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A Hybrid ARIMA-ANN Model for Forecasting Egyptian Exports

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Abstract

The present study examined the potential of a hybrid model based on the autoregressive integrated moving average (ARIMA) model and multilayer perceptron artificial neural network (ANN) for predicting Egyptian exports. Box-Jenkins methodology was applied to the annual data 1960-2016. Four ARIMA models (ARIMA(0,1,1), ARIMA(1,1,1), ARIMA(2,1,1), ARIMA(1,1,2)) were estimated and compared using the Bayesian information criterion (BIC), diagnostic residual analysis (DRA), and parameter significance. Due to the low reported BIC (47.223), the linear component was chosen as ARIMA (1,1,1) and the reported diagnostic conditions were met. Finally, the estimated ARIMA models and lagged export observations were used as inputs in the ANN model. The performance of forecasting was evaluated with mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). The lower errors presented by the hybrid model compared to time-series model only were reported as MAE decreased from 523.451 to 32.594, RMSE from 7211.342 to 58.977, and MAPE from 12.859% to 4.623%. From these results, it is concluded that the ARIMA-ANN framework is useful for the export series analyzed. The number of annual observations should be reconcilable with the number of cases reported in the training/testing case summary for the 1960-2016 period prior to journal submission. The number of cases in the dataset should be 57, and there are 56 cases reported in the training/testing case summary.

Keywords

ARIMA;
Artificial Neural Network;
Multilayer Perceptron;
Hybrid Forecasting;
Egyptian exports;
BIC;
Forecast Accuracy.



1. Introduction

The importance of forecasting economic time series is in planning, resource allocation and policy analysis. ARINMA models are a class of traditional statistical models used to model temporal dependence and ANNs can be used to model nonlinear relationships. A hybrid approach can thus be based on a combination of complementary modeling features, instead of a single model [1-5].

The reasons to use the ARIMA and ANN model combination are especially applicable when a series has a linear and a nonlinear temporal structure. A hybrid ARIMA-ANN approach has been shown to have better forecasting accuracy than its constituent models, and other hybrid models and series/parallel type hybrid models have been studied and reviewed [3-10]. In more recent studies, hybrid forecasting systems and neural network based techniques for forecasting time series have also been assessed [11-18].

The time-series behavior often features complex patterns that reflect shifts in market conditions, economic policies, technology, seasonal variations, and unforeseen events. The information presented above renders the forecasting task difficult, especially in the presence of nonlinear patterns in the data and because of the presence of systematic linear dependences. Accurate forecasting is thus crucial for sound economic decision making, better financial planning, efficient use of resources and minimizing risk to uncertainty in the future economy [19,20].

Traditional statistical forecasting models, such as the Autoregressive Integrated Moving Average (ARIMA) model, have been extensively used for their ability to model temporal dependencies and autocorrelation structure in data that are linear. However, if the series contains a nonlinear relationship which is not properly captured by a linear framework, the performance of ARIMA models can be limited. Artificial Neural Networks (ANNs), on the other hand, are flexible data-driven models which can

learn to capture nonlinear and complex relationships, without the need of specifying a functional form. However, some linear stochastic structures are also difficult to be represented by ANN models and special care should be taken in selecting the architecture of networks and training parameters [21,22].

The ARIMA and ANN models are complementary, and it is clear that their model fusion has a solid theoretical foundation. The complementarity of ARIMA and an ANN model gives a theoretical basis for model fusion. In this method, the ARIMA model is employed to model the linear characteristics of the original series and the ANN model is employed to model the nonlinear characteristics of the residuals of the original series. These two modeling capabilities can be combined to potentially present a more holistic picture of the underlying data-generating process than either model. This method seems to be especially applicable when there are both linear and nonlinear dynamics in economic time series [23,24].

There has been, accordingly, a great deal of interest in the development of hybrid forecasting techniques in time-series studies. The statistical and AI-driven approaches can be synergized to enhance the forecasting accuracy, as shown in various studies, including those measuring the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). But the usefulness of a hybrid model is sensitive to the features of the time series, the quality and time span of the data, model specification, and the choice of forecasting parameters. So, comparing the performance of ARIMA, ANN and hybrid model of both on the same economic time series set is the important criterion for deciding the significance of improvement in forecasting accuracy due to combination of linear and nonlinear modelling approaches [25].

Thus, the present study aims at applying and comparing ARIMA, ANN and hybrid ARIMA-ANN models for export forecasting of Egypt. The study follows the structure of the original data and analysis and compares the capability of each model to represent the temporal dynamics in the series. Special focus is placed on the evaluation of whether inclusion of the chosen ARIMA model and ANN can further minimize the forecasting errors and enhance the forecast accuracy over that of the ARIMA model alone.

2. Research Problem

While useful for a homogeneous linear time series, the ARIMA approach may fail if the time series has mixed structures, but ANNs are able to represent non-linear relationships. Thus, the research problem was to see if a combination of the two models (univariate ARIMA and ANN) was a better export model of the exports of the Egyptian state than the univariate ARIMA model.

3. Objectives

- To make a suitable identification of the suitable ARIMA model for the Egyptian export series for the years.
- To make estimates and diagnosis of the candidate ARIMA models.
- To build an ANN model with the lags of the export observations and the chosen ARIMA information.
- To evaluate the forecasting capability of individual time-series model and integrated ARIMA- model with the help of MAE, RMSE and MAPE.

4. Data and Data Source

Analysis was conducted on annual Egyptian export data on national level and local prices for the period 1960-2016. The data has been drawn from the source manuscript, which is a combination of annual reports presented by Ministry of Trade and Industry. There are 57 annual observations in the indicated calendar period.

During revision a data accounting problem was discovered. There are 57 annual observations for the calendar period 1960-2016, and 56 case-processing observations are reported in a summary of the cases processed in the last 10 years. Since the original annual observation file and the original SPSS case-processing file were not provided with the manuscript, it was not possible to identify the missing case reliably. There was no imputation or invention of values. The discrepancy was therefore left as it is and was considered as a "reproducibility limit" that needs confirmation with the original source files before submitting to journal.

5. Materials and Methods

5.1 ARIMA Model Identification

Box-Jenkins framework was used. From the visual examination of the original export series, it is noted that the series is showed a very distinct upward trend, suggesting that the mean is non-stationary. Thus, first order non-seasonal differencing was performed. The revised series was tested using the autocorrelation function (ACF) and partial autocorrelation function (PACF) and a sufficient number of candidate models were derived from the structures reported in the original analysis [1,2].

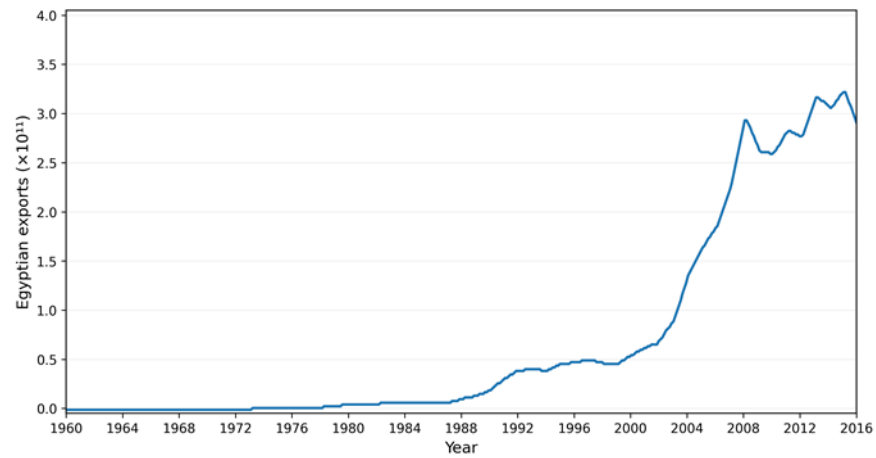


Figure 1. Annual Egyptian export series, 1960-2016.

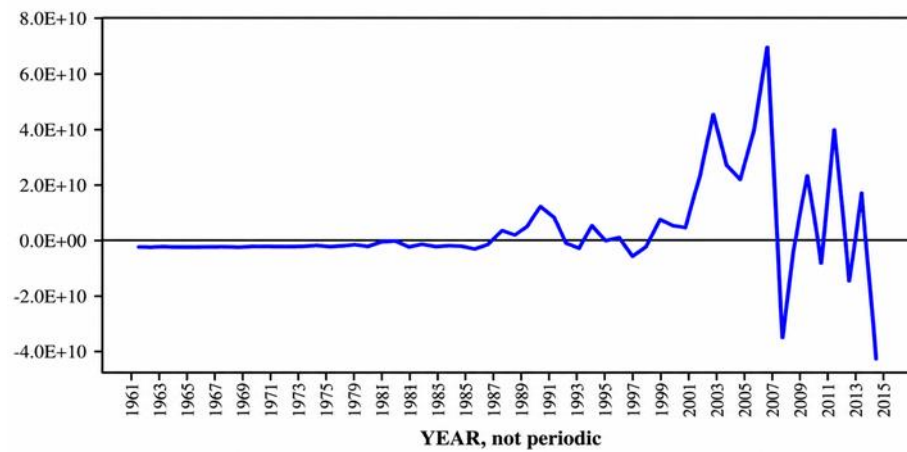


Figure 2. First-order non-seasonal differences of the Egyptian export series.

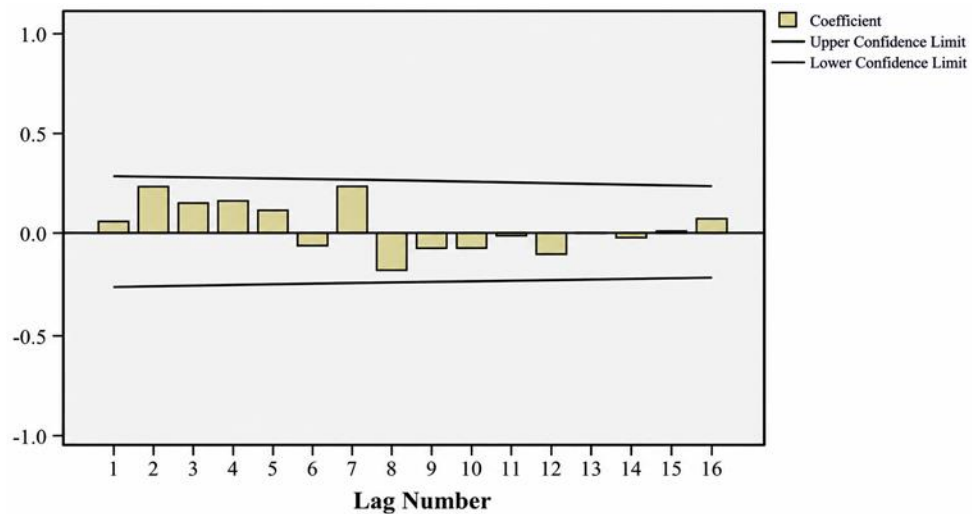


Figure 3. ACF of the first-differenced Egyptian export series.

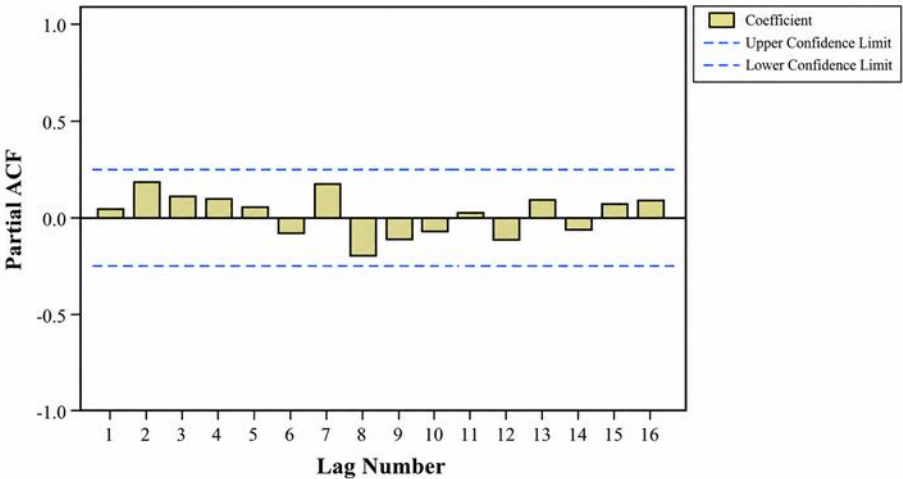


Figure 4. PACF of the first-differenced Egyptian export series.

5.2 Candidate ARIMA Models and Parameter Estimation

Four candidate models were estimated: ARIMA (0,1,1), ARIMA (1,1,1), ARIMA (2,1,1), and ARIMA (1,1,2). The parameter estimates and t-ratios in the source analysis are provided below. Model whose BIC values were lowest and its parameters/diagnostic behavior were acceptable was chosen.

Table 1. Parameter estimates and BIC values for the candidate ARIMA models.

Model	AR1 (φ_1)	AR2 (φ_2)	MA1 (θ_1)	MA2 (θ_2)	BIC
ARIMA (0,1,1)	—	—	-0.103	—	47.229
ARIMA (1,1,1)	0.879	—	0.727	—	47.223
ARIMA (2,1,1)	0.569	0.235	0.553	—	47.272
ARIMA (1,1,2)	0.815	—	0.815	-0.229	47.273

5.3 Model Diagnostics

The model adequacy was evaluated by parameter importance, BIC and the inspection of the residual ACF/PACF. The residual auto-correlation and partial auto-correlation coefficients were reported for the selected ARIMA (1,1,1) model and they were still within the confidence limits, implying that the residuals were approximately uncorrelated. The model chosen was thus used as the linear part of the hybrid system.

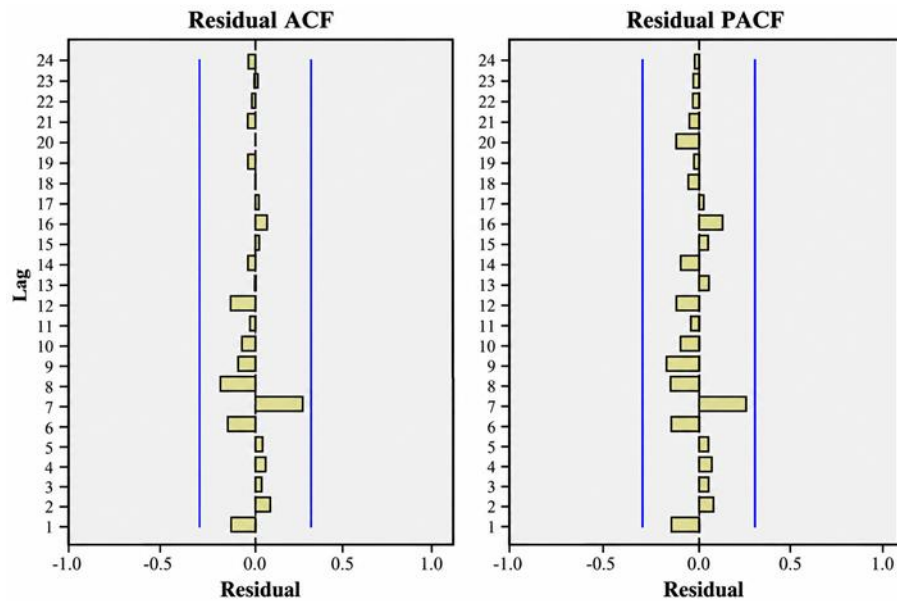


Figure 5. Residual ACF and PACF for the selected ARIMA (1,1,1) model.

5.4 ARIMA Forecast Equation

The values of these parameters are reported in the source manuscript for the selected model:

$$(1 - 0.879B)(1 - B)y_t = (1 - 0.727B)a_t$$

In this equation, y_t is the exports, a_t is the random error term, and B is the backshift operator.

5.5 Artificial Neural Network Model

The ANN part was realized using a multilayer perceptron (MLP). The reported architecture had an input layer using lagged export observations (y_{t-1} and y_{t-2}), a hidden layer and an output layer with the forecasted value of export. The results from the original SPSS showed sigmoid activation functions. Network weights reported are kept since they are part of the analyzed model.

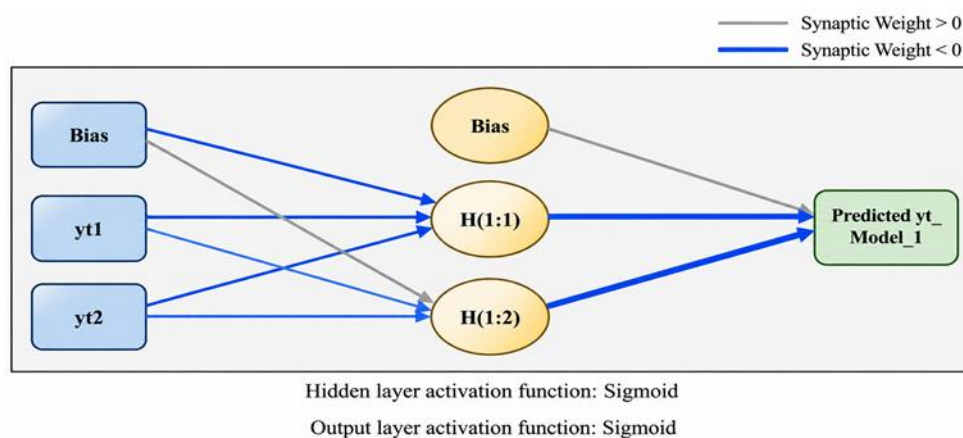


Figure 6. Architecture of the multilayer perceptron used in the forecasting analysis.

For the first hidden neuron, the input-to-hidden weights that were reported were -2.192 and -1.934 for the inputs y_{t-1} and y_{t-2} , respectively, while for the second hidden neuron they were -0.186 and -0.909 for y_{t-1} and y_{t-2} , respectively. The hidden-layer biases

were -1.412 and 2.839. The output-layer bias was 3.528, while the weights for the hidden neurons were -3.909 and -5.111. The following values repeated from original SPSS output.

Table 2. ANN training/testing case summary as reported in the source analysis.

Case group	Number of cases	Reported percentage
Training	37	67.3%
Testing	18	32.7%
Training + testing	55	100.0%
Excluded/labelled unlikely in source output	1	—
Reported SPSS total	56	—

Note: There are 56 reported cases for the SPSS summary (37 training cases, 18 testing cases, and 1 excluded/labelled-unlikely). There are 57 observations for the calendar period 1960-2016. The unaccounted observation should be clearly marked in the original data set before submitting the manuscript.

Table 3. ANN training and testing error summary.

Subset	Sum of squared errors	Relative error
Training	0.005	0.006
Testing	0.078	0.037

Table 4. Reported MLP connection weights.

Connection	H(1:1)	H(1:2)	Output
Input bias	-1.412	2.839	—
y_{t-1}	-2.192	-0.186	—
y_{t-2}	-1.934	-0.909	—
Hidden bias	—	—	3.528
H(1:1)	—	—	-3.909
H(1:2)	—	—	-5.111

5.6 Hybrid ARIMA-ANN Integration

The hybrid model combined information generated by the model selected ARIMA (1,1,1) and the past export observations in the ANN. This was a sequential approach to keep the linear time series structure of the ARIMA and include the other nonlinear relationship in the ANN. Hybrid forecasting has been extensively studied since different models' classes can capture complimentary patterns [10-18]. Combined model built was reported as ARIMA-ANN (1,1,1). The model was compared to the time-series approach with the same reported forecasting comparison criteria.

5.7 Forecast Accuracy Measures

There were three error measures:

- Mean Absolute Error (MAE) = $\text{mean}(|y_i - \hat{y}_i|)$.
- Root Mean Squared Error (RMSE) = $\sqrt{\text{mean}[(y_i - \hat{y}_i)^2]}$.
- Mean Absolute Percentage Error (MAPE) = $100 \times \text{mean}(|(y_i - \hat{y}_i)/y_i|)$.

The smaller the value, the better the forecasting. Both approaches were reported and measured the same way.

6. Results

6.1 ARIMA Model Selection

The ARIMA (1,1,1) model was the one with the lowest reported BIC (47.223) among the four candidate models. In the original analysis, other significant terms included the AR and MA terms of this model, and there was good residual behavior. Therefore, the linear forecast part ARIMA (1,1,1) was selected.

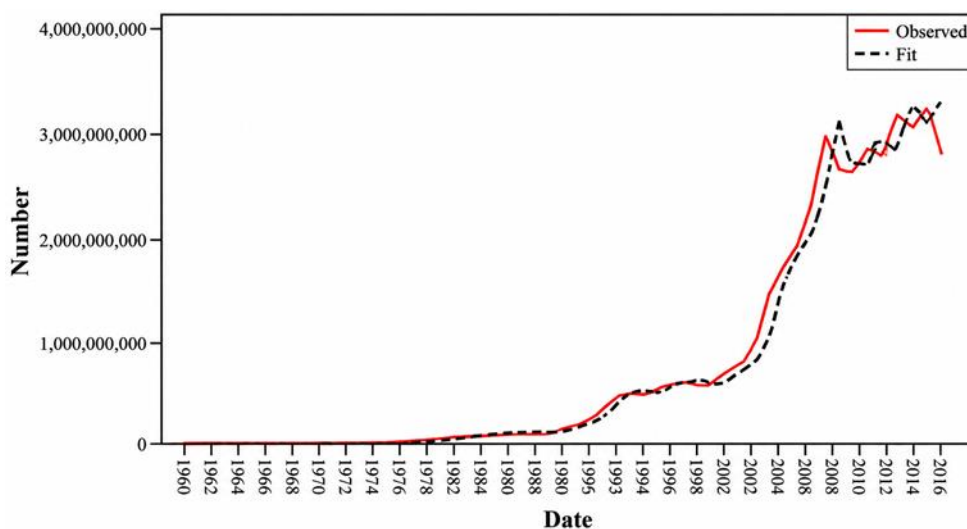


Figure 7. Observed and ARIMA (1,1,1)-estimated Egyptian export values.

6.2 ANN Training and Testing

From the SPSS output, there were 37 training cases and 18 testing cases. The training sum of squared errors was

of the testing was 0.037. These values were not recalculated as the source data for these values was not included with the document.

6.3 Comparative Forecasting Performance

The errors of the reported performance measures were much smaller for the integrated model than for the time-series model alone.

Table 5. Forecast accuracy comparison between the reported ARIMA and ARIMA-ANN models.

Model	MAE	RMSE	MAPE (%)
Time-series ARIMA	523.451	7211.342	12.859
Hybrid ARIMA-ANN	32.594	58.977	4.623

The hybrid model was found to be superior to the time-series model in terms of its approximate reduction of 93.8%, 99.2% and 64.1% in MAE, RMSE and MAPE, respectively. The percentage reductions are arithmetic transformations of the reported values, and should not be interpreted as a new model fit.

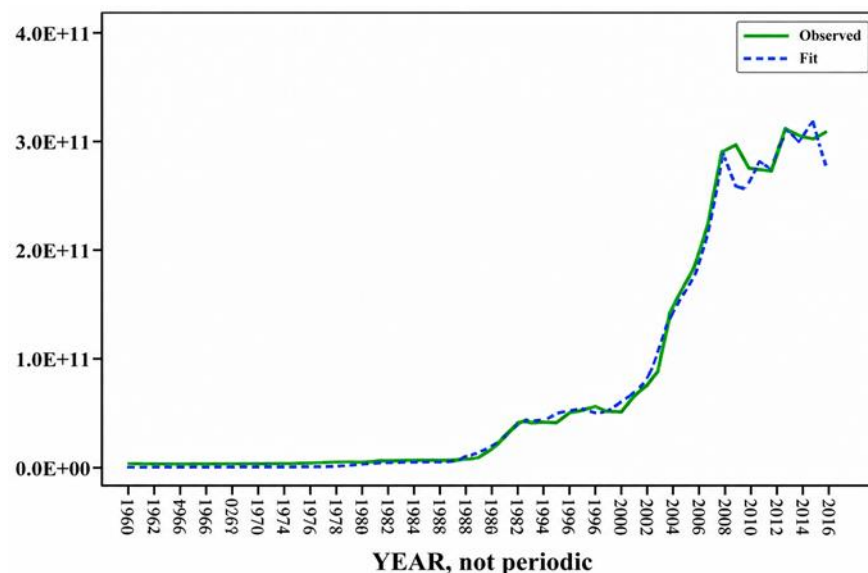


Figure 8. Observed and predicted Egyptian exports using the hybrid ARIMA-ANN model.

7. Discussion

Based on the results, the hybrid model achieved improved reported forecast accuracy, compared to the ARIMA model. This result is in line with the overall idea behind hybrid forecasting statistical models can model the linear dependence, while neural networks can model other non-linear dependences.

Hybrid ARIMA-ANN structures have been demonstrated to be useful in enhancing the accuracy of the forecasts in various time-series applications in the past [3-10]. Recent publications have focused on the hybrid and neural network forecasting structures, noting that there is not a single model that is best for all data and all evaluation designs,

and that the selection of models should be based on the data and the evaluation design [11-18,19-25].

In the ARIMA stage, a clear statistical baseline was provided and ARIMA (1,1,1) was suggested as a candidate for the model by the report of the BIC and the residual diagnostics. Lagged observations and information obtained from ARIMA was then supplied to the ANN stage to give a nonlinear forecasting component. The large discrepancies of the reported MAE, RMSE, and MAPE shown in Table 5 suggested the superiority of the hybrid approach [19-25].

But the accuracy comparison reported should be taken with caution, until the annual series reported can be reconciled with the SPSS case summary. Additionally, the document that's available does not give an entire independent hold-out forecast horizon nor does it offer the raw observations needed to replicate all of the reported metrics. Reported calculations need not be considered invalid because of these issues, but they must be corrected or be discussed in advance of journal submission to allow independent reproduction [20-25].

8. Conclusion

In the next step, the hybrid ARIMA-ANN model was applied to predict the Egyptian exports data from the annual data for the period from 1960 to 2016. The best model based on BIC among models reported was selected as the ARIMA (1,1,1) model and its behavior was found to be acceptable by the diagnostic tests. The ANN integration results in lower MAE, RMSE and MAPE values compared to ARIMA time-series only. In the current data set and forecasting methodology, the hybrid ARIMA-ANN method thus demonstrated better forecasting accuracy.

A main methodological problem that arose during revision was that the number of annual observations in 1960-2016 (57) did not match the number of cases reported in the ANN summary (56). Before submission the raw data and SPSS case-processing

output must be reconciled but no unsupported observation was added during the revision process.

9. Limitations

The main shortcoming was that the annual data set and the original SPSS project file were not provided in the manuscript. Thus, model parameters reported, the errors obtained from the ANN and the comparative metrics of forecasts were left unchanged and maintained as published. There are also 57 calendar observations for the 1960-2016 periods of data, while the case summary (reported) for the ANN period covers 56 cases. This difference should be compared with the original data before it can be published. The benefit of "hybrid" model was then discussed in the context of what was provided in the documents.

10. Data Consistency and Reproducibility

The annual series were for the time period 1960 to 2016, with 57 calendar observations. But it was reported that only 56 cases were taken up as the case processed by the ANN. The missing observation could not be determined reliably as the entire year's data set and the original SPSS case-processing file were not provided. Nothing was added or left out during revision. The values of the ARIMA and ARIMA-ANN coefficients and forecasting errors were, therefore, kept as reported in the source analysis. If a final version is to be submitted, it is recommended that the annual series, case record of inclusion/exclusion, training/testing split and SPSS output be reconciled for full reproducibility.

According to the annual export series, it had been taken from the annual reports of the Ministry of Trade and Industry. The authors should keep the original SPSS model-output file and provide the file to the journal or reviewers upon request if it is available and authorized to provide the information. The analysis is not completely reproducible until the

57 annual observations are confirmed with the 56 reported ANN cases.

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