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An empirical-mode-decomposition-based support vector regression hybrid model: a combined model for foreign direct investment forecasting Mogari Ishmael Rapoo, Martin Chanza and Andrew Ncube Cape Peninsula University of Technology, North-West University and Walter Sisulu University

INTRODUCTION & AIM

Foreign direct investment (FDI) is a key economic phenomenon and a key driver of economic growth, thereby making its accurate forecasting crucial for policymakers and investors. It further brings capital, technology, and expertise into emerging markets, fostering job creation and innovation.

The current study compares four machine learning models namely; support vector regression (SVR), a Deep Neural Network (DNN), empirical mode decomposition based SVR, and an empirical mode decomposition based DNN to improve the forecasting accuracy for foreign direct investment using the exchange rate and gross domestic product as the independent variables. The figure displays time series plots for foreign direct investment (FDI), gross domestic product (GDP), and the exchange rate (ZAR/USD). GDP shows a steady upward trend indicating consistent economic growth, while exchange rate is volatile with fluctuations, and FDI exhibits a generally low trend with occasional spikes, suggesting irregular investment patterns.



The empirical mode decomposition technique is applied to decomposing the series into intrinsic mode functions (IMFs) before feeding it into the machine learning model(s). The models' forecasting performance is evaluated using the mean squared error (MSE), the root mean squared error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the symmetric mean absolute percentage error (SMAPE), and the mean bias deviation (MBD).



RESULTS & DISCUSSION

To develop an optimal forecasting model for foreign direct investment, the data series was normalized using the Min-Max method to ensure all input features contributed equally during model training, thereby enhancing convergence and performance. The normalized series was then split into 80% for training and 20% for testing to enable effective model evaluation using unseen data

The figure above displays the IMFs and residue from the decomposed series of FDI using the empirical mode decomposition (EMD) technique. Based on the figure, it is apparent that the EMD technique decomposed FDI series to four intrinsic mode functions (IMFs) and one residue component.

Metric	EMD – SVR	Support Vector Regression	EMD – DNN	DNN
Root mean squared error	0.1088	0.1259	0.3082396	0.2402
Mean absolute error	0.0499	0.0469	0.2120677	0.1357
Mean squared error	0.0118	0.0158	0.09501163	0.0577
Mean absolute percentage error	106.1115	INF	100	6924.413
Symmetric mean absolute percentage error	50.4064	53	200	58.0238
Mean bias deviation	-2.0998	-0.03	-100	-24.443
Median absolute error	0.0128	0.0122	0.1365932	0.0633

The table above presents the forecasting performance and accuracy of EMD–SVR, SVR, EMD–DNN, and DNN. The results reveal that the EMD–SVR hybrid model achieved the lowest error metrics overall, indicating superior predictive accuracy compared to the other models. In contrast, both the EMD–DNN and traditional DNN models showed considerably high error metrics, suggesting poor performance. The SVR model performed slightly better than the DNN approaches, though still fell short of the EMD–SVR model. These findings highlight the advantage of combining EMD with SVR in a hybrid model to effectively capture nonlinear and nonstationary patterns in the data, resulting in more reliable forecasts.



CONCLUSION

EMD-based SVR model outperformed all the other models, achieving the highest accuracy due to its ability to filter noise and capture economic noise. Decomposition-based hybrid models are effective in financial forecasting, and they provide valuable insights for economic decision-making.

FUTURE WORK / REFERENCES

Future research could explore other machine learning models and add more macroeconomic variables.