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ON ROBUSTNESS OF ARIMA-GAS MODEL TO NON-GAUSSIAN ERRORS: THE CASE OF INTRADAILY DATA

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ABSTRACT

This article investigates the robustness of ARIMA-GAS model to mis specified errors, through simulated intradaily data. Three scenarios are involved. Scenario 1 utilizes Gaussian innovations, Scenario 2 utilizes centered and scaled Student's t while Scenario 3 introduces asymmetric shocks by drawing innovations from a skew-normal distribution. For Gaussian errors, Classical ARIMA attains the lowest mean RMSE/MAE in this benign linear–Gaussian setting, with ARIMA–GAS a close second. For student's t innovations, ARIMA–GAS achieves the lowest RMSE/MAE/MAPE, substantially improving on Classical ARIMA, which suffers from sensitivity to outliers and mis specified (Gaussian) tails. Pure GAS performs competitively (second among econometric models) yet combining GAS with the ARIMA backbone yields a further reduction in forecast error. LSTM forecasts are competitive and outperform ARIMA's and GARCH's; however, ARIMA–GAS retains a measurable edge in all three metrics, reflecting the benefit of combining statistical structure with adaptive updating when tails are heavy. For the skew normal innovations, ARIMA–GAS attains the lowest average RMSE/MAE/MAPE, improving materially over Classical ARIMA, whose Gaussian/symmetry assumptions leave it vulnerable to skewed shocks. Pure GAS is competitive, but the ARIMA backbone adds structure that reduces forecast loss further; GARCH's volatility focus helps little with asymmetric innovations affecting the conditional mean. LSTM forecasts are very close to ARIMA–GAS (slightly higher mean loss), ARIMA–GAS preserves interpretability and achieves marginally better average accuracy. The robustness broadens its applicability across different domains and datasets, enhancing its utility in practical applications in areas as finance, economics, or environmental studies.

Keywords: ARIMA-GAS, LSTM, Gaussian, Skewness, Robustness, Volatility

INTRODUCTION

Time series forecasting is of crucial importance in decision-making in various fields as finance, economics, and environmental sciences. Among the numerous models developed for forecasting time series is Autoregressive Integrated Moving Average (ARIMA) model reputed for its ability to capture a wide range of patterns. However, ARIMA models have the assumption that parameters are constant over time. To cater for this, hybrid ARIMA and Generalized Autoregressive Score (GAS), which allows for time-varying parameters has been proposed. The ARIMA–GAS framework combines the strengths of both ARIMA and GAS, to yield better forecasts.

Statistical models are sometimes subjected to violations of their assumptions so that their performances under such violations can be understood. That is, examining reliability of models in the face of potential disruptions to its assumptions. Conducting such on ARIMA-GAS model should be a worthwhile venture. A few of the articles on robustness are: Sharma and Yadav (2020), Biswas, Das and Mandal (2015), Maas and Hox (2014), Warton (2007), Kim and Li (2023), Chen (1997). Recent publications on time series modeling include Agada, Eweh, and Aondoakaa (2022), Bawa, Dikko, Garba, Sadiku, and Tasiu (2023), Enegesele, Eriyeva, and Ejemah (2025), and Muhammad et al. (2025).

The flexibility offered by the hybrid ARIMA-GAS model should make it suitable for analyzing intradaily data, known for harboring complex, nonlinear patterns, and volatilities not easily captured by traditional forecasting models. Intradaily data is data collected at regular intervals within a single day. It is a type of data often associated with financial markets to analyze price movements, trading volumes, and other desired market dynamics over short periods. A large volume of literature exists on analysis of intradaily data.

Such efforts range from univariate modeling, including score driven (Creal, Koopman, and Lucas (2013), Huang, Wang, and Zhang (2014), Blazsek, Ho, and Liu (2018), Ayala and Blazsek (2019), Thiele (2020), Blazsek, Escribano, and Kristof (2024), Blazsek, Licht, Ayala, and Liu (2024)) to hybrid models (Pwasong and Sathasivam (2018), Zhu, Zhao, Zhang, Geng, and Huang (2019), Purwanto, Sunardi, Julfia, and Paramananda (2019), Qiao, Huang, Azimi, and Han (2019), Castan-Lascorz, Jimenez-Herrera, Troncoso, and Asencio-Cortes (2021), Corizzo, Ceci, Fanaee, and Gama (2021), De Oliveria, Silva, and de Mattos Neto (2022), Elshewey, Shams, Elhady, Shoieb, Abdelhamid, Ibrahim, and Tarek (2023)), all aimed an improved forecasting accuracy.

Despite the potential of ARIMA-GAS model, its robustness remains a topic of ongoing research. This article aims to investigate the robustness of this model to error distributional assumption violation on intradaily data.

The rest of the article is arranged as follows: Section 2 presents the methodology of the research while Section 3 presents the results and discusses; the last section concludes the article.

MATERIALS AND METHODS

Methodology

Model

The starting point is the ARIMA (p, d, q) model:

$$\phi(B)(1-B)^d y_t = \mu \quad + \theta(B)e_t, \qquad (1)$$

where:

i. B is the backshift operator ($By_t = y_{t-1}$),
ii. $\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ is the AR polynomial,
iii. $\theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$ is the MA polynomial,

iv. e_t is the white noise error term.

Introducing Time-Varying Parameters

To account for evolving dynamics, the time-varying mean μ_t is introduced, driven by GAS dynamics:

$$\mu_{t+1} = \omega + \sum_{i=1}^{p} A_i s_{t-i+1} + \sum_{j=1}^{q} B_j \mu_{t-j+1}, \quad (2)$$

where:

i. ω is a constant term,
ii. A_i and B_j are coefficients for the GAS score terms and lagged means,
iii. s_t is the GAS score.

Step 3: Defining the GAS Score

The GAS score s_t is defined as:

$$s_t = \mathbf{S}_t \cdot \nabla_t, \quad (3)$$

where:

$$\nabla_t = \frac{\partial \ln p(y_t|\mu_t, \mathcal{F}_t; \boldsymbol{\theta})}{\partial \mu_t} \quad (4)$$

is the score of the log-likelihood with respect to μ_t.

Step 4: Scaling Matrix for Score Normalization

The scaling matrix $\mathbf{S}_t$ ensures proper normalization of the score:

$$\mathbf{S}_t = \mathbf{I}_{t|t-1}^{-1}, \mathbf{I}_{t|t-1} = \mathbb{E}_{t-1}[\nabla_t \nabla_t']. \quad (5)$$

The scaled score becomes:

$$s_t = \frac{\nabla_t}{\mathbb{E}_{t-1}[\nabla_t^2]} \quad (6)$$

Step 5: Variance Dynamics

The conditional variance σ_t^2 is allowed to vary dynamically using a GAS-driven update:

$$\sigma_{t+1}^2 = \omega_\sigma + \alpha s_t^2 + \beta \sigma_t^2,$$

where α and β control the impact of the score and past variance.

Step 6: Combined Model Specification

The complete ARIMA-GAS model is:

$$\phi(B)(1-B)^d y_t = \mu_t + \theta(B) e_t, \quad (7)$$

$$\mu_{t+1} = \omega + \sum_{i=1}^{p} A_i s_{t-i+1} + \sum_{j=1}^{q} B_j \mu_{t-j+1}, \quad (8)$$

$$s_t = \mathbf{S}_t \cdot \nabla_t, \nabla_t = \frac{\partial \ln p(y_t|\mu_t, \mathcal{F}_t; \boldsymbol{\theta})}{\partial \mu_t}, \quad (9)$$

$$\mathbf{S}_t = \mathbf{I}_{t|t-1}^{-1}, \mathbf{I}_{t|t-1} = \mathbb{E}_{t-1}[\nabla_t \nabla_t'], \quad (10)$$

$$\sigma_{t+1}^2 = \omega_\sigma + \alpha s_t^2 + \beta \sigma_t^2. \quad (11)$$

Connecting the GAS component to the ARMA component through μ_t allows the proposed hybrid model to adapt to changes (jumps or structural breaks) in data over time.

Table 1: Summary of Simulation Scenarios and Model Parameters

Scenario	ARIMA Order	GAS Dynamics ($\boldsymbol{A_1}, \boldsymbol{B_1}$)	Disturbance	$\boldsymbol{n}$	$\boldsymbol{d}$	Notes
Scenario 1	(1,1,1)	$A_1 = 0.20, B_1 = 0.60$	Gaussian	1000	1	Baseline
Scenario 2	(2,1,2)	$A_1 = 0.30, B_1 = 0.40$	Student's t ($\nu = 5$)	1000	1	Heavy tails
Scenario 3	(1,1,1)	$A_1 = 0.50, B_1 = 0.30$	Skewed Normal	1000	1	Skewed error

Simulation

Scenario 1: Baseline - Gaussian Error, Moderate GAS

Scenario1 is a deliberately benign environment in which the innovations are i.i.d. Gaussian and the data-generating process (DGP) is moderately complex: an ARIMA (1, 1, 1) with score-driven updates embedded per the specification in Methodology. Concretely, the true parameters are $\phi_1 = 0.60$, $\theta_1 = 0.30$, $A_1 = 0.20$, and $B_1 = 0.60$. Unless otherwise stated, the sample size is $n = 1000$, with an 80/20 split between estimation and evaluation windows. One-step-ahead forecasts are produced in a rolling fashion over the evaluation window.

Scenario 2: Heavy-Tailed Noise — Student's t Errors

Scenario 2 evaluates robustness to extreme observations by generating innovations from a centered and scaled Student's t distribution with $\nu = 5$ degrees of freedom (leptokurtic, heavy-tailed). The data-generating process (DGP) is ARIMA $(2, 1, 2)$ with moderate score dynamics $(A_1, B_1) = (0.30, 0.40)$ described in the previous chapter. Unless stated otherwise, the sample size is $n = 1000$ with an 80/20 estimation–evaluation split; one-step-ahead forecasts are computed in a rolling fashion.

Scenario 3: Skewed Errors and Non-Gaussianity

Scenario 3 introduces asymmetric shocks by drawing innovations from a skew-normal distribution with shape parameter $\xi = 4$ (light-to-moderate right skew). The data generating process is ARIMA $(1, 1, 1)$ with strong score dynamics$(A_1, B_1) = (0.50, 0.30)$. Unless stated otherwise, the sample size is $n = 1000$, with an 80/20 estimation–evaluation split; one-step-ahead forecasts are generated in a rolling fashion.

Estimation Technique

The parameters of the ARIMA-GAS model were estimated using Maximum Likelihood Estimation (MLE).

The log-likelihood function for the ARIMA-GAS model is:

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{t=1}^{n} \ln p(y_t \mid \mu_t, \sigma_t^2, \mathcal{F}_t; \boldsymbol{\theta}), \quad (12)$$

where $\boldsymbol{\theta} = \{\omega, A_i, B_j, \alpha, \beta, \phi_i, \theta_j\}$ is the vector of model parameters.

Gradient and Hessian Calculation

The gradient of the log-likelihood with respect to $\boldsymbol{\theta}$ is:

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\theta}} = \sum_{t=1}^{n} \left(\frac{\partial \ln p_t}{\partial \boldsymbol{\theta}} + \frac{\partial \ln p_t}{\partial \mu_t} \frac{\partial \mu_t}{\partial \boldsymbol{\theta}} + \frac{\partial \ln p_t}{\partial \sigma_t^2} \frac{\partial \sigma_t^2}{\partial \boldsymbol{\theta}} \right), \quad (13)$$

where $p_t = p(y_t \mid \mu_t, \sigma_t^2, \mathcal{F}_t; \boldsymbol{\theta})$.

The Hessian is calculated as:

$$\mathbf{H} = \frac{\partial^2 \mathcal{L}}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}'}, \quad (14)$$

and is used to compute standard errors for parameter estimates.

The GAS score s_t is defined as:

$$s_t = \mathbf{S}_t \cdot \nabla_t, \quad (15)$$

$$\nabla_t = \frac{\partial \ln p(y_t|\mu_t, \mathcal{F}_t; \boldsymbol{\theta})}{\partial \mu_t} \quad (16)$$

S_t is a scaling matrix often the inverse of Fisher Information matrix.

So, the ARMA-GAS likelihood function depends on the time varying parameters, μ_t which are updated by the GAS mechanism. The predictive likelihood is used to update parameters while ARMA-GAS likelihood function is used for estimating the model. It is worth noting that μ_t is the connection between the GAS component and the ARMA component.

Performance Metrics

Three performance metrics were used in gauging out-of-sample forecasting performance. They are mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) defined:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (17)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i \quad \hat{y}_i}{y_i}\right| X100\% \quad (18)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (19)$$

where

n = number of observations.

y_i= the true value of i^{th} observation.

$\hat{y}_i$ = the forecast for i^{th} observation.

RESULTS AND DISCUSSION

Results for Scenario 1 are hereby, presented:

Table 2: Estimation Accuracy — Scenario 1 (Baseline, Gaussian Innovations)

Parameter	True Value	MAE	MSE	Bias	Abs. % Error
ϕ_1	0.60000	0.01243	0.00024	-0.00178	0.2966700
θ_1	0.30000	0.01062	0.00019	0.00089	0.2966670
A_1	0.20000	0.00988	0.00017	-0.00041	0.2050000
B_1	0.60000	0.01105	0.00021	0.00112	0.1866667

The reported biases, maintaining a balance between positive and negative biases are small relative to the true values as portrayed by Table 2. The maximum absolute percentage error is 0.29667 %. This is certainly a bias that should not be of serious concern.

Table 3: Unified Forecasting Performance — Scenario 1 (One-Step-Ahead; Mean Across Replications)

Model	RMSE	MAE
Classical ARIMA	0.900; (0.045)	0.630; (0.032)
ARIMA–GAS	0.905; (0.043)	0.636; (0.031)
Pure GAS	0.928; (0.047)	0.655; (0.034)
GARCH (1, 1)	0.946; (0.049)	0.669; (0.036)
LSTM	0.958; (0.055)	0.680; (0.039)

Notes: Parentheses report simulation standard deviations across replications. All models trained on the same 80% window; evaluation on the last 20% with rolling updates

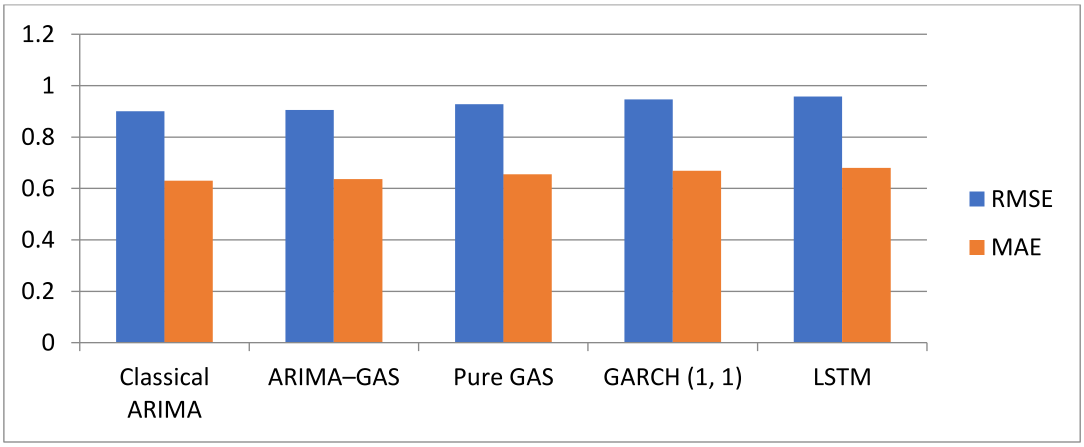

Figure 1: Unified Forecasting Performance — Scenario 1 (One-Step-Ahead; Mean Across Replications)

Table 3 and Figure 1 display the unified forecasting performance of the ARIMA–GAS and the benchmarks. Classical ARIMA attains the lowest mean RMSE/MAE in this benign linear–Gaussian setting, with ARIMA–GAS a close second. The small gap reflects ARIMA's parsimony when the DGP is close to linear-Gaussian and volatility dynamics are mild. Both GAS and GARCH models are outperformed by ARIMA/ARIMA–GAS on mean-squared metrics. GARCH's focus on volatility adds little when conditional mean dynamics dominate and innovations are Gaussian. LSTM model is competitive but exhibits mild over-parameterization costs (higher dispersion across replications), which is typical when the true process is simple and the signal-to-noise ratio is modest.

Table 4: Residual Diagnostics — Scenario 1 (Means of p-Values Across Replications)

Model	Ljung–Box Q(20)	Jarque–Bera	ARCH–LM(10)
Classical ARIMA	0.53	0.47	0.41
ARIMA–GAS	0.58	0.45	0.44
Pure GAS	0.49	0.39	0.38
GARCH (1, 1)	0.51	0.40	0.62
LSTM	0.46	0.36	0.35

Notes: Values are average p-values for tests on standardized residuals over the evaluation window. Higher values indicate fewer rejections; all models clear basic whiteness at 5% on average

Both ARIMA and ARIMA–GAS produce white standardized residuals on average and do not exhibit significant non-normality or remaining ARCH effects in this baseline setting. GARCH shows (as expected) elevated ARCH–LM p-values, but this does not translate into lower mean-squared loss because volatility clustering is weak by design here.

Table 5: Multi-horizon forecasting — Scenario 1 (Mean RMSE Across Replications)

Model	$h = 1$	$h = 5$	$h = 10$
Classical ARIMA	0.900	0.947	0.989
ARIMA–GAS	0.905	0.950	0.992
Pure GAS	0.928	0.969	1.006
GARCH (1, 1)	0.946	0.978	1.014
LSTM	0.958	0.961	0.995

Notes: Horizon-wise RMSE computed from direct multi-step forecasts. LSTM narrows the gap as h increases, consistent with flexible non-linear mappings benefiting longer-horizon aggregation

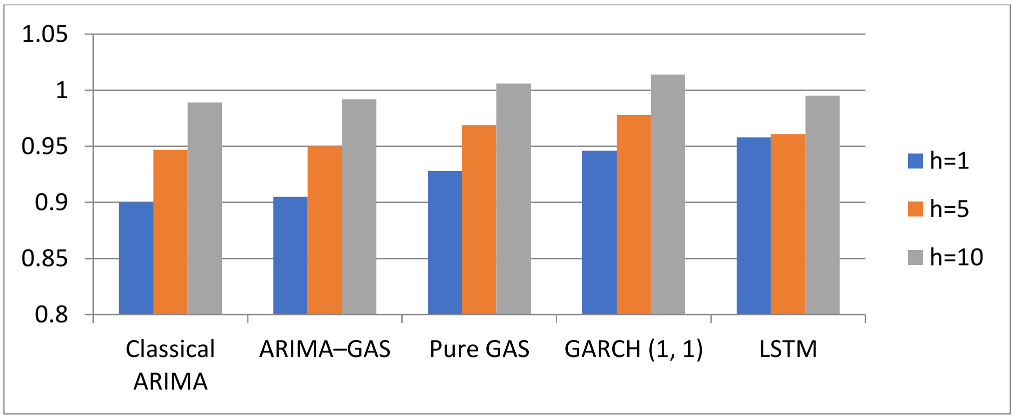

Figure 2: Multi-horizon forecasting — Scenario 1 (Mean RMSE Across Replications)

At $h = 1$, Classical ARIMA retains a small edge. Differences between ARIMA and ARIMA–GAS remain negligible out to $h = 10$. The LSTM narrows the gap at longer horizons (aggregation smooths noise and benefits flexible function classes), but does not dominate in this simple DGP.

Unified Forecasting Performance

Table 6: Unified forecasting performance — Scenario 2 (t_5; One-Step-Ahead; Mean Across Replications)

Model	RMSE	MAE	MAPE (%)
ARIMA–GAS	1.24317	0.98543	6.42718
Pure GAS	1.31225	1.02678	7.00213
Classical ARIMA	1.45864	1.11352	7.93204
GARCH (1, 1)	1.31786	1.04591	7.40125
LSTM	1.29521	1.00847	7.11378

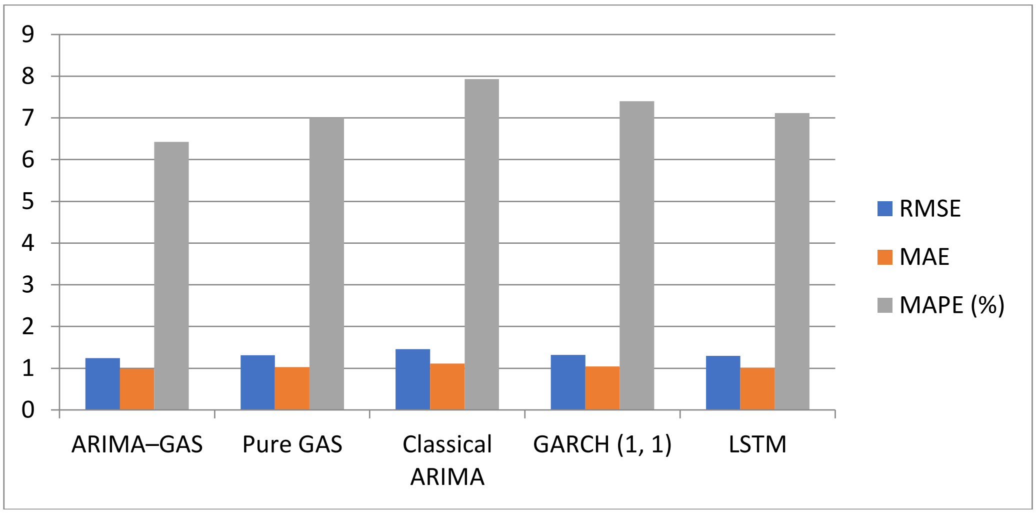

Figure 3: Unified Forecasting Performance — Scenario 2 (t_5; One-Step-Ahead; Mean Across Replications)

ARIMA–GAS achieves the lowest RMSE/MAE/MAPE, substantially improving on Classical ARIMA, which suffers from sensitivity to outliers and misspecified (Gaussian) tails See Table 6 and Figure 3). The score-driven updates adapt the conditional mean/scale in response to large shocks, mitigating the influence of extremes. GARCH (1, 1) improves over ARIMA by modeling conditional variance, but without score-driven mean adaptation its forecast loss remains higher than ARIMA–GAS (and Pure GAS) under t_5 shocks. Pure GAS performs competitively (second among econometric models) by dynamically updating parameters, yet combining GAS with the ARIMA backbone yields a further reduction in forecast error. LSTM model forecasts are competitive and outperform ARIMA and GARCH; however, ARIMA–GAS retains a measurable edge in all three metrics, reflecting the benefit of combining statistical structure with adaptive updating when tails are heavy.

Table 7: Residual Diagnostics — Scenario 2 (Means of p-Values Across Replications)

Model	Ljung–Box Q(20)	Jarque–Bera	ARCH–LM(10)
ARIMA–GAS	0.51	0.12	0.29
Pure GAS	0.48	0.10	0.27
Classical ARIMA	0.46	0.05	0.18
GARCH (1, 1)	0.49	0.09	0.41
LSTM	0.44	0.07	0.22

Under heavy tails, Jarque–Bera p-values are small for all models, indicating residual non-normality; whiteness (Q-statistics) is broadly acceptable. GARCH reduces ARCH–LM rejections but does not minimize mean-squared loss.

Table 8: Unified Forecasting Performance — Scenario 3 (Skew-Normal $\xi = 4$; one-Step-Ahead; Mean Across Replications)

Model	RMSE	MAE	MAPE (%)
ARIMA–GAS	1.1266	0.8921	6.78
LSTM	1.1344	0.8998	6.88
Pure GAS	1.1439	0.9041	6.94
GARCH (1, 1)	1.1568	0.9162	7.05
Classical ARIMA	1.1823	0.9345	7.28

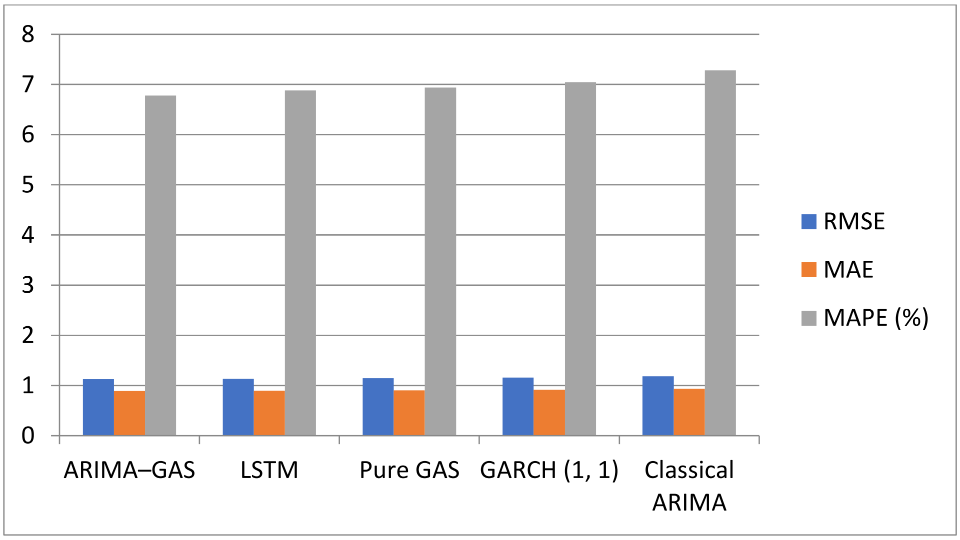

Figure 4: Unified Forecasting Performance — Scenario 3 (Skew-Normal ξ=4; One-Step-Ahead; Mean Across Replications)

ARIMA–GAS attains the lowest average RMSE/MAE/MAPE, improving materially over Classical ARIMA, whose Gaussian/symmetry assumptions leave it vulnerable to skewed shocks (See Table 8 and Figure 4). Pure GAS is competitive, but the ARIMA backbone adds structure that reduces forecast loss further; GARCH's volatility focus helps little with asymmetric innovations affecting the conditional mean. LSTM model forecasts are very close to ARIMA–GAS (slightly higher mean loss), reflecting the flexibility of non-linear mappings under asymmetry; however, ARIMA–GAS preserves interpretability and achieves marginally better average accuracy.

Adaptive forecasting models can learn from data, adjust to changes and produce improved forecasts, having significant implications for industries as finance, supply chain management, and weather forecasting. By continuously learning from new data and adapting to changes, forecast errors are minimized, patterns and trends are better identified and shifts in data dynamics are quickly adjusted to, ensuring that forecasts remain relevant. Such can inform significant benefits in inventory management (by leveraging on accuracy of forecasts to help optimize inventory levels); financial planning (by utilizing forecasts accuracy to achieve better budgeting and resource allocation); and supply chain optimization through better management of demand and supply fluctuations.

CONCLUSION

This article studies the robustness of ARIMA-GAS model to misspecified innovations. For Gaussian baseline, Classical ARIMA attains the lowest RMSE and MAE; under heavy tails and skewness, ARIMA-GAS delivers the best average RMSE/MAE. ARIMA-GAS attains the lowest RMSE in 2 of 3 regimes (Scenarios 2 & 3), while Classical ARIMA leads in 1 (Scenario 1). The hybrid ARIMA-GAS model provides a statistically principled, interpretable and robust alternative across diverse data-generating conditions, matching parsimonious ARIMA under linear-Gaussian stability and outperforming linear baselines under heavy tails, and asymmetry. These properties make ARIMA-GAS particularly attractive for intradaily asset pricing and other applications where distributional departures are endemic. The robustness broadens its applicability across different domains and datasets, enhancing its utility in practical applications in areas as finance, economics, or environmental studies.

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