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Forecasting Exchange Rate using ARIMA-ANN Hybrid Model

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Abstract

Very few studies delve into modeling the future movement of the Peso-Dollar exchange rate. Notwithstanding the critical role the FX rate played in the economy is enormous. The study attempts to develop a hybrid model of Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) in forecasting the future of the Peso-Dollar exchange rate. Using the Bangko Sentral ng Pilipinas (BSP) FX rate from 2000-2020 to predict the January and February FX rate, the ARIMA-ANN hybrid was developed and compared with the result Holt-Winters Model, ARIMA, and ANN. The outcome demonstrates that the hybrid is a better model with an absolute difference of less than 1 percent, 0.21 percent, and 0.42 percent forecast for January and February 2021, respectively, compared with the actual FX rate. Furthermore, the three statistical measures, MAE, MSE, and RMSE, were used to compare the four methods' performance and demonstrate that the hybrid model has the lowest measurement of errors (0.341, 0.208, and 0.457). Therefore, it is possible to present a more accurate technique in forecasting the FX rate with hybrid modeling.

***Keywords**: Peso-Dollar Exchange Rate, ARIMA, ANN*

Introduction

Current global business practices depend on the exchange rate forecast as a foundation of most, if not all, international business and banking decisions (Arize, Campanelli Andreopoulos, Kallianiotis, Malindretos, 2018). An enormous variety of market participants' currency risk hedgers, importers and exporters of goods and services, overseas foreign workers, investors, speculators, and the central bank. The regular market movement of foreign exchange rates accompanied by the rapid internationalization of business increased the demand for forecasting methods (Galeshchuk, 2016).

The foreign exchange (FX) is the most volatile market, attracting several researchers to present a forecast model (Pilbeam & Langeland, 2015). Admittedly, numerous elements can cause the price to change. The decision to buy or sell currency is the most challenging part of FX trading. To some extent, traders are willing to sell when they deemed it most profitable (Sermpinis, Stasinakis, Theofilatos, & Karathanasopoulos, 2015). Several people believe that timing in the market is the most crucial element of success. Constantly, traders weigh between the desire to maximize their gains and minimize losses and the sustained appreciation of their position's value (Sermpinis et al., 2015).

Time series analysis is an important area of forecasting in which the past observations are gathered and analyzed to propose a model to depict the underlying behavior (Babu & Reddy, 2015). An essential and popular time series model is the Autoregressive Integrated Moving Average (ARIMA). A statistical method used for analyzing and building a forecasting model, ARIMA, models the correlation in the data that best describes a time series (Maria & Eva, 2011).

On the other side, there are inherent disadvantages of ARIMA forecasting, such as it is difficult to understand the model identification techniques from the ranges of possible models. Also, the model's reliability depends on the skills and experience of the forecaster (Wadi, Almasarweh, Alsaraireh, & Aqaba, 2018). Moreover, the ARIMA lacks a distinctive theoretical and structural relationship compared to other simple forecast models such as Holt-Winters and exponential smoothing. Finally, the ARIMA, similar to other forecasting methods, showed poorly at forecasting series with turning points (Zhu & Shen, 2012).

The causes of the difficulty attributed to some new information (Omrane & Hafner, 2015) announced or a random international event (Kennedy & Nourzad, 2016) that abruptly changed the market. However, nobody can anticipate the timing and content of the report or event, which causes the FX rate to swing unpredictably. Thus, the future changes in the FX rate are independent of the past fluctuations making it difficult to predict (Beckmann & Czudaj, 2017). However, some studies suggest models that can overcome these difficulties better than the standard forecasting models (Baffour, Feng, & Taylor, 2019).

Recently, the Artificial Neutral Network (ANN) is becoming a popular modeling tool that can successfully process the non-linearity in the data (Henriquez & Kristjanpoller, 2019). Combining two or more computational models creates synergy, which can provide a better formulation for prediction problems. In addition, each technique's unique capability is helpful to different data model patterns (Omar, Hoang, & Liu, 2016).

The flexibility of ARIMA models and the computational power of ANN was combined to create a forecasting tool as the hybrid ARIMA-ANN model. Several researchers demonstrate that the combination of ANN and ARIMA performed better than the individual model and the result are much significant with nonstationary series (Hansen & Nelson, 2003). Therefore, the study's objective is to develop a comparative hybrid model better than individual forecast techniques.

Framework

Earlier and succeeding frameworks proved that linear and nonlinear methods are better (Foster, Collopy & Ungar, 1992; Aras & Kocakoç, 2016). For instance, both the statistical and linear models show a better result compared to ANN. While data with high volatility and multicollinearity showed, the ANN performed better (Callen, Kwan, Yip, & Yuan, 1996). Each technique does not apply to all types of data. However, combining both linear and nonlinear method as a hybrid technique harness the strength of both models. The hybrid model is capable of decomposing the time series data into linear and nonlinear forms.

Moreover, a hybrid model produces a more accurate price forecast than the individual models (Zhang, 2003). A similar technique using the hybrid model succeeded in defining the relationship between components (Khashei & Bijari, 2011). Also, a hybrid model used the smoothing and average filter to offer a solution in a highly volatile time series (Babu & Reddy, 2014). A significant advantage of a novel hybrid method in forecasting time series data is to overcome the boundaries of making a solid assumption.
Brief information about the particular time series forecasting method such as Holt-Winters, ARIMA, ANN was used as a benchmark to evaluate the hybrid method. ARIMA assumed that the variable to forecast is a linear function of the past observations. In the case of this study, the first differencing method was applied to attain static data. Thus the ARIMA applies to the static data reflected on the equation below:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q} \tag{1}$$

The moving average (θ's) in the equation (eq.1) following the Box and Jenkins convention, the coefficient ($\emptyset'$'s) are autoregression coefficients, while the random errors (e_{t-q}) are identically distributed with constant variance and a mean of zero. The p and q coefficients are referred to the model orders similar to the d parameter. If q equals zero, the model is reduced to the AR model of order p ($AR(p)$). On the other side, the model becomes the MA model of order q *($MA(q)$).*

ANN method for nonlinear modeling furnishes a flexible computation framework in a wide range of applications. The ANN number of layers and the neurons at each layer are easily adjusted to the flexible architecture. Also, ANN does not need any prior assumption, such as stationarity of data. The ANN network configuration contains three layers that are acyclically linked. Such nonlinear function is raised as reflected in the following equation:

$$y_t = w_0 + \sum_{j=1}^{H} w_j\, f\left(w_{0j} + \sum_{i=1}^{N} w_{ij}\; y_{t-i}\right) + e_t \tag{2}$$

At any given time t, the model weights are w_{ij} and w_j, and the hidden input and nodes are H and N, respectively. The error terms are identified as e_t. The sigmoid, tahn ANN architecture functions are the hidden layer f of the transfer function.

This study adopted the Zhang (2003) proposed hybrid ARIMA-ANN model in the time series forecast. The Zhang model assumed that time series are combinations of linear and nonlinear components reflected equation below as

$$y_t = L_t + N_t \tag{3}$$

The linear component and nonlinear components are denoted as L_t andN_t, respectively. ARIMA is used with the given time series data to obtain linear forecast and ANN for the nonlinear component. In improving the overall forecast performance, the two models were combined. The

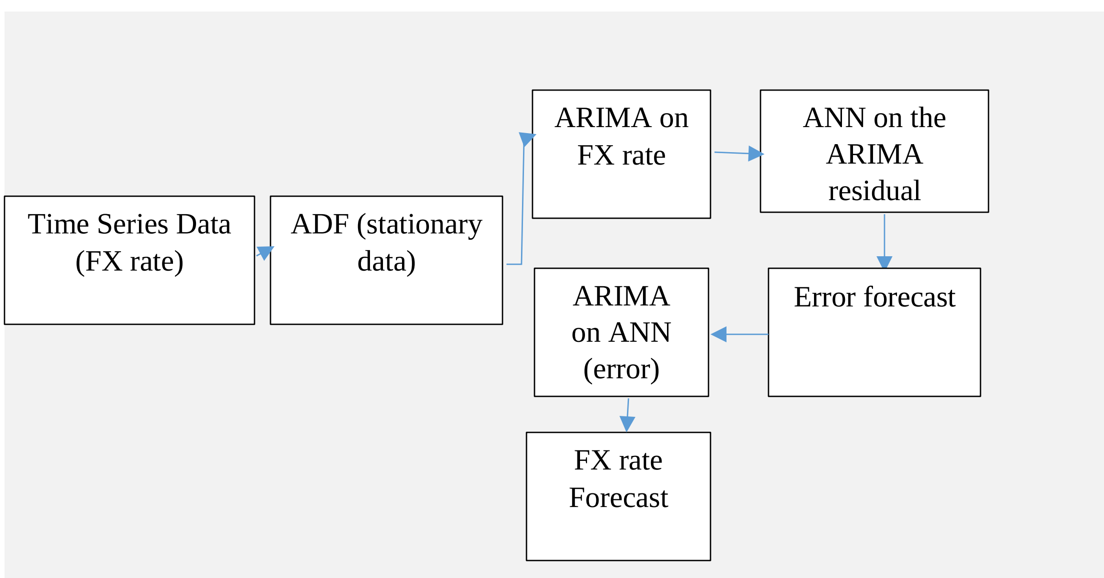
Zhang hybrid model provides a better forecasting accuracy than using the individual ARIMA and ANN methods, proven in the pound-dollar exchange rate data. However, unlike the two-step Zhang model, the process in this study is a three-step.

Method

The data for analysis taken from the Bangko Sentral ng Pilipinas (BSP) published the average monthly Peso-Dollar Exchange rate from 2000 to 2021. The predicted exchange rate using the Holt-Winter, ARIMA, ANN, and the ARIMA-ANN hybrid. This study compares the ARIMA-ANN-ARIMA hybrid performance to the Holt-Winters, ARIMA, and ANN by computing the error measure.

This study proposed a hybrid method for time series that aims to circumvent individual forecasting techniques. As depicted in Figure 1, the designed hybrid method to overcome the challenges in making accurate forecasts with a linear-nonlinear data set. The method of the designed forecast as a hybrid reduced the error risk of employing an inappropriate method. The model consists of three stages. In the initial stage, the ARIMA is used to predict the exchange rate. The Augmented Dickey-Fuller (ADF) was used to test the time series stationarity as a first step. Reflect on Table 1, the high volatility of the FX rate showed that the ADF stationarity test result of tau-stat (0.287) is less than the tau critical (1.94). The result implies the non-stationarity of the data. The first differencing was used to convert the data to stationary time series. By using the ACF and PACF, the three parameters (p,d,q) were identified as (0,0,1). The second stage was to use the residual from the ARIMA as the input in the ANN. The final stage is a process that further refined the trends, which used the residual in the ANN as input in the ARIMA to arrive at the forecast finally.

Figure 1
Steps for the three-stage hybrid forecasting technique



Three metrics were used to compare forecast accuracy, Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). The MAE depicts the degree of error. The MAE measures the absolute difference between the predicted value and the actual value expected from the forecast on average. The MSE is positive, which indicates more weight on significant errors. Moreover, the RMSE was adjusted for large rare errors, emphasizing more frequent significant errors than the mean. Finally, comparing the difference between RMSE and MAE if the forecast contains infrequent and significant errors. The more negligible difference between RMSE and MAE indicates a more consistent error size.

Table 1
ADF test for data volatility

	FX rate	first differencing
tau-stat	0.287535	-11.2045
tau-crit	-1.94212	-1.94212
aic	1.956848	1.949181
bic	1.98502	1.963267
lags	1	0
coeff	0.00024	-0.67044
p-value	> .1	< .01

Results and Discussions

The model comprises three major procedures that involved the ARIMA modeling and ANN modeling in three consequential order. Initially, the ARIMA was used to show the degree of regularity and predictable pattern over time. In the case of the FX, data trends are apparent, but stationarity was not evident. Thus the ARIMA modeling was initially used to prepare the data for the next forecasting step to be made with greater efficacy. After the data was fitted, the residuals obtained in the process are forecasted using the ANN. With the residual from the ANN as an input in ARIMA to produce the forecast.

In Table 2, the hybrid model using ARIMA-ANN-ARIMA forecasted results were compared with other conventional models, Holt-Winter, ARIMA, and ANN, using the error measures of Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). It proved that it has the lowest among the error measures.

Table 2
Measure of Error

Error Measures	*Holt-Winters*	*ARIMA*	*ANN*	*ARIMA-ANN-ARIMA*
MAE	0.5393	0.4710	0.5135	0.341
MSE	0.5306	0.4052	0.4064	0.208
RMSE	0.7284	0.6366	0.6375	0.457

Several obtained essential outcomes from the various forecasting technique attempted. Based on individual methods, ARIMA outperforms ANN, depicted in Tables 2 and 3 for FX data that contain more linearity. Further, the hybrid method performed better than the individual methods. The ARIMA-ANN-ARIMA hybrid performed better even with an unexpected situation that occurred in the data. The hybrid decomposes the data to linear and nonlinear components, which ARIMA extract of the hybrid depicted higher forecasting performance, mainly when unexpected events occurred. The hybrid model did not assume the residual to show a nonlinear pattern. Instead, the hybrid method is a specific model and outperforms individual methods.

Table 3 depicted each model used to compare the actual FX rates in January and February 2021. Again, the outcome showed the ARMA-ANN-ARIMA hybrid with less than 1 percent difference from the real exchange rate forecast better than other models.

Table 3

Forecasting results of each model compared with actual exchange rates result.

	Actual	*Holt-Winters*	*ARIMA*	*ANN*	*ARIMA-ANN-ARIMA*
January 2021 Absolute % difference	48.0614	47.87065 (19%)	47.92333 (0.29%)	47.79 (27%)	48.16338 (0.21%)
February 2021 Absolute % difference	48.2042	47.58833 (62%)	47.81321 (0.81%)	47.4721 (73%)	48.40825 (0.42%)

Considering the different techniques used to forecast the Peso-Dollar Exchange rates, the result showed in Table 2 that the ARIMA-ANN-ARIMA is a better model than other methods presented. The RMSE in Table 3 shows the dominance of the hybrid model. Compared to the Holt-Winter, the ARIMA, and ANN, ARIMA-ANN-ARIMA is a better alternative in predicting FX rate time series data based on the lowest value of the error measures.

Conclusion

The various business persons interested in the FX rate movement faced choosing a time series forecast from different application domains. The ARIMA, as a unique linear modeling technique, provides a better forecast accuracy than a nonlinear method such as ANN. However, the nonstationary data undermine the strength of the ARIMA technique. Conversely, the hybrid technique was able to draw the power of each method by using the linear and nonlinear techniques on a corresponding decomposed component and combine the results.

As future research, the hybrid model may require a pre-processing step as a requirement for the appropriate method to apply. Moreover, refinement is needed to target an additive or multiplicative data set to enhance hybrid multi-step forecasting.

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