Advanced Materials Research *Online: 2013-12-04*
ISSN: 1662-8985, Vol. 845, pp 510-515
doi:10.4028/www.scientific.net/AMR.845.510

Evaluating ARIMA-Neural Network Hybrid Model Performance in Forecasting Stationary Timeseries

S. N. Seyedi[1, a], P. Rezvan[2,b], S. Akbarnatajbisheh[3], S. A. Helmi[4]

[1, 2, 3, 4]University Technology Malaysia, Johor Bahru, Malaysia

[a]Seyedi.Navid@gmail.com, [b]Pouyan.Rezvan@gmail.com

Keywords: ARIMA; Artificial Neural Network; Timeseries Forecasting; Forecasting; Hybrid models.

Abstract. Demand prediction is one of most sophisticated steps in planning and investments. Although many studies are conducted to find the appropriate forecasting models, dynamic nature of forecasted parameters and their effecting factors are apparent evidences for continuous researches. ARIMA, Artificial Neural Network (ANN), and ARIMA-ANN hybrid model are well-known forecasting models. Many researchers concluded that the Hybrid model is the predominant forecasting model in comparison with ARIMA and ANN individual models. Most of these researches are based on non-stationary or seasonal timeseries, whereas in this article, hybrid model's forecast ability by stationary time series is studied. Some following demand time steps from a paint manufacturing company are forecasted by all previously mentioned models and ARIMA-ANN hybrid model fails to present the best forecasts.

Introduction

Prominent role of sales prediction is recognized by commercial enterprises which are looking for a way to reach globalization and competitive advantages. Sales prediction has direct influence on production, purchasing, inventory level, and is a guide for just in time (JIT) and agile manufacturing [1]. Time series, which are continuous observations of a parameter during equally time intervals, are available inputs for predictions [2]. Prediction is done by a developed model based on historical data. This method named time series forecasting and is based on this hypothesis that the historical data is a reliable indicator for future changes. This method is more effective when, there is no significant change in data pattern from one year to another and is very useful when, there is not enough knowledge about data generating process or there is no trustable model to relate forecasted variable to other explanatory variables [3]. Although a lot of forecasting methods are developed, researches for checking their performance in different cases, in addition to developing more accurate methods never finish.

Autoregressive integrated moving average (ARIMA) is a linear forecasting model with high level of versatility. Pre-processing ability is one of significant advantage of ARIMA model [4]. Theoretical properties and experimental evidence of ARIMA, makes it as a reliable forecasting method. ARIMA was used in a study by Ediger to predict future energy demand in turkey [5]. The positive effect of demand forecasting on inventory performance was mentioned by Babai through the using ARIMA (0,1,1) model [6].

Artificial neural network (ANN) is a nonlinear forecasting model which is not able to model some nonstationary time series [7]. Flexibility and universal approximation by ANN result the high level of accuracy in problems modeling, while, mixed previous results required more precision in application of ANN in linear timeseries[8]. While, Inability of ARIMA in recognition of extreme events is the result of its limited accuracy, ANN is possible to capture these extremes [9]. Capability of ANN in presenting more accurate forecasts rather than ARIMA is mentioned in several articles. Neural network backpropagation method is selected for sales prediction in a medium size enterprise in Brazil in comparison with ARIMA [10].

Pervious empirical and theoretical findings show the role of forecast methods combination especially when there are different models in increasing forecast accuracy [8, 11]. Forecast combination was introduced by Bates and Granger [12] and expanded to neural network by Hashem

[13, 14]. It is accepted that forecast combination, such as a combination of nonlinear models (computational intelligence based models) and linear models, is required to achieve a high performance and accurate model [15,16]. Combination of both ARIMA and ANN models was applied by Zhang as a method for both linear and nonlinear problems [4]. Gutierrez-Estrada et al also concluded that combination of ARIMA-ANN model improves forecasting accuracy [17].

In a study by Zhang, the ability of ARIMA-ANN in representing high accurate forecast in comparison with its individual models is concluded in an exchange rate case study [4]. Higher performance of hybrid model in three case studies (Canadian lynx data, exchange rate data, and Sunspot data set) is shown by Khashei [8]. In some cases like wind speed prediction, hybrid models always release the best forecast result in comparison with individual models [18]. Hybrid model which is applied in an air quality prediction case study in Chile succeeded to predict 100% of alerts and 80% of pre-emergency conditions [9].

It is worthwhile to mention that according to many experimental studies, complex and statistically sophisticated methods are not necessary outperform simpler methods [19]. Although a hybrid forecasting model is successful to present better results and higher performance than individual models in most of cases [20], it does not have proper performance in all cases [21]; this failure of hybrid models was also mentioned by Temizel [22]. The inability of ARIMA-ANN model in predicting underperformed individual methods in nine nonstationary cases was concluded [23].

ARIMA

Autoregressive integrate moving average was developed as a linear model by Box and Jenkins in 1970. This method was suggested to use in situations in which there is not enough data to use regression models or the knowledge about regression model structure is limited [24]. ARIMA is a univarient model based on autocorrelation and non-stationary assumptions. Time series would be stationary through differentiation step. A stationary timeseries has a constant mean and variance over time. Eq. 1 represents the box-Jenkins ARIMA (p,q) model, contains of p past observations or historical data and q random errors terms :

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{1}$$

Where c is the mean of Y_t, ε_t is the error term at time t with variance σ_m^2, φ_i presents the i th autoregressive coefficient. The φ term could be found out by linear regression. The j th moving average coefficient is shown by θ_j, ε_{t-j} is the random error of a prior point at time t-j. In this model, moving average coefficients' can be calculated by maximum likelihood estimation (MLE) method. When $q = 0$, the equation changes to an AR model of order p and if $p = 0$, the model becomes an MA model of order q.

ARIMA appropriate forecasting model is selected based on three steps: Checking stationary, parameter estimation and model identification, and diagnostic checking. ARIMA Statistical properties and its flexibility to represent several different types of time series such as autoregressive (AR), moving average (MA) and their combination, in addition to Box-Jenkins model building methodology are some strength points of ARIMA model. On the other hand, ARIMA limitation as a pre-assumed linear model causes linear correlation structure assumption among time series; so this model is not able to capture nonlinear patterns which are more common in real world problems [4]. Applying other nonlinear machine learning methods like neural network instead or in combination with linear ones can improve the result.

Neural Network

Machine learning involves computers learning ability from experiences, examples and analogy through adaptive mechanisms. Although, machinery learning (AI/ML) methods usually are implicit and computationally intensive, they improve the performance and form the basis for adaptive systems. One of the most popular machine learning approaches is artificial neural network.

ANN is one of the best data-driven approaches for the situations in which data generating process is unknown. The ability of neural network model in accurate forecasting, rooted from its learning ability from experience, provides precise estimates of complex relationships among functions in order to discover adaptive pattern from the data. It is apparent that neural network works better than ARIMA models in all situations unless the data are not appropriate pre-processed [25].

Underlying relationship according to time series presented features, leads to elimination of any assumption in model making and problem solving prior knowledge, provides the ability to handle any level of complexity. But it has problems in finding global optimum model and it is time consuming [26]. To avoid getting stuck in local optimum answer, multiple starts in neural network training will be applied, so each time series will be trained several times with several sets of initial random weights. It results to several neural network models among which the best one will be chosen. Adaptive learning parameter can be used in Levenberg and Marquardt algorithms which are provided by MATLAB toolbox to increase probability of reaching to global optimum answer.

An study by Werbos [27] has shown Artificial neural networks (ANNs) is able to outperform classical statistical methods like linear regression and Box-Jenkins approach and some others introduced the ANN as a promising alternative method instead of traditional linear methods.

Hybrid Model

A hybrid model with linear and nonlinear parts can be represented as Eq. 2 where the L_t is linear component and N_t is non linear component of the model. The ARIMA model captures the linear part of the model. If $\hat{L}_t$ represents the ARIMA forecast value, Eq.3 represents e_t as the model residual

$$Y_t = L_t + N_t \tag{2}$$

$$e_t = Y_t - \hat{L}_t \tag{3}$$

In the next step, an ANN model with *n* input nodes is applied for forecasting the nonlinear part of the model. The new model for residuals is according to Eq.4:

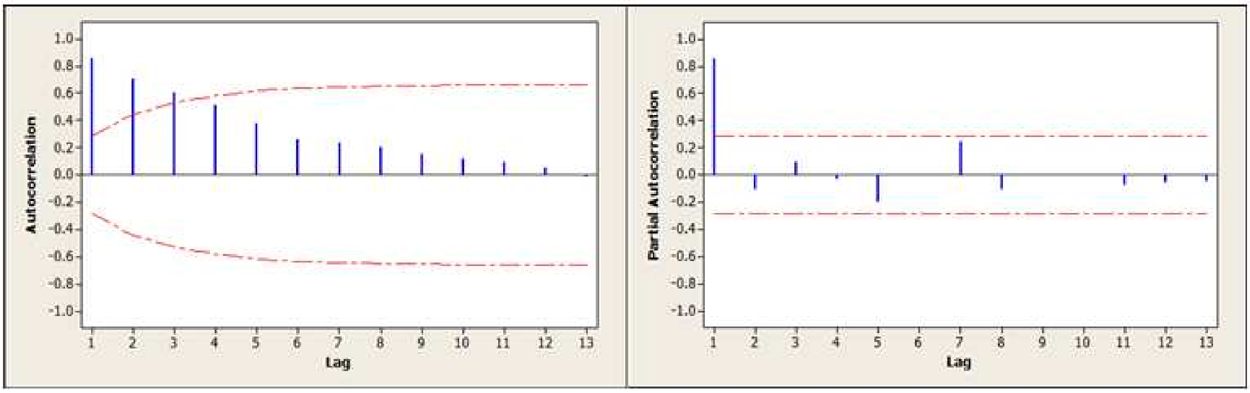
$$e_t = g(e_{t-1}, e_{t-2}, \dots, e_{t-n}) + \varepsilon_t \tag{4}$$

Where g is the function for nonlinear model (sigmoid function) and Ɛt is model fit random error. The forecast result for the ARIMA-ANN is represented as Eq. 5, where $\hat{N}_t$ is ANN forecasted residual

$$Y_t = \hat{L}_t + N_t \tag{5}$$

Results and Discussion

To check the inability of hybrid model to present the best prediction results in comparison with its individual models in stationary timeseries, a paint manufacturing company is selected in Malaysia. Historical data for paint sales is gathered for fifty months and applied for developing model to predict future time steps. By checking the time series there is no gap, unusual data and seasonal pattern. Figure 1 shows autocorrelation function (ACF) and partial autocorrelation function (PACF); ACF spikes die out to zero and except the first lag of PACF the rest of spikes are in the confidence intervals. As a result the stationary of the data is assumed and ARIMA (p,d,q) changes to autoregressive model or AR(p).



a b

Fig. 1. ACF diagram (a) and PACF diagram (b)

By checking the lowest mean square error and Bayesian information criterion (BIC) for possible values of p, AR (1) is selected as appropriate ARIMA forecasting model. The fitness of mentioned model on time series is checked by Ljung-Box statistics.

To find suitable neural network forecasting model, nonlinear autoregressive (NAR) standard network is selected as a two layer feed-forward network with a hidden layer and an output layer. To avoid getting stocked in local optimum answers the model was run several times with different initial weights and retrained several times to find most suitable model. In addition Levenberg-Marquardt back propagation algorithm is used as training method.

ARIMA-Neural network hybrid model is developed based on forecasting the linear part of demand by ARIMA and using residuals to predict nonlinear part of demand by neural network. Table 1 mean percentage error (MAPE) for all forecasting models.

Table 1: Models' Performance (Demand Forecasting)

Forecast model	Mean Percentage Error
ARIMA	31.9%
Neural network	27.3%
Hybrid model	27.7%

By comparing forecast models' performance, neural network is selected as the most appropriate forecasting model with minimum level of MAPE.

Conclusion

The importance of having a precise forecast of demand in paving organization way to achieve better decisions and plans is a reason for continuous studies by comparing and selecting suitable forecasting models. In this study the hypothesis that ARIMA-ANN hybrid model always can outperform its individual models, is checked by applying stationary time series. By comparing the paint demand forecast result, hybrid model was not successful to give the best result. Subsequently, there is no evidence that hybrid model will always present the best forecast.

There are some possible reasons for hybrid model inability. First one is ANN model is built on residual of ARIMA model so, if ANN fails to model ARIMA residual, the hybrid model performance will reduce. Second reason, hybrid model is more suitable for time series which needs to differentiation, detrending and deseasonalization; nevertheless, for other cases especially when time series is nonlinear, ARIMA presents a large level of error as the first predicting model. The last reason is ANN model will have better fitness to stationary nonlinear time series, so Appling ARIMA as the first forecasting model in the hybrid model has a negative effect on forecast. For future researches, testing the performance of hybrid model in other stationary nonlinear case studies is suggested.

References

[1] Z.L. Sun, T.M. Choi, K.F. Au, Y. Yu, Sales forecasting using extreme learning machine with applications in fashion retailing, Decision Support Systems. 46 (2008) 411-419.

[2] B. L. Bowerman, R. T. O'Connell, Time series forecasting. Duxbury, Boston. (1987).

[3] S. Chopra, P. Meindl, SUPPLY CHAIN MANAGEMENT, PEARSON. (2010) 198-226.

[4] G. P. Zhang, Time series forecasting using a hybrid ARIMA and neural network model, Neurocomputing. 50 (2003) 159-175.

[5] V.S. Ediger, S. Akar, ARIMA forecasting of primary energy demand by fuel in Turkey, Energy Policy. 35 (2007) 1701-1708.

[6] M. Z. Babai, M. M. Ali, J. E. Boylan, A. A. Syntetos, Forecasting and inventory performance in a two-stage supply chain with ARIMA (0, 1, 1) demand: Theory and empirical analysis, International Journal of Production Economics (2011).

[7] B. F. Francesco Virili, Nonstationarity and Data Preprocessing for Neural Network Predictions of an Economic Time Series, In Proceedings ofIEEE-INNS-ENNS International Joint Conference on Neural Networks (IJCNN'00). 5 (2000) 5129-5136.

[8] M. Khashei, M. Bijari, A novel hybridization of artificial neural networks and ARIMA models for time series forecasting, Applied Soft Computing. 11 (2011) 2664-2675.

[9] L. A. Diaz-Robles, J. C. Ortega, J. S. Fu, G. D. Reed, J. C. Chow, A hybrid ARIMA and artificial neural networks model to forecast particulate matter in urban areas: The case of Temuco, Chile. Atmospheric Environment. 42 (2008) 8331-8340.

[10] A.P. Ansuj, M.E. Camargo, R. Radharamanan, D.G. Petry, Sales forecasting using time series and neural networks, Computers and Industrial Engineering. 31 (1996) 421–424.

[11] F. C Palm, A. Zellner, To combine or not to combine? Issues of combining forecasts, Journal of Forecasting. 11 (1992) 687-701.

[12] J. M. Bates, C. W. J. Granger, The combination of forecasts. (1969) 451-468.

[13] S. Hashem, Optimal linear combinations of neural networks, Purdue University. Ph.D. (1993).

[14] S. Hashem, B. Schmeiser, Improving model accuracy using optimal linear combinations of trained neural networks. Neural Networks, IEEE Transactions. 6 (1995) 792-794.

[15] R. R. Andrawis, A. F. Atiya, H. El-Shishini, Forecast combinations of computational intelligence and linear models for the NN5 time series forecasting competition. International Journal of Forecasting. 27 (2011) 672-688.

[16] J. S. Armstrong. Principles of forecasting: a handbook for researchers and practitioners, Springer. (2001).

[17] J. C. Gutiérrez-Estrada, C. Silva, E. Yáñez, N. Rodríguez, I. Pulido-Calvo, Monthly catch forecasting of anchovy Engraulis ringens in the north area of Chile: Non-linear univariate approach, Fisheries Research. 86.2 (2007) 188-200.

[18] H. Liu, H. Q. Tian, Y. F. Li, Comparison of two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed prediction, Applied Energy. (2012).

[19] S. De Leeuw, K. V. Donselaar, T. D. Kok, Forecasting techniques in logistics, Advances in distribution logistics, Springer Berlin Heidelberg. (1998) 481-499.

[20] S. Makridakis, M. Hibon, The M3-Competition: results, conclusions and implications, International journal of forecasting. 16 (2000) 451-476.

[21] J. Shi, J. Guo, S. Zheng, Evaluation of hybrid forecasting approaches for wind speed and power generation time series, Renewable and Sustainable Energy Reviews. 16 (2012) 3471-3480.

[22] T. Taskaya-Temizel, M. C. Casey, A comparative study of autoregressive neural network hybrids, Neural Networks. 18 (2005) 781-789.

[23] T. Taskaya-Temizel, K. Ahmad. Are ARIMA neural network hybrids better than single models?, Neural Networks. 2005.

[24] G. Box, G. Jenkins, Time series analysis; forecasting and control. Holden-Day, San Francisco(CA). (1970).

[25] G. P. Zhang, M. Qi, Neural network forecasting for seasonal and trend time series, European journal of operational research. 160 (2005) 501-514.

[26] W. C. Hong, Y. Dong, L. Y. Chen, S. Y. Wei, SVR with hybrid chaotic genetic algorithms for tourism demand forecasting, Applied Soft Computing. 11 (2011) 1881-1890.

[27] P. J. Werbos, Generalization of backpropagation with application to a recurrent gas market model. Neural networks. 1 (1988) 339-356.