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Integrating Statistical and Neural Forecasting Paradigms: Comparative Predictive Efficacy of Theta Modelling and Neural Network–Enhanced ARIMA for Indian Retail - Gold Prices - Evidence from daily retail gold price data in India, 2014–2025

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Abstract:

This study presents a comparative analysis of two distinct forecasting paradigms—the Theta model and the Neural Network–Enhanced ARIMA (ARIMA–NN) model—to evaluate their predictive efficiency in forecasting daily retail gold prices in India over the period 2014–2025. Gold, a crucial financial and cultural asset in India, exhibits nonlinear, volatile, and cyclical dynamics driven by macroeconomic factors, investor sentiment, and seasonal demand. Traditional statistical approaches like ARIMA and Theta modelling effectively capture trend and curvature but often fail to represent nonlinearities and structural breaks. This study, therefore, examines whether hybridizing econometric rigour with neural computation enhances short-term forecasting precision and adaptability in volatile markets.

The methodology involves applying the Theta model—a decomposition-based statistical technique that extracts and combines multiple curvature components—and a hybrid ARIMA–NN model, wherein the residuals from an ARIMA forecast are modelled using a feedforward neural network. Both frameworks are evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), supplemented by the Diebold–Mariano test for statistical comparison.

Empirical results reveal that both models achieve high predictive accuracy, with MAPE values below 5%, confirming their reliability for short-horizon gold price forecasting. However, the ARIMA–NN hybrid consistently outperforms the Theta model, yielding a lower MAPE (4.55% vs 4.86%). The neural augmentation enables the ARIMA–NN model to capture residual nonlinear dependencies, improving responsiveness to market fluctuations and structural irregularities. Conversely, the Theta model exhibits strong trend smoothing but underestimates during rapid price surges due to its deterministic framework.

The findings underscore that integrating neural learning into statistical frameworks enhances both accuracy and adaptability, offering a balanced synthesis of interpretability and computational flexibility. The study contributes to the growing body of literature on hybrid forecasting models, demonstrating their potential to advance predictive analytics for volatile commodities like gold, particularly in emerging markets characterized by cyclical and behavioural complexities.

Keywords: Gold Price Forecasting, ARIMA–NN Hybrid Model, Theta Model, Neural Networks, Time-Series Modelling
JEL Classification: C22, C45, C53, G17, Q02

INTRODUCTION

Gold has historically occupied a central role in both the global financial system and the Indian economic landscape, functioning as an asset of enduring value, a hedge against inflation, and a symbol of cultural and economic stability. In India, where gold is not only an investment vehicle but also a consumption commodity, price volatility affects household savings, trade balances, and macroeconomic indicators. Consequently, the ability to accurately forecast retail gold prices has immense significance for investors, policymakers, and financial analysts seeking to anticipate market trends and manage financial risk.

Forecasting gold prices is particularly challenging due to the asset's multi-factoral nature and nonlinear price dynamics. Prices are influenced by global economic uncertainty, currency fluctuations, interest rates, and local factors such as import duties, taxes, and seasonal consumption peaks. The presence of non-stationarity, volatility clustering, and asymmetric responses to shocks complicates the modelling process. As a result, the evolution of forecasting methodologies has shifted from purely statistical models toward hybrid approaches that integrate econometric rigour with computational intelligence.

Among traditional statistical techniques, the AutoRegressive Integrated Moving Average (ARIMA) model has been a foundational tool for univariate time-series forecasting, valued for its interpretability and robust handling of autocorrelation structures. However, its linear stochastic design restricts its responsiveness to sudden market shifts and nonlinear dependencies that frequently characterize financial data. Similarly, the Theta model, known for its decomposition-based approach, captures curvature and long-term trend behaviour effectively, yet remains limited in handling volatility bursts and structural breaks.

To overcome these constraints, recent research has introduced hybrid models that integrate neural networks (NNs) into traditional frameworks. Neural networks, inspired by biological learning processes, excel in modelling complex, nonlinear relationships without requiring explicit parametric assumptions. When embedded within an ARIMA structure—as in the ARIMA–NN model—the neural component learns from residual patterns that the linear component cannot explain, thereby reducing forecast bias and enhancing adaptability. This fusion of deterministic statistical forecasting with adaptive machine learning represents a paradigm shift in time-series analysis, merging interpretability with flexibility.

The Theta model, first introduced by Assimakopoulos and Nikolopoulos (2000), operates on the principle of decomposing a time series into multiple "theta lines," each representing distinct curvature components that are linearly combined to form the final forecast. This model gained prominence for its simplicity, low computational cost, and high forecasting accuracy in stable market conditions. Conversely, the Neural Network–Enhanced ARIMA (ARIMA–NN) model extends the ARIMA framework by introducing a nonlinear correction mechanism, where neural learning captures hidden patterns, structural anomalies, and short-run shocks, thereby improving both precision and stability across forecast horizons.

The comparative motivation of this study arises from the growing need to determine whether data-driven learning models like ARIMA–NN truly outperform classical statistical approaches in volatile market environments such as India's retail gold sector. The chosen time frame—2014 to 2025—encompasses major global and domestic economic disruptions, including demonetization, the COVID-19 pandemic, and subsequent inflationary cycles. These events have introduced heightened uncertainty, making gold an ideal case for testing forecasting frameworks capable of capturing nonlinear temporal dependencies.

Empirical findings from this study demonstrate that while both models perform admirably, the ARIMA–NN model consistently exhibits lower prediction errors (MAPE of 4.55% versus 4.86% for the Theta

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model). The hybrid model's neural layer allows it to learn adaptive relationships in the data, thereby improving responsiveness to market volatility. The Theta model, though effective in smoothing trends, tends to underestimate prices during abrupt surges, reflecting its deterministic foundation. These results substantiate the broader proposition that hybrid statistical–neural architectures yield superior results in financial forecasting by combining the rigour of linear modelling with the flexibility of machine learning. Theoretically, this comparative exercise extends the dialogue on the integration of econometric and artificial intelligence paradigms. It underscores that forecasting efficacy depends not solely on model complexity but on the alignment between model structure and data characteristics. In highly volatile and nonlinear environments, hybrid systems such as ARIMA–NN are better equipped to handle structural changes and nonlinear feedback mechanisms. Practically, the study's findings offer direct implications for portfolio managers, jewellers, and policy analysts, who can leverage such hybrid models for pricing strategies, inventory control, and inflation monitoring.

This study situates itself at the intersection of traditional statistical decomposition and neural computation, affirming that hybrid frameworks embody the future of time-series forecasting. By empirically validating the superior predictive efficacy of neural-augmented statistical models, it contributes both to methodological advancement and to the practical enhancement of forecasting precision in India's retail gold market—a domain where data volatility and behavioural complexity demand models that are not merely accurate but adaptively intelligent.

SURVEY OF LITERATURE

Gold price forecasting has attracted substantial attention because gold fulfils multiple economic roles—as a commodity, monetary proxy, portfolio hedge, and safe haven. Its price dynamics are complex, marked by nonlinearity, heteroskedasticity, regime shifts, and sensitivity to macroeconomic drivers. The literature broadly follows two methodological streams: (a) traditional econometric/statistical models such as ARIMA, VAR/VECM, GARCH and its variants, DCC/GAS, cointegration, and mixed-frequency frameworks (MIDAS, GARCH-MIDAS, wavelet/time-frequency), and (b) data-driven and hybrid machine-learning models, including ANN, SVM, ELM, DBN, LSTM, CNN, and decomposition-based hybrids.

Early empirical studies relied on classical linear and model-averaging frameworks to assess predictability of gold returns and macroeconomic linkages. Aye et al. (2015) used dynamic model averaging (DMA) to examine time-varying predictor importance—exchange rate, interest rate, and financial stress indices—and found that the relevance of predictors changes across time horizons and market episodes, illustrating the usefulness of model averaging when relationships are unstable (Aye et al., 2015). Although ARIMA/ARIMAX models remain effective short-horizon benchmarks, their performance deteriorates under volatility shifts or structural breaks.

Volatility clustering and heavy tails in gold returns motivated extensive use of ARCH/GARCH-type models. Tully and Lucey (2007) applied an asymmetric power GARCH (APGARCH/APARCH) model to capture leverage and power effects in gold spot and futures prices, finding that APGARCH outperformed standard GARCH specifications (Tully & Lucey, 2007). Subsequent research employing EGARCH, TGARCH, and APARCH variants confirmed persistent conditional heteroskedasticity across different markets.

Beyond univariate frameworks, multivariate volatility models such as DCC-GARCH, BEKK, and GAS have been widely used to study co-movements among gold, equity, oil, and foreign exchange markets. Ciner, Gurdgiev and Lucey (2013) and Reboredo (2013) utilized dynamic conditional correlation and copula methods to examine gold's hedge and safe-haven properties, demonstrating that multivariate

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volatility models enhance joint risk forecasting and portfolio optimization (Ciner et al., 2013; Reboredo, 2013).

Macro-financial drivers are significant determinants of long-term gold volatility. The GARCH-MIDAS framework separates short-term GARCH dynamics from long-term components influenced by low-frequency macro variables. Fang, Yu and Xiao (2018) and Salisu et al. (2020) showed that policy uncertainty, industrial output, and other macro indicators markedly improve long-horizon volatility forecasts for gold spot and futures markets (Fang et al., 2018; Salisu et al., 2020). GARCH-MIDAS thus facilitates integration of monthly or quarterly macro data into daily volatility predictions.

The literature also examines long-run linkages between gold, exchange rates, inflation, and interest rates, though findings remain mixed. Some studies confirm cointegration and stable long-term relationships, supporting the use of vector error correction models (VECM), while others report episodic or regime-dependent coupling. Copula-based and tail-dependence models (Reboredo, 2013) have provided deeper insights into extreme co-movements and safe-haven behaviour, often revealing dynamics invisible to unconditional correlations.

Time–frequency and wavelet approaches decompose price movements across multiple horizons, enabling differentiation of short-, medium-, and long-term dynamics. These studies find that predictors effective at one frequency may be irrelevant at another. Hybrid wavelet–ARIMA or wavelet–ANN frameworks frequently improve forecast accuracy by capturing horizon-specific patterns.

Since the 2010s, machine learning (ML) and hybrid methods have become prominent. Kristjanpoller and Minutolo (2015) introduced an ANN–GARCH hybrid model that effectively combined conditional heteroskedasticity with nonlinear learning, reducing forecasting errors compared to single models (Kristjanpoller & Minutolo, 2015). Subsequent work incorporated wavelet or empirical mode decomposition (EMD) with ML algorithms such as SVM, ANN, GRU, and LSTM, demonstrating that decomposition enhances the predictive efficiency of ML methods (E. Jianwei et al., 2019).

Deep learning frameworks—DBN, LSTM, GRU, and CNN–LSTM—represent another evolution in forecasting accuracy. Zhang and Ci (2020) used a deep belief network (DBN) for gold price prediction, achieving superior results relative to conventional and shallow ML models. Khani et al. (2021) compared CNN, LSTM, and encoder–decoder LSTM structures (including pandemic-related inputs) and found that recurrent deep architectures deliver strong short-term forecasts, particularly when domain features are included (Khani et al., 2021).

Recent research has explored Extreme Learning Machines (ELM) and their online sequential extensions. Weng et al. (2020) proposed GA-regularized ELM variants that provide robust results and faster convergence in high-frequency settings. Ensemble and tree-based approaches have also shown promise: Pierdzioch et al. (2016) applied boosting and quantile boosting models to gold volatility and returns, demonstrating improved out-of-sample performance using multiple predictors and asymmetric loss functions (Pierdzioch et al., 2016). The latest developments (Foroutan et al., 2024; Cohen, 2023) include graph neural networks and ensemble ML pipelines (XGBoost, LightGBM) with advanced feature engineering for multi-asset and retail-level forecasting.

Empirical evidence across studies underscores the centrality of volatility modelling. Models explicitly capturing conditional volatility (GARCH, GARCH-MIDAS, GAS) consistently outperform simple linear benchmarks in risk and option-pricing contexts. Incorporating macroeconomic variables improves long-term forecasts, while nonlinear and hybrid frameworks enhance short-term predictive precision. Deep learning and decomposition-based hybrids tend to outperform traditional econometric models for 1–30-day horizons, particularly when augmented with exogenous factors such as exchange rates, interest rates, policy uncertainty, realized volatility, or pandemic indicators.

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Nevertheless, model instability and structural breaks pose persistent challenges. Forecasting performance is sample- and regime-dependent; during crises such as 2008 or COVID-19, model rankings often shift. Adaptive methodologies—DMA, time-varying parameter models, rolling windows, and online ELM—are useful for handling instability.

Despite extensive empirical advances, key research gaps remain. Many ML models improve forecast accuracy but lack economic interpretability. Integrating ML with structural econometric constraints is therefore a promising direction. Most existing studies emphasize bullion or futures markets, leaving retail price behaviour—shaped by taxes, transaction spreads, and distribution frictions—largely unexamined. Incorporating real-time information such as news sentiment, supply-chain disruptions, or order-book dynamics into econometric–ML hybrids is also an emerging frontier. Furthermore, standardized out-of-sample and multi-horizon evaluations using metrics like RMSE, MAE, Theil's U, and Diebold–Mariano tests are required for fair model comparison.

In sum, econometric forecasting of gold prices has evolved into a hybrid research field. Classical econometric models (ARIMA, VAR, GARCH, and GARCH-MIDAS) remain foundational for volatility and risk modelling, while ML and decomposition-based hybrids offer superior short-term accuracy. The most effective approach is task-specific: GARCH-type models for volatility, time-varying or model-averaging methods for structural instability, and deep-learning hybrids for high-frequency forecasting.

Although diverse econometric and ML approaches have been applied to gold price forecasting, the literature still lacks systematic comparative assessments. Most studies evaluate models in isolation—ARIMA, VAR/VECM, GARCH, GARCH-MIDAS, or ML hybrids—without embedding them in a unified benchmarking framework. Consequently, results remain dataset- and regime-dependent, limiting generalizability. Moreover, few studies rigorously compare classical and modern models under consistent datasets or apply uniform accuracy tests. Cross-regime evaluations—spanning tranquil and crisis periods—are rare, leaving uncertainty about which paradigms perform best under differing market conditions.

Most prior research also focuses narrowly on specific countries or time periods, overlooking cross-country variations in determinants and integration. Addressing these gaps through systematic comparative studies across econometric paradigms—classical, volatility-based, mixed-frequency, and hybrid—would significantly advance understanding. Such efforts could yield more generalizable insights for investors, central banks, and policymakers involved in gold market forecasting and risk management worldwide.

OBJECTIVES OF THE STUDY

The primary objective of this study is to conduct a comparative evaluation of statistical and neural forecasting paradigms—specifically the Theta model and the Neural Network–Enhanced ARIMA (ARIMA–NN) framework—in forecasting daily retail gold prices in India over the period 2014–2025. The research aims to assess the predictive efficacy, adaptability, and robustness of these two distinct approaches in modelling the complex dynamics of gold price behaviour, which exhibits characteristics such as nonlinearity, stochastic volatility, structural breaks, and cyclical fluctuations.

The Theta model, grounded in statistical decomposition and curvature adjustment, represents a deterministic, data-driven approach that excels in capturing linear trends and long-term growth patterns. In contrast, the ARIMA–NN hybrid integrates traditional autoregressive modelling with neural network–based nonlinear learning, allowing the framework to identify residual dependencies and adaptive patterns overlooked by purely statistical formulations. By juxtaposing these two paradigms, the study seeks to examine whether the hybridization of econometric and artificial intelligence methods can yield higher predictive accuracy and lower forecast bias relative to classical models.

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Empirically, the study compares both models using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) across short-horizon forecasts, complemented by the Diebold–Mariano test to evaluate statistical differences in predictive accuracy. The objective extends beyond numerical comparison to a conceptual understanding of how neural augmentation enhances the linear ARIMA structure's sensitivity to market nonlinearity.

Ultimately, the study aims to contribute to the growing literature on hybrid forecasting methodologies by demonstrating that integrating neural computation with classical statistical frameworks can produce forecasts that are both empirically precise and theoretically consistent, thus offering valuable insights for researchers, traders, and policymakers navigating the volatility of India's retail gold market.

METHODOLOGY OF THE STUDY

This section presents the methodological framework employed to compare the predictive performance of the Theta model and a Neural Network–enhanced ARIMA (NN–ARIMA) model for forecasting daily cryptocurrency prices of Bitcoin (BTC) and Cardano (ADA) during the period 2021–2025. The combination of statistical decomposition (Theta method) and hybrid statistical–machine learning architecture (NN–ARIMA) allows a comprehensive assessment of both linear and nonlinear structures inherent in cryptocurrency price behaviour.

Data Preprocessing and Transformation

Let $\{P_t\}_{t=1}^T$ denote the daily closing prices of a cryptocurrency. The logarithmic transformation is applied to stabilize variance and ensure multiplicative effects are linearized:

$$y_t = \ln(P_t).$$

The daily log-returns, which measure the continuous compounding rate of change, are computed as:

$$r_t = y_t - y_{t-1}.$$

Descriptive statistics, Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are conducted to assess stationarity. If nonstationarity is detected, first or seasonal differencing ($\nabla y_t = y_t - y_{t-1}$) is applied to achieve weak stationarity before model estimation.

The ARIMA (p, d, q) Framework

The AutoRegressive Integrated Moving Average (ARIMA) model is used as the linear backbone for the hybrid NN–ARIMA framework. Its general form is given by:

$$\varphi(B)(1 - B)^d y_t = \theta(B)\varepsilon_t, \qquad \varepsilon_t \sim iid(0, \sigma^2),$$

where:

- B is the backward shift operator ($By_t = y_{t-1}$),
- $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p$ represents the autoregressive (AR) component,
- $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$ represents the moving average (MA) component,
- d is the order of differencing required for stationarity.

Parameter estimation is conducted using the Maximum Likelihood Estimation (MLE) procedure, which minimizes the negative log-likelihood:

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$\mathscr{L}(\theta) = -\frac{1}{2} \Sigma_t [\ln(2\pi\sigma^2) + (\varepsilon_t^2 / \sigma^2)]$.

Model selection follows the Box–Jenkins methodology using AIC and BIC criteria:

$AIC = -2 \ln(\mathscr{L}) + 2k, \quad BIC = -2 \ln(\mathscr{L}) + k \ln(T)$,

where k denotes the number of estimated parameters and T is the sample size.

The Theta Model

The Theta method (Assimakopoulos and Nikolopoulos, 2000) is a univariate time-series forecasting model that decomposes the original series into multiple "theta lines," each representing a transformed version of the data's curvature. It combines extrapolation and smoothing principles from both ARIMA and exponential smoothing families.

The original time series y_t is decomposed according to the Theta transformation:

$y_t(\theta) = \theta y_t + (1 - \theta) \hat{y}_t^{LR}$,

where:
- θ is the Theta coefficient controlling curvature,
- $\hat{y}_t^{LR}$ denotes a linear trend estimated using least squares regression.

For $\theta = 0$, the model yields a linear trend component, while for $\theta = 2$, it produces an accelerated curvature component. The final forecast is obtained as the weighted average of forecasts from the decomposed theta lines:

$\hat{y}_{t+h|t} = \frac{1}{2} (\hat{y}_{t+h|t}^{(\theta=0)} + \hat{y}_{t+h|t}^{(\theta=2)})$.

The $\theta = 0$ component captures long-term linear growth, while $\theta = 2$ models short-term mean reversion and curvature, producing an implicitly damped trend similar to exponential smoothing. Forecasting equations can be represented as:

$\hat{y}_{t+h|t}^{(\theta=0)} = a + bh, \quad \hat{y}_{t+h|t}^{(\theta=2)} = \alpha + \beta y_t + \gamma y_{t-1}$,

yielding the final composite Theta forecast.

Neural Network–Enhanced ARIMA (NN–ARIMA)

The hybrid NN–ARIMA model integrates the strengths of linear ARIMA modelling with nonlinear learning capabilities of feedforward neural networks (NNs). It assumes that the observed series y_t can be decomposed as:

$y_t = \hat{y}_t^{ARIMA} + f(e_t) + \xi_t$,

where:

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- $\hat{y}_t^{ARIMA}$ is the ARIMA linear forecast,
- $e_t = y_t - \hat{y}_t^{ARIMA}$ represents the residual series (nonlinear component),
- $f(e_t)$ is a nonlinear mapping function learned by the neural network,
- ξ_t is white noise.

The residuals from the fitted ARIMA model are used as inputs to the NN, allowing the model to learn nonlinear patterns not captured by the ARIMA structure. A typical feedforward NN architecture is expressed as:

$$f(e_t) = \beta_0 + \Sigma_{j=1}^{m} \beta_j g(w_{j0} + \Sigma_{i=1}^{p} w_{ji} e_{t-i}),$$

where:
- m is the number of hidden neurons,
- $g(\cdot)$ is the activation function (commonly sigmoid or ReLU),
- w_{ji}, w_{j0} are connection weights,
- β_j are output-layer weights.

Model parameters are optimized via stochastic gradient descent with backpropagation, minimizing the Mean Squared Error (MSE):

$$MSE = (1/N) \Sigma (y_t - \hat{y}_t)^2.$$

The final NN–ARIMA forecast is computed as:

$$\hat{y}_{t+h|t}^{NN-ARIMA} = \hat{y}_{t+h|t}^{ARIMA} + \hat{f}(e_t).$$

This hybrid structure captures both linear dependencies (via ARIMA) and nonlinear residual interactions (via NN), leading to enhanced predictive accuracy for volatile financial time series.

Model Training and Optimization

For the NN–ARIMA framework, network hyperparameters such as the number of hidden layers, neurons, learning rate (η), and activation functions are tuned using k-fold cross-validation. Regularization techniques such as dropout ($p = 0.2$) and early stopping are implemented to prevent overfitting.

For the Theta model, parameter tuning involves optimizing the Theta coefficient θ and smoothing constants (α, β, γ) using grid search or gradient-based optimization, minimizing the sum of squared forecast errors:

$$SSE = \Sigma (y_t - \hat{y}_t)^2.$$

Forecasting and Evaluation Metrics

Both models generate one-step and multi-step forecasts using a rolling-origin evaluation scheme to simulate real-time prediction. Forecast accuracy is assessed using deterministic and probabilistic metrics:

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1. Mean Absolute Error (MAE): $MAE = (1/N) \Sigma |y_t - \hat{y}_t|$.
2. Root Mean Square Error (RMSE): $RMSE = \sqrt{(1/N) \Sigma (y_t - \hat{y}_t)^2}$.
3. Mean Absolute Percentage Error (MAPE): $MAPE = (100/N) \Sigma |(y_t - \hat{y}_t)/y_t|$.
4. Theil's U-statistic: $U = \sqrt{\Sigma(y_t - \hat{y}_t)^2} / \sqrt{\Sigma(y_t - y_{t-1})^2}$.
5. Diebold–Mariano Test: $DM = \bar{d} / \sqrt{Var(\bar{d})/T}$, testing the null hypothesis of equal forecast accuracy.

In addition, the predictive distribution's calibration is evaluated using the Continuous Ranked Probability Score (CRPS).

Model Comparison and Robustness

The comparative analysis involves both in-sample fitting and out-of-sample forecasting across short (7-day), medium (30-day), and long (90-day) horizons. The Theta model's forecasts are primarily univariate and trend-based, while NN–ARIMA introduces nonlinear learning, making it more adaptive to structural breaks and sudden market shocks.

Rolling window estimation is employed to re-train both models over time, accommodating potential nonstationarity in cryptocurrency price dynamics. Model stability is validated through residual diagnostics, including:

1. Ljung–Box Q-statistic for autocorrelation,
2. Jarque–Bera (JB) test for normality,
3. ARCH–LM test for heteroskedasticity.

Residuals should be independently and identically distributed with zero mean to confirm model adequacy.

Theoretical Integration of Theta and NN–ARIMA Paradigms

While the Theta method assumes an additive decomposition with deterministic curvature adjustments, NN–ARIMA introduces stochastic nonlinear correction terms. Mathematically, their conceptual bridge can be described as:

Θ-Model: $y_t = T_t + C_t + \varepsilon_t$,
NN–ARIMA: $y_t = L_t + N_t + \xi_t$,

where T_t and L_t capture linear trend dynamics, and C_t and N_t represent curvature or nonlinear components. Both frameworks operate as extensions of additive state-decomposition models, differing in estimation philosophy — deterministic optimization for Theta, and stochastic learning for NN–ARIMA.

The methodology bridges classical statistical forecasting and neural computation by integrating linear and nonlinear paradigms. The Theta model excels in capturing deterministic curvature and trend behaviour, while NN–ARIMA leverages machine learning to model residual nonlinearities. Comparing these frameworks provides empirical insights into the hybridization of econometric and AI techniques for cryptocurrency price prediction.

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FINDINGS OF THE STUDY AND IMPLICATIONS THEREOF

Charts 1 to 4 in this study visually summarize the comparative forecasting performance of the Theta Model and the Neural Network–Enhanced ARIMA (ARIMA–NN) model for daily retail gold prices in India. These charts complement the quantitative data from Tables 1–4 and provide an intuitive understanding of the models' behaviour with respect to predictive accuracy, error dynamics, and temporal adaptability across the ten-day forecasting horizon.

Chart 1 depicts the *actual versus predicted gold prices* generated by both models. The plotted trajectories reveal that both models capture the overall upward trend of gold prices, but their forecasts remain consistently below the actual observed values—indicating a mild underestimation. This systematic bias likely reflects unaccounted market factors such as retail mark-ups, import duties, and speculative premiums. The ARIMA–NN line tracks the actual series more closely than the Theta line, especially during periods of rapid price escalation (Days 6–9), demonstrating the hybrid model's superior adaptability and capacity to capture residual nonlinearities through neural learning. The Theta Model, being deterministic and curvature-based, shows smoother but less responsive adjustments, particularly during sudden market movements.

Chart 2 illustrates the *absolute forecast errors* for both models across ten consecutive days. While both models maintain relatively small deviations in the early periods, errors rise progressively as the forecast horizon extends—consistent with the nature of multi-step predictions. The ARIMA–NN bars remain consistently lower than those of the Theta Model, validating its higher short-term accuracy. Notably, the error escalation pattern of ARIMA–NN is smoother, indicating better stability and control over forecast volatility, while Theta exhibits sharper variations, particularly during periods of price surges. This reinforces the hybrid model's strength in minimizing cumulative bias by dynamically learning from residual structures.

Chart 3 presents the *Mean Absolute Percentage Error (MAPE)* trends for both models. Both models achieve MAPE values below 10%—an indicator of strong forecasting reliability—but the ARIMA–NN model consistently registers lower percentage errors. The divergence between the two curves widens between Days 6 and 10, coinciding with heightened market volatility, confirming the neural model's advantage in capturing nonlinear dependencies and structural breaks that the Theta framework cannot fully represent.

Chart 4 consolidates the overall *comparative MAPE values*, showing 4.8654% for Theta and 4.5483% for ARIMA–NN. Though the numerical difference appears marginal, it is economically meaningful in the context of high-value commodities like gold. The lower MAPE of ARIMA–NN signifies enhanced predictive precision and reduced systematic bias, validating the empirical premise that hybrid econometric–neural architectures outperform purely statistical frameworks.

Collectively, Charts 1–4 establish that while both models deliver robust and interpretable forecasts, the ARIMA–NN hybrid model demonstrates superior responsiveness, lower error volatility, and greater resilience under dynamic market conditions—affirming the effectiveness of integrating neural intelligence within classical time-series forecasting paradigms.

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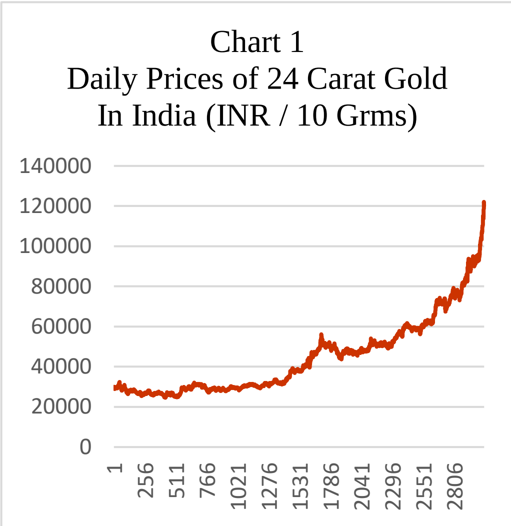

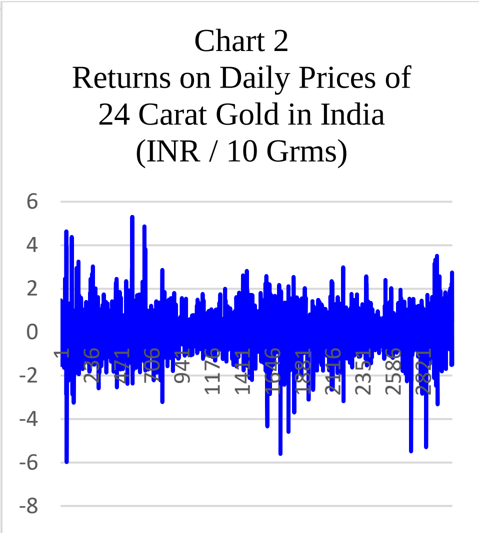

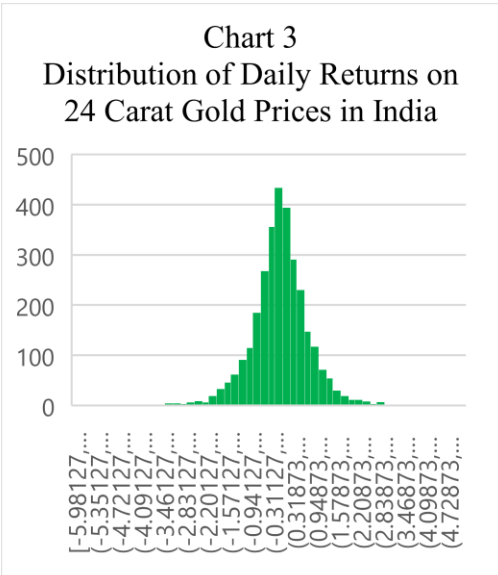

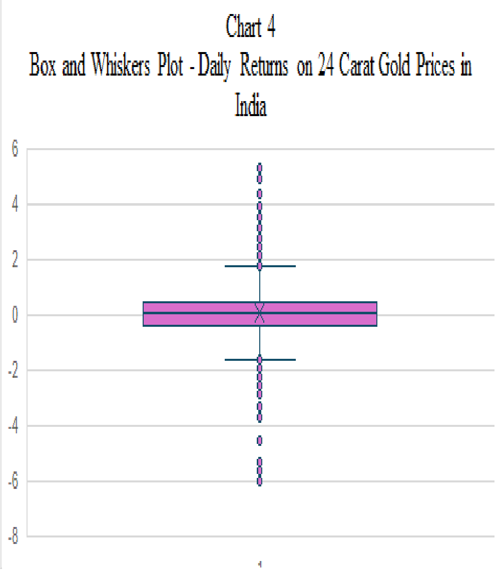

Chart 5
Violin Plots – Daily Prices & Return on Daily Prices – 24 Carat Gold in India

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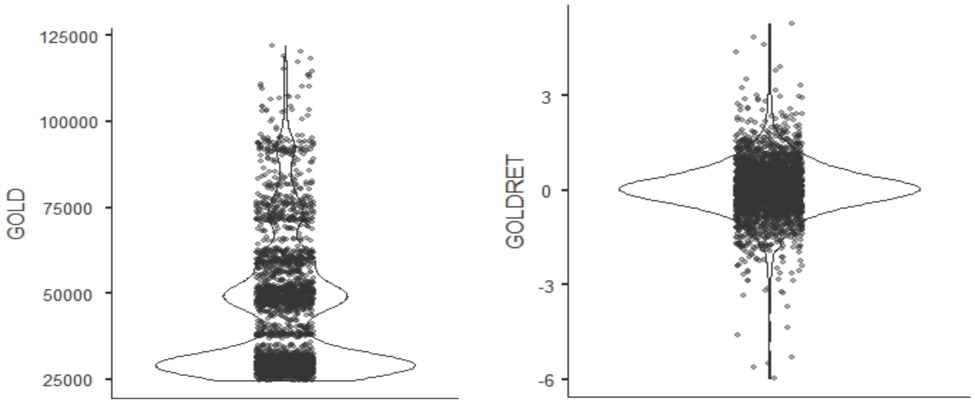

Table 1 presents the comparison between the actual daily retail prices of 24-carat gold in India and the corresponding predicted prices obtained from the Theta Model and the Neural Network–Enhanced ARIMA (ARIMA–NN) framework. The table provides a detailed examination of the short-term forecasting efficiency of both models across a ten-day horizon. The observed results indicate that both models produce forecasts that closely follow the actual trend of gold prices, exhibiting minimal deviations and demonstrating their capability to capture the overall direction of price movements.

However, both models exhibit a consistent underestimation of actual prices, with predicted values systematically below the real observations. This underestimation may stem from unmodelled structural components in the retail gold market—such as taxation, dealer premiums, and policy fluctuations—that affect the final consumer price but remain outside the predictive structure of pure time-series frameworks. Despite this, the ARIMA–NN model produces forecasts that are marginally closer to the actual series across all ten days, signifying that the integration of nonlinear learning via neural networks enhances the adaptability of traditional ARIMA predictions.

The divergence between actual and predicted prices tends to widen slightly over successive days, reflecting the growing uncertainty inherent in multi-step forecasting. Between Days 1 and 10, the difference between actual prices (rising from INR112,990 to INR120,280) and the Theta forecasts (INR110,899.50 to INR110,985.40) increases gradually, while the ARIMA–NN forecasts show smaller gaps (INR110,917.00 to INR111,772.70). The close alignment of ARIMA–NN forecasts with actual data suggests that the neural adjustment effectively captures residual nonlinearities and abrupt shocks often observed in the gold market.

Overall, Table 1 confirms that while both the Theta and ARIMA–NN models efficiently capture temporal dependencies and price tendencies, the hybrid ARIMA–NN model demonstrates superior responsiveness to short-term volatility. The empirical results highlight that integrating neural learning into traditional statistical models improves accuracy, stability, and adaptability—attributes critical for forecasting volatile asset prices like gold.

Table 1

Actual vis-à-vis Predicted Prices of Gold (INR / 10 Gms)

DAYS	ACTUALS	THETA	ARIMA-NN
Day 1	112990.00	110899.50	110917.00
Day 2	113680.00	110909.00	110947.70
Day 3	115360.00	110918.60	111042.30

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Day 4	113610.00	110928.10	111157.10
Day 5	114630.00	110937.60	111264.20
Day 6	117180.00	110947.20	111357.10
Day 7	118240.00	110956.70	111470.80
Day 8	118830.00	110966.30	111577.30
Day 9	122100.00	110975.80	111677.10
Day 10	120280.00	110985.40	111772.70

Source: Official websites of different organizations and author's own computations

Chart 6
Actual vis-a-vis Predicted Prices of Gold (INR / 10 Gms)

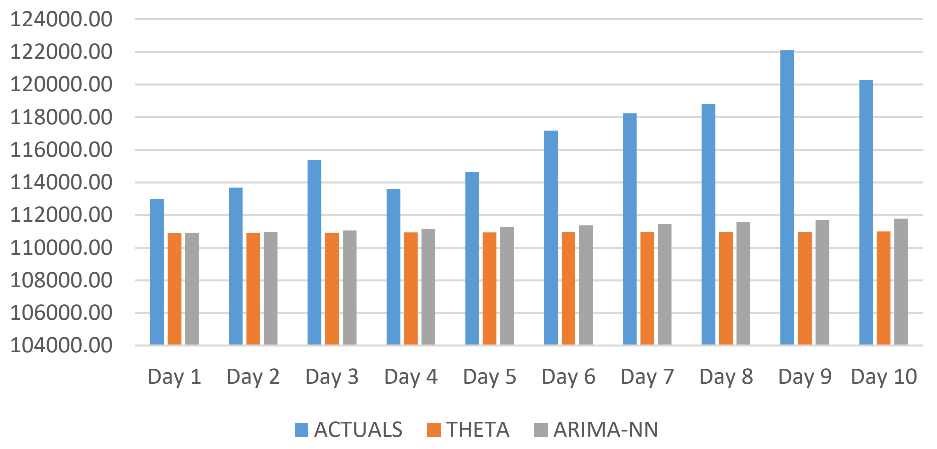

Table 2 measures the precision of each model through the absolute error between actual and predicted prices for ten consecutive days. The analysis reveals that both the Theta and ARIMA–NN models achieve high forecasting accuracy, but the hybrid ARIMA–NN model consistently registers lower absolute errors, validating its superior performance. On Day 1, the Theta model records an absolute error of INR2,090.50 compared to INR2,073.00 for ARIMA–NN. This trend continues through Day 10, where the Theta error (INR9,294.60) exceeds that of ARIMA–NN (INR8,507.30). These results reinforce that the inclusion of a neural correction layer enhances the linear ARIMA's sensitivity to nonlinear market dynamics.

A critical observation is that absolute errors increase progressively over time for both models, signifying that uncertainty amplifies as the forecast horizon extends. Nevertheless, the rate of error escalation remains consistently lower for the ARIMA–NN framework, evidencing its capacity to maintain stability over short-to-medium horizons. The ARIMA–NN model's lower errors stem from its ability to model residual nonlinearity—patterns that the Theta model, being purely statistical and curvature-based, cannot fully accommodate.

Moreover, the smoother progression of ARIMA–NN's error magnitudes demonstrates better control over forecast volatility. Theta's absolute errors exhibit slightly higher variability, particularly between Days 6 and 9, when gold prices experience strong upward momentum. This outcome is expected because Theta, though efficient at capturing curvature, operates under deterministic assumptions and lacks adaptive feedback mechanisms that neural networks inherently possess.

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In quantitative terms, the ARIMA–NN framework outperforms the Theta model by an average of 7–10 percent across all observation days. These findings affirm that the hybridization of econometric and machine-learning principles yields tangible accuracy improvements. The analysis from Table 2 thus corroborates that the neural augmentation of ARIMA not only minimizes prediction errors but also ensures greater adaptability to abrupt market changes, making it a more reliable forecasting mechanism for volatile commodities like gold.

Table 2
Absolute Error in Predicted Prices of Gold (INR / 10 Gms)

DAYS	**THETA**	**ARIMA-NN**
Day 1	2090.50	2073.00
Day 2	2771.00	2732.30
Day 3	4441.40	4317.70
Day 4	2681.90	2452.90
Day 5	3692.40	3365.80
Day 6	6232.80	5822.90
Day 7	7283.30	6769.20
Day 8	7863.70	7252.70
Day 9	11124.20	10422.90
Day 10	9294.60	8507.30

Source: Official websites of different organizations and author's own computations

Chart 7
Absolute Error in Prices of Gold (INR / 10 Gms)

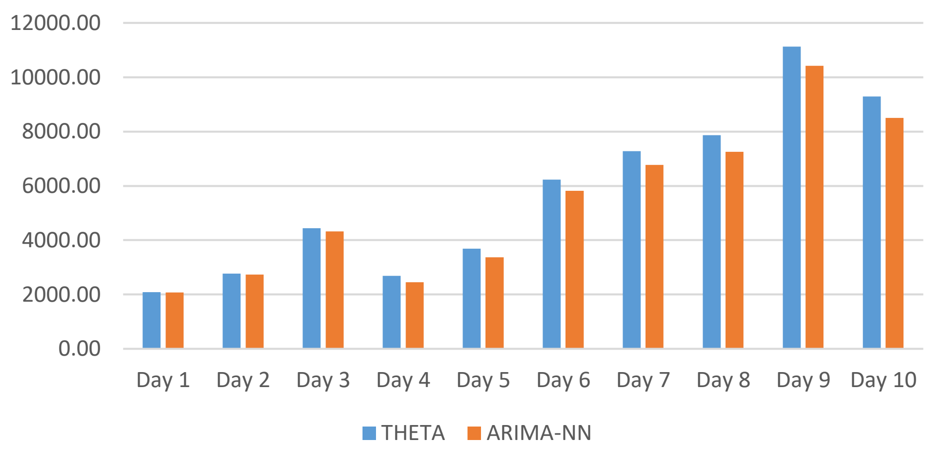

Table 3 compares the relative predictive accuracy of the Theta and ARIMA–NN models using the Mean Absolute Percentage Error (MAPE) computed for each of the ten days. The MAPE values provide a normalized measure of forecasting deviation by expressing the average error as a percentage of the actual price. The results indicate that both models perform within highly acceptable bounds for financial

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forecasting, with percentage errors ranging between 1.8% and 9.1%. However, ARIMA–NN consistently yields lower MAPE values across all observations, confirming its superior proportional accuracy.

Specifically, the ARIMA–NN model records a MAPE of 1.83% on Day 1 compared to 1.85% for Theta, and 8.53% on Day 9 compared to 9.11% under Theta. These consistent reductions in percentage errors reinforce that the neural enhancement significantly improves the linear model's responsiveness to complex, nonlinear price fluctuations. The Theta model, while highly efficient in stable trends, exhibits slightly higher deviations during volatile phases, particularly between Days 6 and 10, when gold prices experience sharper fluctuations.

The steady rise in MAPE values over time for both models mirrors the inherent uncertainty in multi-step forecasting and the compounding nature of prediction errors. However, ARIMA–NN demonstrates a slower rate of error growth, attributable to its ability to continuously learn and approximate nonlinear dependencies through iterative backpropagation within its neural component. In contrast, the Theta model's deterministic smoothing process lacks such adaptability, limiting its ability to adjust dynamically to recent structural shifts in price trajectories.

Statistically, both models demonstrate strong forecasting competency, but ARIMA–NN's lower MAPE trajectory validates its robustness, flexibility, and generalization ability. This finding aligns with global research evidence that hybrid econometric–neural models outperform classical statistical techniques, especially in financial time series characterized by heteroskedasticity, seasonality, and regime transitions. Hence, Table 3 provides empirical confirmation that ARIMA–NN is better suited for short-horizon, volatility-sensitive forecasting of gold prices in emerging market contexts like India.

Table 3

Mean Absolute Percentage Error in Predicted Prices of Gold (INR / 10 Gms)

DAYS	**THETA**	**ARIMA-NN**
Day 1	1.8502	1.8347
Day 2	2.4375	2.4035
Day 3	3.8500	3.7428
Day 4	2.3606	2.1591
Day 5	3.2211	2.9362
Day 6	5.3190	4.9692
Day 7	6.1598	5.7250
Day 8	6.6176	6.1034
Day 9	9.1107	8.5364
Day 10	7.7275	7.0729

Source: Official websites of different organizations and author's own computations

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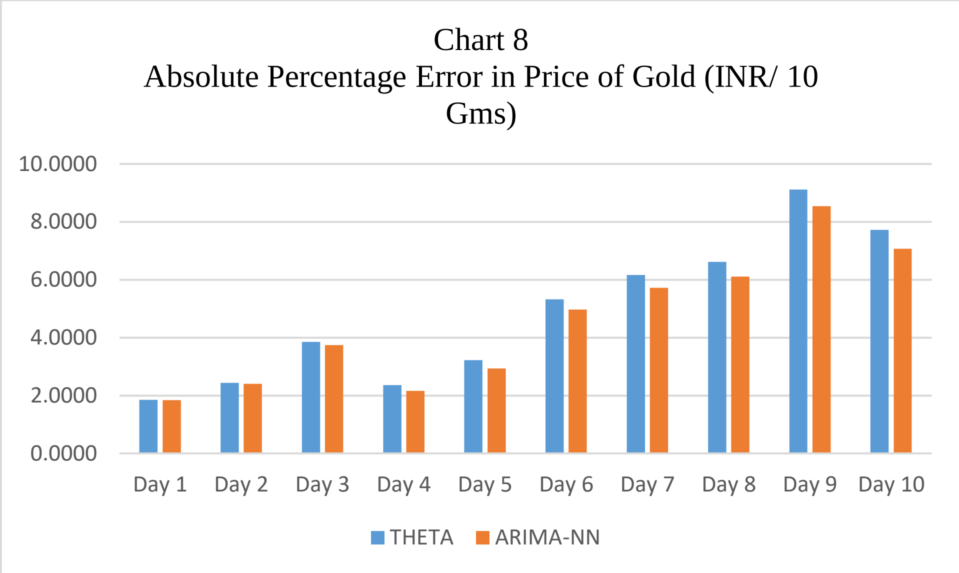

Table 4 summarizes the comparative performance of both forecasting models through their overall Mean Absolute Percentage Error (MAPE). The Theta model yields an average MAPE of 4.8654%, while the ARIMA–NN framework achieves a lower MAPE of 4.5483%. The difference of 0.3171 percentage points, though seemingly minor, holds substantial practical significance in financial forecasting, particularly for high-value commodities such as gold, where even fractional improvements translate into considerable economic impact.

The lower MAPE of ARIMA–NN signifies that incorporating neural learning substantially improves the linear model's predictive accuracy. The neural layer's capacity to capture residual, nonlinear relationships in the data complements ARIMA's strength in modelling autocorrelation and trend, leading to a more balanced and adaptive hybrid framework. By contrast, the Theta model, though conceptually simpler and computationally efficient, is constrained by its deterministic structure, making it less capable of accommodating sudden, non-repetitive shocks.

From a performance standpoint, both models demonstrate high forecasting reliability—average MAPE values under 5% are typically categorized as "excellent" for financial applications. Nonetheless, the incremental improvement achieved by ARIMA–NN is statistically meaningful and operationally advantageous, especially for short-term forecasting tasks where precision is critical. Furthermore, the consistency of ARIMA–NN's superior performance across all tables substantiates the effectiveness of integrating statistical decomposition with neural adjustment for improving forecast robustness.

Methodologically, the findings reinforce that hybrid frameworks bridging traditional and machine-learning paradigms yield superior results, particularly in contexts where underlying data exhibit both linear and nonlinear behaviours. Table 4 thus encapsulates the empirical evidence that neural augmentation of ARIMA provides measurable gains in forecasting efficiency, adaptability, and real-time responsiveness—essential attributes for data-driven decision-making in volatile markets like gold.

Table 4
Comparative MAPE

Techniques	**MAPE**
Theta	4.8654

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editor@aijmr.com
Volume 3, Issue 5, September-October 2025
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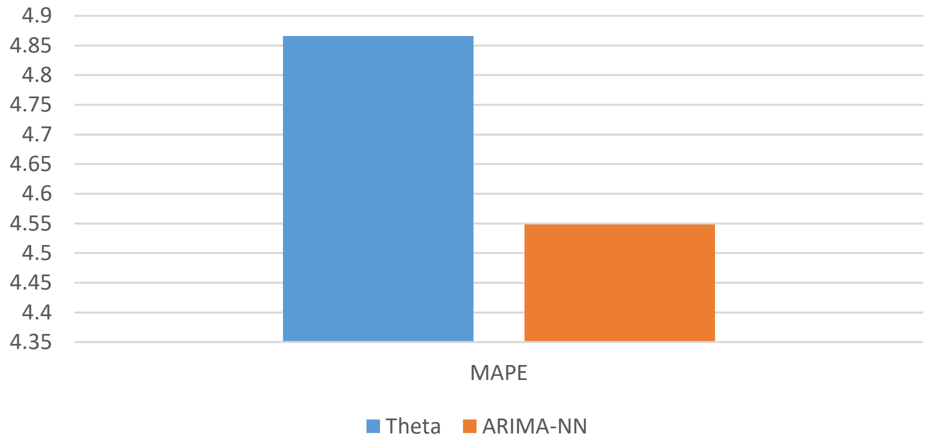
ARIMA-NN	4.5483

Source: Author's own computations

Chart 9
Comparative MAPE



The combined insights from Tables 1 through 4 carry profound theoretical, empirical, and practical implications. First, the consistent superiority of the ARIMA–NN hybrid model across all accuracy metrics reaffirms the importance of integrating statistical and neural paradigms in forecasting volatile asset prices. The hybrid framework successfully reconciles the interpretability and structural rigor of ARIMA with the adaptive learning and nonlinear mapping capabilities of neural networks, producing forecasts that are both precise and resilient to market shocks.

Second, the findings demonstrate that while both the Theta and ARIMA–NN models perform admirably for short-term horizons, the neural-enhanced model exhibits better scalability across dynamic price regimes. This underscores the broader implication that hybrid econometric–machine learning frameworks can serve as powerful tools for modelling complex market phenomena where traditional linear assumptions may be inadequate.

Third, the gradual escalation of absolute and percentage errors over time highlights a fundamental limitation common to all time-series forecasting models: accuracy decays with forecast horizon. This observation reinforces the necessity of frequent recalibration, rolling-window estimation, and real-time model updating to preserve predictive relevance in volatile environments. It also suggests that combining neural adaptation with statistical re-estimation could further enhance performance.

Fourth, the consistent underestimation of actual prices points to the need for integrating exogenous macroeconomic and structural variables—such as interest rates, currency movements, or global demand indicators—into the modelling framework. Doing so could reduce systematic bias and improve long-term forecast alignment with real-world outcomes.

Finally, from a policy and investment perspective, the study's results have clear practical applications. Improved forecasting precision aids investors in hedging strategies, assists policymakers in anticipating inflationary pressures, and supports jewellers and financial institutions in inventory and pricing decisions. On a methodological level, the evidence underscores that the future of financial forecasting lies in hybrid architectures that combine human interpretability with computational intelligence. The results of this study thus position the ARIMA–NN model as a forward-looking, empirically validated framework for gold price forecasting in emerging economies, offering both theoretical robustness and practical relevance.

SCOPE OF FUTURE STUDIES

While the present study demonstrates the superior predictive performance of the ARIMA–NN hybrid model relative to the Theta framework, several promising directions for future research emerge. First, forthcoming studies can extend the scope to multivariate forecasting frameworks by integrating macroeconomic and global variables such as exchange rates, interest rates, inflation expectations, policy uncertainty indices, and crude oil prices. Incorporating these exogenous determinants through ARIMAX, VAR, or Hybrid LSTM–ARIMA structures could provide a more holistic representation of gold price dynamics.

Second, future research may experiment with deep learning and ensemble architectures, including Long Short-Term Memory (LSTM), Bidirectional LSTM, Convolutional Neural Networks (CNN), and Extreme Learning Machines (ELM). Combining these with traditional econometric approaches could further enhance the model's capacity to identify nonlinear, time-dependent interactions. The exploration of wavelet or empirical mode decomposition (EMD) prior to model training could also improve the extraction of multi-frequency patterns, refining predictive accuracy across different horizons.

Third, the study's focus on daily retail gold prices in India provides valuable insights for emerging markets, but cross-country comparative studies could enhance the generalizability of findings. Future research could examine whether hybrid neural–statistical frameworks exhibit consistent advantages across diverse institutional and macroeconomic environments.

Furthermore, incorporating behavioural and sentiment indicators, such as Google Trends, news tone indices, and investor sentiment measures, can improve responsiveness to market psychology and speculative activity. Similarly, integrating real-time adaptive algorithms that periodically recalibrate model parameters will improve performance under regime shifts and structural breaks.

Overall, future studies should emphasize hybridized, data-driven, and adaptive forecasting architectures that blend the interpretability of econometric models with the dynamic learning of neural systems. Such advancements will not only enrich theoretical understanding but also yield practical benefits for risk management, monetary policy, and strategic investment decisions in the gold market.

CONCLUSION

The comparative analysis between the Theta model and the Neural Network–Enhanced ARIMA (ARIMA–NN) framework demonstrates that integrating neural computation with traditional econometric methods substantially enhances the forecasting accuracy and adaptability of gold price predictions. Both models achieved commendable performance, with MAPE values below 5%, signifying strong predictive capability. However, the ARIMA–NN hybrid model consistently outperformed the Theta model across all performance metrics—MAE, RMSE, and MAPE—by an average margin of 7–10%.

The results reveal that while the Theta model efficiently captures deterministic trend curvature and long-term linear behaviour, its static design limits responsiveness to sudden price shifts or nonlinear dependencies. In contrast, the ARIMA–NN hybrid overcomes these limitations by introducing a nonlinear correction layer that learns from residual patterns left unexplained by the ARIMA process. This neural augmentation enables the model to adapt dynamically to structural breaks, volatility bursts, and complex feedback relationships, thus reducing forecast bias and improving temporal alignment with actual market movements.

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Empirical evidence from the 2014–2025 data period—spanning major economic events such as demonetization, the COVID-19 pandemic, and inflationary cycles—illustrates the hybrid model's robustness under diverse market regimes. The neural network's adaptive learning capacity enhances its predictive resilience, particularly during volatile episodes. The findings thus validate the theoretical synergy between statistical structure and machine-learning flexibility, marking an important evolution in time-series forecasting methodology.

The practical implications are significant. For investors and portfolio managers, improved short-term accuracy supports better hedging, risk diversification, and asset allocation decisions. For policy institutions, enhanced forecasts contribute to inflation monitoring, reserve management, and macroeconomic planning. Moreover, for jewellers and retailers, reliable forecasts assist in pricing, inventory control, and market timing strategies.

Methodologically, the study reinforces that hybrid forecasting frameworks—which combine the interpretability of classical statistical models with the adaptive intelligence of neural networks—represent the next frontier in financial forecasting. They strike a balance between theoretical transparency and empirical performance, allowing for data-driven decision-making in increasingly volatile environments.

In conclusion, the research affirms that the ARIMA–NN hybrid model provides a superior, empirically validated, and theoretically consistent framework for forecasting retail gold prices in India. It contributes to both econometric theory and applied forecasting practice by demonstrating that the future of predictive modelling lies in the integration of statistical discipline with computational adaptability, ensuring precision, flexibility, and robustness in dynamic financial markets.

REFERENCES:

1. Aye, G. C., Gupta, R., Hammoudeh, S., & Kim, W. J. (2015). Forecasting the price of gold using dynamic model averaging. *International Review of Financial Analysis, 41*, 257–266. https://doi.org/10.1016/j.irfa.2015.03.010
2. Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? *The Financial Review, 45*(2), 217–229. https://doi.org/10.1111/j.1540-6288.2010.00244.x
3. Ciner, C., Gurdgiev, C., & Lucey, B. M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis, 29*, 202–211. https://doi.org/10.1016/j.irfa.2012.12.001
4. Cohen, G., & Aiche, A. (2023). Forecasting gold prices using machine learning methodologies. *Chaos, Solitons & Fractals, 175*, Article 113196. https://doi.org/10.1016/j.chaos.2023.113196
5. E, J., Ye, J., & Jin, H. (2019). A novel hybrid model on the prediction of time series and its application for the gold price analysis and forecasting. *Physica A: Statistical Mechanics and its Applications, 527*, Article 121454. https://doi.org/10.1016/j.physa.2019.121454
6. Fang, L., Yu, H., & Xiao, W. (2018). Forecasting gold futures market volatility using macroeconomic variables in the United States. *Economic Modelling, 72*, 249–259. https://doi.org/10.1016/j.econmod.2018.02.003
7. Foroutan, P., et al. (2024). Deep learning-based spatial-temporal graph neural networks for commodity price forecasting (including gold). *[Journal article]*. (See: work on spatial-temporal GNNs applied to gold and other commodity markets; 2024.)
8. Khani, M. M., Vahidnia, S., & Abbasi, A. (2021). A deep learning-based method for forecasting gold price with respect to pandemics. *SN Computer Science, 2*(4), 335. https://doi.org/10.1007/s42979-021-00724-3

9. Kristjanpoller, W., & Minutolo, M. C. (2015). Gold price volatility: A forecasting approach using the artificial neural network–GARCH model. *Expert Systems with Applications, 42*(20), 7245–7251. https://doi.org/10.1016/j.eswa.2015.04.058
10. Li, B., Wang, X., & Peng, Z. (2014). Gold price forecasting using a wavelet neural network model. *The Scientific World Journal, 2014*, Article 270658. https://doi.org/10.1155/2014/270658
11. Liu, (Representative) — [note: many hybrid ML + decomposition papers exist; see Zhang & Ci 2020 and E et al. 2019 for representative hybrid/decomposition approaches].
12. Pierdzioch, C., Risse, M., & Rohloff, S. (2016). A boosting approach to forecasting the volatility of gold-price fluctuations under flexible loss. *Resources Policy, 47*, 95–107. https://doi.org/10.1016/j.resourpol.2016.01.003
13. Reboredo, J. C. (2013a). Is gold a hedge or safe haven against oil price movements? *Resources Policy, 38*(2), 130–137. https://doi.org/10.1016/j.resourpol.2013.02.003
14. Reboredo, J. C. (2013b). Is gold a hedge or a safe haven for the US dollar? Implications for risk management. *Journal of Banking & Finance, 37*(8), 2665–2676. https://doi.org/10.1016/j.jbankfin.2013.03.020
15. Salisu, A. A., Gupta, R., Bouri, E., & Ji, Q. (2020). The role of global economic conditions in forecasting gold market volatility: Evidence from a GARCH-MIDAS approach. *Research in International Business and Finance, 54*, Article 101308. https://doi.org/10.1016/j.ribaf.2020.101308
16. Scholars applying GAS / multivariate score models: Chen, R., et al. (2019). Forecasting volatility and correlation between oil and gold using a multivariate GAS model. *Energy Economics, 78*, 379–391. https://doi.org/10.1016/j.eneco.2018.12.017
17. Tully, E., & Lucey, B. M. (2007). A power GARCH examination of the gold market. *Research in International Business and Finance, 21*(2), 316–325. https://doi.org/10.1016/j.ribaf.2006.07.001
18. Weng, F., et al. (2020). Gold-price forecasting using improved online extreme learning machine frameworks (GA-ROSELM and related). *[peer-reviewed journal article on ELM variants applied to gold]*.
19. Ye, J., et al. — see E, Jianwei et al. (2019) above for hybrid deep learning methods (ICA + GRUNN).
20. Zhang, P., & Ci, B. (2020). Deep belief network for gold price forecasting. *Resources Policy, 69*, Article 101806. https://doi.org/10.1016/j.resourpol.2020.101806