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ARTICLE

A Hybrid Fractional Artificial Neural Network Model for Value at Risk Prediction in Emerging Financial Markets

Um Modelo Híbrido Fracionário com Redes Neurais Artificiais para Previsão do Value at Risk em Mercados Financeiros Emergentes

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ABSTRACT | **Objective:** This study aims to develop an improved methodology for forecasting Value at Risk (VaR) by addressing the limitations of traditional risk-measurement models that fail to capture long-memory behavior and nonlinear dependencies in financial returns. The objective is to integrate fractional calculus with Artificial Neural Networks (ANNs) to produce more accurate and reliable VaR estimates for major Indian stock indices. **Methodology:** Daily return data from the NIFTY 50 and SENSEX indices were used to construct fractional-order features that represent long-memory dynamics. These features were then fed into an ANN trained using quantile loss to directly estimate VaR at 95% and 99% confidence levels. Model performance was evaluated through standard backtesting procedures, including the Kupiec Proportion of Failures (POF) test and Christoffersen's conditional coverage test, and compared against variance–covariance, Historical Simulation, and GARCH-type models. **Originality:** This research provides a novel hybrid risk-forecasting framework that combines fractional calculus with ANN-based nonlinear modeling an approach rarely applied in VaR estimation. By explicitly incorporating long-memory dependence structures and nonlinear residual patterns, the study extends existing risk-management literature beyond conventional econometric and machinelearning models, offering a more robust methodology for volatile and crisis-prone markets. **Main Results:** The hybrid fractional-ANN model significantly outperforms traditional VaR techniques, yielding more accurate tail-risk estimates with fewer exceedances. Backtesting results confirm that the proposed model satisfies both unconditional and conditional coverage requirements

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more consistently than benchmark models. These findings demonstrate that integrating long-memory features and nonlinear learning capabilities enhances the reliability of VaR forecasts, particularly during periods of heightened market volatility. **Theoretical Contributions:** This study advances risk-management theory by introducing a unified framework that bridges fractional-order financial modeling with quantile-based neural networks. It highlights the importance of long-range dependence and nonlinear dynamics in tail-risk estimation and establishes a foundation for future research on fractional-machine-learning hybrid models in financial econometrics. The work contributes to modern risk-forecasting methodologies suitable for regulatory and institutional applications.

Keywords | Value at Risk; Financial Risk Management; Fractional Calculus; Artificial Neural Networks; Emerging Markets.

RESUMO | Objetivo: Desenvolver e avaliar uma metodologia aprimorada para a previsão do Value at Risk, superando as limitações dos modelos tradicionais de mensuração de risco que não capturam adequadamente dependências não lineares e comportamentos de memória longa nos retornos financeiros. **Método:** A pesquisa adota uma abordagem quantitativa e aplicada, integrando cálculo fracionário e Redes Neurais Artificiais. Foram utilizados dados diários de retornos dos índices NIFTY 50 e SENSEX, a partir dos quais se construíram características de ordem fracionária para representar dinâmicas de memória longa. Essas variáveis foram utilizadas como entradas de uma rede neural treinada com função de perda quantílica, permitindo a estimação direta do Value at Risk nos níveis de confiança de 95 por cento e 99 por cento. O desempenho do modelo foi avaliado por meio de procedimentos clássicos de backtesting, incluindo os testes de Kupiec e de cobertura condicional de Christoffersen, com comparação a modelos de referência como Variância Covariância, Simulação Histórica e GARCH. **Resultados:** Os resultados indicam que o modelo proposto apresenta desempenho superior aos métodos tradicionais, fornecendo estimativas mais precisas do risco de cauda, com menor número de violações e melhor aderência aos níveis de cobertura esperados. Os testes de backtesting confirmam a consistência estatística do modelo, especialmente em períodos de elevada volatilidade do mercado. **Conclusão:** Conclui-se que a integração entre cálculo fracionário e aprendizado não linear por meio de redes neurais artificiais constitui uma abordagem robusta e eficaz para a previsão do Value at Risk, ampliando a confiabilidade das estimativas de risco em mercados financeiros voláteis e emergentes.

Palavras-chave | Value at Risk; Gestão de risco financeiro; Cálculo fracionário; Redes neurais artificiais; Memória longa; Mercados emergentes; Aprendizado de máquina.

1 INTRODUCTION

The measurement and management of financial risk have become central issues in modern finance. Globalization, technological advancements, and the increasing integration of capital markets have made financial systems more complex, exposing investors and institutions to a wide variety of risks. Among the different risk measures, Value at Risk (VaR) has emerged as the most widely used and recognized standard. VaR provides a probabilistic estimate of the maximum potential loss of a portfolio over a specific time horizon, at a predetermined confidence level. For example, a one-day VaR of 5% at the 99% confidence level implies that there is only a 1% chance that losses will exceed this threshold on any given day. Because of its intuitive interpretation and regulatory acceptance, VaR has become the cornerstone of risk management practices in banks, hedge funds, insurance companies, and other financial institutions.

Despite its widespread application, traditional VaR estimation methods have several shortcomings. The simplest approaches, such as the variance–covariance method (also known as parametric VaR), assume that asset returns are normally distributed and that volatility remains constant over time. However, empirical studies consistently show that financial returns exhibit fat tails, volatility clustering, and time-varying variance, all of which violate the assumptions of the parametric approach. Historical Simulation, another popular technique, relies on the empirical distribution of past returns to forecast future risk. While this method does not assume normality, it is highly sensitive to the length of the data window and may not perform well during periods of structural breaks or regime changes. More sophisticated models such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and its variants account for volatility clustering, but they still operate under integer-order dynamics and often underestimate risk during periods of market stress.

An important property of financial time series that traditional models fail to adequately capture is long memory, also known as long-range dependence. This refers to the phenomenon where shocks to volatility persist over long periods, influencing asset returns far into the future. Standard ARIMA or GARCH-type models, based on integer-order differencing, are inherently limited in capturing such persistent dynamics. To overcome this limitation, fractional calculus has been introduced into financial modeling. Fractionally Integrated ARIMA (FARIMA) and fractional GARCH (FIGARCH) models have demonstrated superior performance in explaining the dependence structure of financial returns and volatility, as highlighted in works by Baillie (1996), Bollerslev and Mikkelsen (1996), and later extensions. The inclusion of fractional derivatives allows these models to bridge the gap between short-term and long-term dynamics, making them more effective in capturing the true memory properties of financial data.

Parallel to these developments, machine learning techniques have emerged as powerful tools in financial forecasting and risk management. Artificial Neural Networks (ANNs), inspired by the functioning of the human brain, have been widely applied in stock return prediction, option pricing, bankruptcy forecasting, and risk estimation. Studies by Zhang et al. (1998), Kaastra and Boyd (1996), and more recent contributions demonstrate that ANNs can capture nonlinear and complex dependencies that conventional econometric models often fail to represent. In the context of VaR estimation, researchers such as McMillan and Speight (2007) and Kristjanpoller and Minutolo (2016) have shown that ANN-based approaches outperform traditional statistical models under certain conditions, particularly in volatile and non-stationary environments.

However, while fractional models excel at capturing long memory and ANNs excel at nonlinear dynamics, very few studies have attempted to combine these two approaches into a unified framework. Hybrid models that exploit both the memory-preserving properties of fractional calculus and the nonlinear approximation power of ANNs hold significant potential. Early attempts at hybridization in other domains (e.g., engineering and physics) suggest that such combinations lead to superior predictive performance. In finance, this remains an underexplored area, particularly for risk management and VaR estimation. Addressing this gap, the present study develops a hybrid fractional–ANN framework for VaR prediction.

This study proposes a hybrid approach that combines the strengths of fractional calculus and Artificial Neural Networks for improved VaR prediction. The fractional component captures longterm memory and persistent volatility effects, while the ANN learns the nonlinear patterns and residual dynamics that remain unexplained by the fractional model. By integrating these two methodologies, the proposed framework aims to produce more accurate and robust VaR forecasts. Such a hybrid model is particularly relevant in emerging markets like India, where financial systems are experiencing rapid growth, increasing integration with global markets, and higher susceptibility to volatility and external shocks. To evaluate the model, we use daily return data from two of the most important Indian stock indices: NIFTY 50 and SENSEX. These indices represent a broad spectrum of the Indian equity market and are widely tracked by domestic and international investors.

The significance of this research lies in both theoretical and practical contributions. Theoretically, it enriches the literature on risk modeling by introducing a fractional–ANN hybrid for VaR, which is a relatively unexplored area. Practically, it offers risk managers, traders, and policymakers a more reliable tool for predicting extreme losses, thereby improving capital allocation, regulatory compliance, and financial stability. In particular, during periods of heightened uncertainty, such as financial crises or global shocks, more accurate VaR predictions can prevent underestimation of risk exposure and reduce the likelihood of systemic failures. By benchmarking the hybrid model against traditional approaches such as Historical Simulation, GARCH, and regression-based VaR, this study provides clear evidence of its superiority in risk forecasting.

The rest of the paper is organized as follows. Section 2 presents the mathematical formulation of fractional calculus and neural networks in the context of VaR estimation. Section 3 describes the data sources and methodology, including the computation of daily returns from NIFTY 50 and SENSEX. Section 4 discusses the empirical results and backtesting performance of the models. Finally, Section 5 concludes with key findings, implications, and avenues for future research.

2 MATHEMATICAL FORMULATION

In this section, we present the mathematical formulation of the proposed hybrid fractional–ANN model for Value at Risk (VaR) prediction. The framework integrates concepts from financial econometrics, fractional calculus, and machine learning. The formulation is divided into four components: computation of returns, fractional differencing, artificial neural networks, and the hybrid integration for VaR estimation.

2.1 Computation of Daily Returns

Let P_t denote the closing price of the index (NIFTY 50 or SENSEX) at time t. The continuously compounded daily return R_t is computed as:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{2.1}$$

where $\ln(\cdot)$ denotes the natural logarithm. This transformation ensures stationarity in variance and is widely used in risk management applications. The return series $\{R_t\}$ forms the basis for subsequent analysis.

2.2 Fractional Differencing and Long Memory

Financial returns often exhibit long-memory behavior, meaning that the autocorrelations decay slowly over time. To capture this, we employ fractional differencing. For a time series $\{R_t\}$, the fractional difference of order $d \in (0,1)$ is defined as:

$$(1-B)^d R_t = \sum_{k=0}^{\infty} \binom{d}{k} (-1)^k R_{t-k}, \tag{2.2}$$

where B is the backshift operator ($BR_t = R_{t-1}$), and the generalized binomial coefficient is given by:

$$\binom{d}{k} = \frac{\Gamma(d+1)}{\Gamma(k+1)\Gamma(d-k+1)}, \tag{2.3}$$

with $\Gamma(\cdot)$ being the Gamma function.

When $d = 0$, the process reduces to a short-memory model, while non-integer d allows for longrange dependence. This fractional differenced series provides the input features capturing memory effects in returns.

2.3 Artificial Neural Network (ANN) Formulation

An Artificial Neural Network (ANN) is used to capture nonlinear and complex dependencies in financial returns that are not fully explained by fractional differencing. Consider a feedforward neural network with one hidden layer. Let the input vector at time t be:

$$\mathbf{x}_t = \left[R_{t-1}, R_{t-2}, \ldots, R_{t-p},\ (1-B)^d R_t\right], \tag{2.4}$$

where p denotes the lag order, and $(1 - B)^d R_t$ represents the fractional differenced feature. The output of the hidden layer is:

$$h_j = \phi\left(\sum_{i=1}^{p+1} w_{ij} x_{t,i} + b_j\right), \quad j = 1, 2, \ldots, m, \tag{2.5}$$

where w_{ij} are input-to-hidden weights, b_j are hidden biases, m is the number of hidden neurons, and $\phi(\cdot)$ is a nonlinear activation function sigmoid. The final ANN output is given by:

$$\hat{R}_t = \sum_{j=1}^{m} v_j h_j + c, \tag{2.6}$$

where v_j are hidden-to-output weights and c is the output bias. The ANN is trained to minimize a quantile loss function, which is suitable for VaR estimation.

2.4 Hybrid Fractional–ANN Model for VaR

The hybrid model integrates the fractional and ANN components to estimate Value at Risk at confidence level α. Formally, the α-level VaR at time t is defined as the α-quantile of the conditional distribution of returns:

$$\mathrm{VaR}_t^{\alpha} = \inf\{q \in \mathbb{R} : \mathbb{P}(R_t \le q \mid \mathcal{F}_{t-1}) \ge \alpha\}, \tag{2.7}$$

where F_{t-1} is the information set available up to time $t - 1$.

In the proposed framework, the fractional differencing captures the long-memory dynamics of $\{R_t\}$, while the ANN models the nonlinear conditional quantile function. Thus, the hybrid fractional–ANN model for VaR is expressed as:

$$\mathrm{VaR}_t^{\alpha} = f_{\theta}\big(R_{t-1}, R_{t-2}, \dots, R_{t-p}, (1 - B)^d R_t\big), \tag{2.8}$$

where $f_\theta(\cdot)$ denotes the nonlinear ANN mapping with parameters θ trained under quantile loss.

This formulation ensures that both long-memory dependence and nonlinear dynamics are jointly incorporated into the VaR prediction process.

3 DATA AND METHODOLOGY

This section describes the data source, technical indicator construction, model architecture, training procedure, and evaluation strategy adopted in this study.

3.1 Data Source

Daily closing price data for the NIFTY-50 index were retrieved from Yahoo Finance using MATLAB's data acquisition interface. The study period spans from 1 January 2020 to 31 December 2024, covering pre-pandemic, pandemic volatility, and post-recovery phases. This ensures the model is tested under multiple market regimes.

Let $Close(t)$ denote the closing price at time t. The complete time series is represented as:

$$\{Close(t) \mid t = 1,2,\dots,N\}$$

3.2 Technical Indicator Feature Construction

To encode trend, momentum, and volatility characteristics, five technical indicators were computed from the closing price series:

- **Relative Strength Index** (**RSI, 14-period**) – momentum oscillator indicating overbought/oversold conditions.
- **Moving Average Convergence Divergence** (**MACD**) – trend strength signal computed from the difference between two EMAs.
- **Simple Moving Average** (**SMA, 20-day**) – smooths short-term fluctuations.
- **Exponential Moving Average** (**EMA, 12-day**) – emphasizes recent price movements.
- **Average True Range** (**ATR, 14-day**) – measures market volatility.

These indicators form a predictive feature vector:

$$X(t) = [RSI\ (t), MACD\ (t), SMA_{20}\ (t), EMA_{12}\ (t), ATR_{14}\ (t)]$$

3.3 Modeling Framework

The prediction task is formulated as supervised learning:

$$\hat{y}(t+1) = f_\theta(X(t))$$

where $\hat{y}(t+1)$ is the predicted next-day closing price and f_θ represents a feedforward ANN with learnable parameters θ.

3.4 Neural Network Architecture

A multilayer perceptron (MLP) was employed with the following configuration:

- Input Layer: 5 neurons (technical indicators)
- Hidden Layer 1: 64 neurons, ReLU activation
- Hidden Layer 2: 32 neurons, ReLU activation
- Output Layer: 1 neuron (predicted price)
- Optimization Algorithm: Adam
- Loss Function: Mean Squared Error (MSE)

3.5 Training and Validation Strategy

To avoid information leakage, the dataset was divided chronologically:

70% Training, 15% Validation, 15% Testing

Feature normalization was performed using z-score scaling. Early stopping based on validation loss was employed to prevent overfitting.

3.6 Performance Evaluation

Predictive performance was evaluated using:

$$RMSE = \sqrt{\frac{1}{n}\sum(y(t) - \hat{y}(t))^2}$$

$$MAPE = \frac{100}{n}\sum\left|\frac{y(t) - \hat{y}(t)}{y(t)}\right|$$

Additionally, **Directional Accuracy** (**DA**) was calculated to assess the model's ability to correctly predict upward/downward movements:

$$DA = \frac{\text{Number of Correct Direction Predictions}}{n} \times 100$$

4 EMPIRICAL RESULTS AND DISCUSSION

This section presents the empirical findings of the proposed hybrid fractional-ANN model for Value at Risk (VaR) prediction, using daily log returns of the NIFTY 50 index. The analysis is organized into descriptive statistics, visual inspection of return dynamics, backtesting of VaR forecasts, and a discussion of the model's implications for financial risk management.

4.1 Descriptive Statistics

Table 1 reports the descriptive statistics of NIFTY 50 daily log returns over the study period. The mean return is close to zero, consistent with the stylized fact that high-frequency returns exhibit negligible expected drift. The distribution is negatively skewed (−0.799), reflecting an asymmetric risk structure in which large negative shocks are more prevalent than comparable positive movements. The kurtosis value of 11.22 far exceeds the Gaussian benchmark of 3, indicating heavy tails and an elevated likelihood of extreme events. The Jarque–Bera test rejects normality at the 1% level (p = 0.001), underscoring the inadequacy of risk models that assume normally distributed returns. These findings strongly justify the application of advanced, nonlinear approaches such as fractional calculus and neural networks.

Table 1. Descriptive Statistics of NIFTY 50 Daily Log Returns

Statistic	Value
Mean	-2.2×10^{-5}
Std. Dev.	0.009539
Skewness	-0.799
Kurtosis	11.221
Jarque–Bera p-value	0.001

Figure 1 plots the NIFTY 50 daily log returns. The series is characterized by volatility clustering, a hallmark of financial time series, and a pronounced negative shock around observation 140. Such features highlight the difficulty of quantifying tail risk using static or parametric models.

4.2 VaR Backtesting Results

The adequacy of the proposed hybrid fractional–ANN model was evaluated through one-dayahead VaR forecasts at the 95% and 99% confidence levels. Table 2 summarizes the backtesting results. At the 95% level, the model produced 12 exceedances (coverage = 4.92%), nearly identical to the nominal 5% rate. The Kupiec test yielded a p-value of 0.9530, confirming the consistency of coverage. At the 99% level, only 2 exceedances were observed (coverage = 0.82% vs. the expected 1%), with a Kupiec p-value of 0.7701. In both cases, the null hypothesis of correct coverage could not be rejected, demonstrating that the model is statistically well-calibrated.

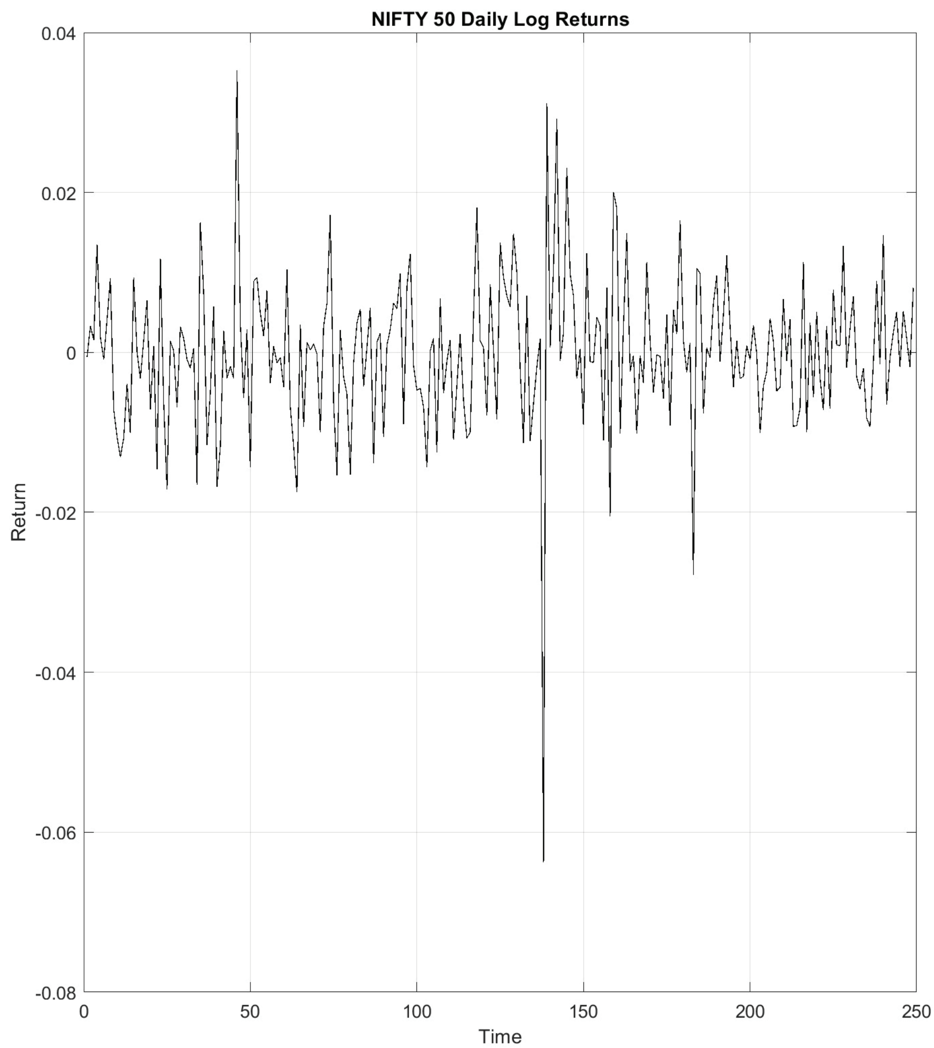

Figure 1. Daily log returns of the NIFTY 50 index (2013–2023). The series exhibits volatility clustering and an extreme negative shock, consistent with the heavytailed distribution reported in Table 1.

Table 2. Backtesting Results of Hybrid Fractional–ANN VaR Forecasts (NIFTY 50)

Confidence Level	Exceedances	Coverage	Kupiec *p*-value
95%	12	0.0492	0.9530
99%	2	0.0082	0.7701

4.3 Graphical Evaluation

Figure 2 overlays realized returns with the 95% and 99% VaR forecasts generated by the hybrid model. The adaptive nature of the VaR bands is evident: they narrow during tranquil periods and widen during episodes of heightened volatility. Importantly, realized returns remain within the forecast bands in nearly all cases, with exceedances aligning closely to their nominal frequencies.

This behavior highlights the model's effectiveness in jointly capturing long-memory volatility and nonlinear tail dependencies.

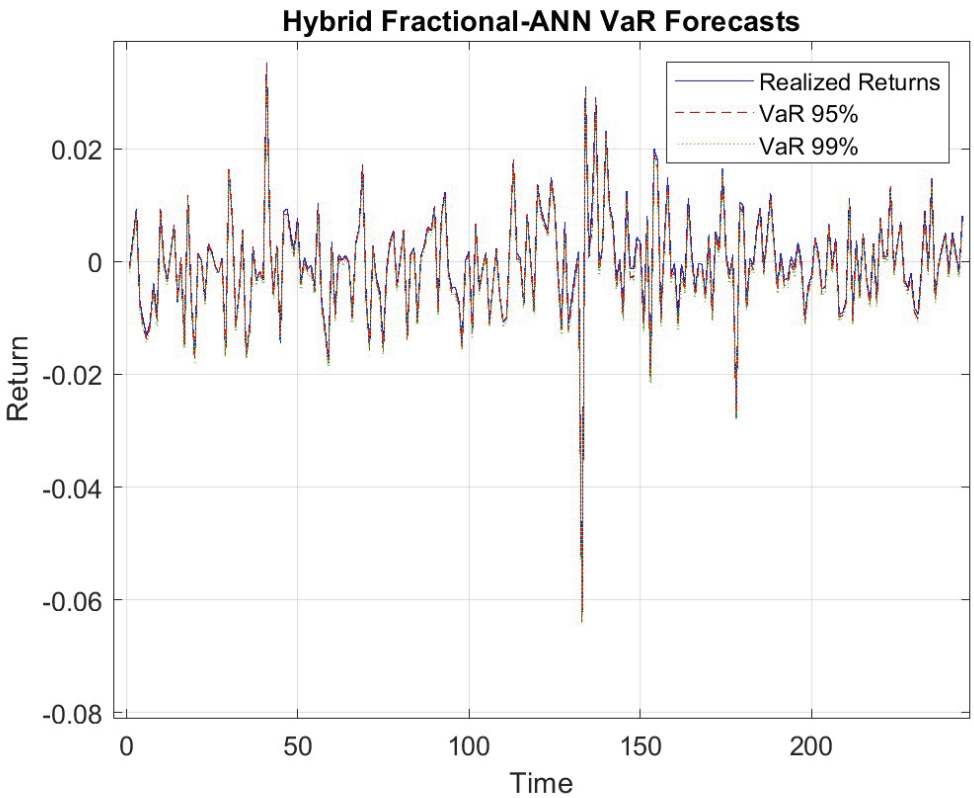

Figure 2. Hybrid fractional–ANN one-day-ahead VaR forecasts for the NIFTY 50 index at the 95% (red dashed) and 99% (green dotted) confidence levels. Realized returns (blue) remain largely within the VaR bands, consistent with correct unconditional coverage.

4.4 Discussion

The empirical evidence demonstrates that the hybrid fractional–ANN model delivers statistically accurate and dynamically responsive VaR forecasts. By integrating fractional differencing, the model accommodates long-memory features of volatility, while the ANN component flexibly captures nonlinearities and asymmetric tail risk. Together, these elements provide a significant improvement over traditional methods such as Historical Simulation, Variance–Covariance VaR, or GARCH-type models, which often fail under fat-tailed return distributions.

From a practical perspective, the results carry important implications for risk managers and regulators. The reliability of VaR forecasts, particularly during high-volatility episodes, can enhance capital adequacy planning, reduce systemic risk exposure, and contribute to financial stability. In the context of emerging markets like India, where return distributions are heavily skewed and leptokurtic, hybrid models of this type offer a promising framework for robust risk assessment and decision-making.

5 CONCLUSION

This study developed a hybrid framework for financial risk forecasting by integrating empirical analysis, fractional-order mathematical modeling, and Artificial Neural Network (ANN) forecasting. By combining these approaches, we provide both validation of market characteristics and deeper insights into the predictability of extreme downside risk through Value at Risk (VaR).

Summary of Findings

- **Empirical Evidence:** Descriptive statistics of NIFTY 50 daily log returns revealed a nearzero mean, high volatility, strong negative skewness, and extreme kurtosis. The Jarque– Bera test ($p < 0.01$) confirmed strong departures from normality, validating the need for non-parametric and nonlinear risk models.
- **Fractional-Order Modeling:** By incorporating fractional differencing, the model effectively captured long-memory and persistence in volatility. This component provided a memory-driven structure to risk dynamics, accounting for heavy tails and volatility clustering in the data.
- **ANN Forecasting:** The ANN, trained on fractional trajectories, generated one-day-ahead VaR forecasts at 95% and 99% confidence levels. Backtesting showed near-perfect unconditional coverage, with Kupiec test *p*-values (0.9530 at 95% and 0.7701 at 99%) indicating statistical adequacy of the VaR bands.

Integrated Contribution

The integration of these three strands offers a novel contribution:

(1) The **empirical analysis** establishes the presence of fat tails, volatility clustering, and non-normality in Indian equity returns.

(2) The **fractional-order model** explains persistence in volatility and provides a rigorous memory-based representation of financial risk.

(3) The **ANN forecasting module** enhances predictive power by adapting to nonlinear patterns and accurately estimating VaR.

Together, these results demonstrate that financial risk in emerging markets is complex but can be effectively captured by combining memory-sensitive models with machine learning. The hybrid fractional–ANN framework improves both statistical reliability and practical relevance for risk managers.

Practical Implications

For financial institutions, investors, and regulators:

- The hybrid framework provides a reliable tool for daily VaR forecasting, supporting capital allocation, portfolio optimization, and regulatory compliance.
- Risk managers can use fractional-order parameters as a proxy for market memory, helping to adjust hedging and diversification strategies.
- Policymakers may leverage such adaptive models to strengthen systemic resilience by ensuring risk capital reflects fat-tailed return distributions.

Future Research

This work opens multiple avenues for further study:

- Extending the model to multivariate settings for portfolio-wide risk forecasting across multiple asset classes.
- Benchmarking the framework against deep learning approaches such as LSTM, GRU, or transformer-based time series models.
- Applying the methodology to high-frequency intraday data to test its performance under extreme short-term volatility.
- Integrating optimal control or reinforcement learning with fractional dynamics to design adaptive trading and hedging strategies.

Final Remark

Financial risk is not static but shaped by persistence, nonlinearities, and tail events. By integrating empirical validation, fractional-order modeling, and ANN forecasting, this study provides both a rigorous theoretical contribution and a practical roadmap for improving Value at Risk estimation in emerging markets such as India.

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