IOCMA 2026 Conference

The 2nd International Online Conference on Mathematics and Applications

10–12 June 2026 | Online

MDPI

A Comparative Analysis of Econometric and Deep Learning Models for Exchange Rate Forecasting: Evidence from Sri Lanka

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INTRODUCTION & AIM

Objective: compare DCC-GARCH, LSTM and DCC-GARCH–LSTM hybrid models for forecasting USD/LKR exchange-rate volatility in a multivariate framework.

Significance: exchange-rate uncertainty affects trade, foreign borrowing, investment decisions and risk management in Sri Lanka. Accurate forecasting of exchange rate volatility is crucial for a country like Sri Lanka, where the country is highly depend on exports and where financial markets are highly sensitive to currency fluctuations.

Contribution: a multivariate framework captures current-account, capital-account and market-risk channels rather than using only past exchange-rate values.

Current account
Crude oil

Capital account
Forward rate + stock returns

Market risk
Sri Lankan risk indices

METHOD

Dependent variable: USD/LKR exchange-rate volatility.

Predictors: crude oil price, 3-month USD/LKR forward rate, ASPI, DAX, DJIA, Hang Seng, S&P SL 20 and MSI Sri Lanka Index.

Pre-tests: ADF, PP and KPSS for stationarity; ARCH-LM for volatility clustering; Granger causality for predictor relevance.

Forecast evaluation: MSE, RMSE and MAE for in-sample and out-of-sample performance.

Data coverage: daily observations from December 2011 to April 2023.

DCC-GARCH (1,1)

LSTM 20-day window

DCC-GARCH → LSTM Hybrid

Models compared using the same multivariate predictors

Model specification

DCC-GARCH: GARCH(1,1) univariate stage; DCC order selected by AIC/BIC.

LSTM: min–max scaled inputs, 20-day rolling window, 50 hidden units, Adam optimizer, MSE loss, 30 epochs.

Hybrid: DCC-GARCH conditional volatility estimates used as LSTM inputs with stacked recurrent layers.

RESULTS & DISCUSSION

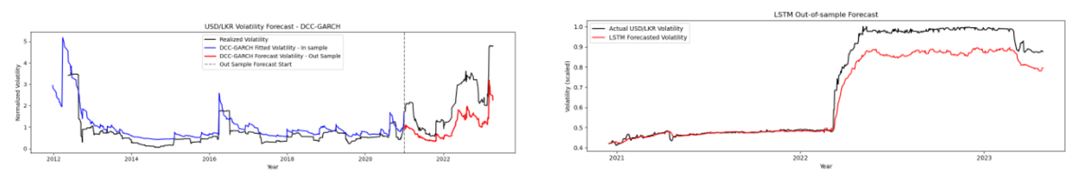
All return series were stationary and displayed significant ARCH effects, confirming volatility clustering.

DCC(1,1) had the lowest AIC and BIC among tested DCC specifications.

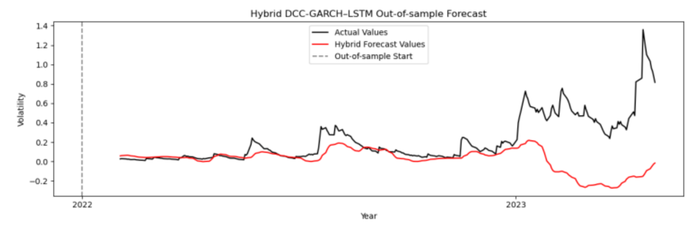
Out-of-sample accuracy ranked: LSTM best, DCC-GARCH second, Hybrid third.

Model	RMSE	MAE	MSE
DCC-GARCH	0.016	0.458	9.044
LSTM	**0.003**	**0.0042**	**0.0092**
Hybrid	7.44	6.00	55.46

Key finding
LSTM produced the lowest out-of-sample errors, indicating stronger ability to learn nonlinear and time-varying exchange-rate dynamics.



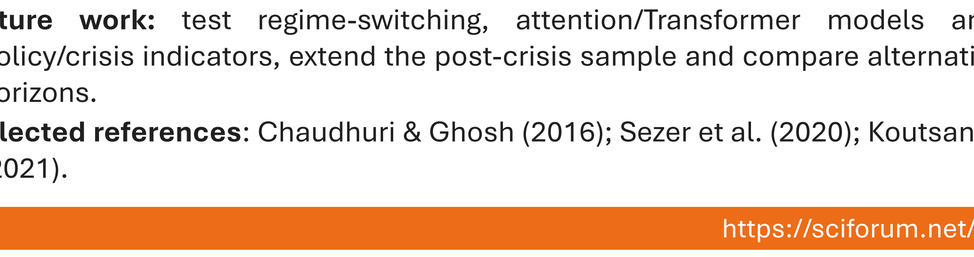
(a) DCC GARCH (b) LSTM



(c) Hybrid

Fig. 6: In Sample & Out-sample forecasting plots

Forecast plots: all models struggled around abrupt crisis-period shocks; LSTM remained closest overall in out-of-sample error metrics.



(a) LSTM Loss Plot (b) Hybrid Loss Plot

Fig. 4: Training loss curves for the LSTM and Hybrid models.

Training loss curves show convergence without major divergence between training and validation loss.

CONCLUSION

- LSTM was the most accurate model for USD/LKR volatility forecasting in the multivariate setting.
- Deep learning better captured nonlinear, time-varying behavior under policy changes, regime shifts and crisis shocks.
- Hybrid performance was constrained by DCC-GARCH smoothing and delayed response to abrupt market changes.

FUTURE WORK / REFERENCES

Future work: test regime-switching, attention/Transformer models and explicit policy/crisis indicators, extend the post-crisis sample and compare alternative forecast horizons.

Selected references: Chaudhuri & Ghosh (2016); Sezer et al. (2020); Koutsandreas et al. (2021).