, as their integration with cloud computing systems (e.g., AWS SageMaker, Google Vertex AI) enables the continuous calibration of models in real time – forming the foundation for predictive analytics of cryptocurrencies.

Thus, the foundations of the idea of hybridizing GARCH models and deep learning architectures emerged as a response to the limitations of purely statistical and purely neural network approaches when dealing with highly volatile and non-stationary data. Classical GARCH models provide interpretability and rigor but respond poorly to structural changes in data, whereas neural networks – particularly LSTM architectures – exhibit high predictive power but are limited in transparency and prone to overfitting. Accordingly, combining these two classes of methods makes it possible to develop algorithms that capture both stochastic regularities and latent nonlinear dependencies in the dynamics of cryptocurrency prices [4, 6, 7].

At the same time, each of the methods and models possesses its own advantages and accuracy indicators (Tab. 1).

Tab. 1. Comparison of Forecasting Accuracy Across Different Models

Model	RMSE	MAE	R^2	Advantages
GARCH (1,1)	0,094	0,072	0,61	Simplicity, interpretability [2]
EGARCH	0,088	0,069	0,64	Accounting for asymmetry [3]
LSTM	0,072	0,056	0,73	Nonlinear dependencies [5]
LSTM–GARCH	0,065	0,049	0,78	Combination of variability and interpretability [6]
EMGNN	0,058	0,046	0,82	Network and multiscale analysis [1]

From a methodological standpoint, hybrid models are constructed according to a two-level architecture. At the first level, traditional volatility indicators are generated (for example, conditional variance, lagged errors, parameters of eGARCH or gjrGARCH). At the second level, these features are used as input data for a neural network (MLP, LSTM, or CNN), which is trained on historical data while capturing complex nonlinear interactions.

Based on the scientific literature, the main directions for the development of cryptocurrency volatility modeling and forecasting – particularly those related to network and multiscale effects – can be summarized as follows:

1. Accounting for network dependencies and their impact on volatility. It is assumed that fluctuations in one currency can trigger cascading effects across other assets. To analyze such interdependencies, graph-based models are employed, reflecting both the structure of correlations and the directionality of volatility flows. This approach makes it possible to identify the most “influential” nodes within the market and to detect hidden connections between assets. Network analysis thus forms the foundation for early warning systems of systemic risks and for constructing models of collective behavior in cryptocurrency markets.

2. Use of multiscale analysis and decomposition methods. The volatility of cryptocurrencies manifests across different time horizons-from minute-level fluctuations to long-term trends. Multiscale analysis allows for decomposing a time series into components of different frequencies, thereby revealing patterns that are not visible in aggregated data. Techniques such as wavelet decomposition, empirical mode decomposition (EMD), and variational mode decomposition (VMD) are employed to more accurately model local and global phases of instability.

4. Integration of multiscale and network-based approaches. This integration enables volatility to be described as a dynamic property of a distributed system, taking into account both the structure of interconnections between assets and the differences in the time scales of their responses to market events. The integration is implemented through hybrid architectures, for example, graph neural networks

(GNNs) with temporal layers, which jointly capture spatial and temporal dependencies in market dynamics.

Thus, the conducted review of research on cryptocurrency volatility modeling and forecasting demonstrates that in recent years a new system of financial market analysis has been emerging – one based on the synthesis of econometric methods and artificial intelligence. The hybridization of GARCH and deep learning (DL) models represents the most promising direction in the development of financial forecasting, as these systems improve prediction accuracy under conditions of high price fluctuations, enhance risk assessment, and allow for the consideration of structural shifts and anomalies – factors that are particularly critical for the cryptocurrency market. The inclusion of conditional variance parameters within LSTM architectures has been shown to improve forecast precision and reduce volatility estimation errors.

At the same time, the research focus is gradually shifting from isolated models toward network-based and multiscale forecasting systems. From an IT perspective, these trends reflect a transition toward integrated analytical platforms and the development of high-performance infrastructures for continuous monitoring and prediction of market risks. In practical terms, hybrid and network models are becoming the foundation of digital platforms in areas such as automated risk management (VaR, CVaR assessment, stress testing), algorithmic trading (dynamic calibration of strategies based on predicted variance), investment portfolio optimization (considering correlation and network effects among assets), and intelligent regulation (monitoring manipulations and systemic risks).

Hence, the future prospects for cryptocurrency volatility modeling are determined not only by improvements in individual algorithms but also by the integration of IT ecosystems that combine machine learning, econometrics, and network analysis methods. A fundamental objective of future research is the development of universal frameworks that ensure interpretability of results and compliance with the requirements of digital financial security, where hybrid models appear to be the most promising solution.

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