Demand forecasting of a first-tier supplier in automotive industry using nonlinear autoregressive network with parsimonious variables

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Presented at 2020 KIIE Conference, South Korea (https://bit.ly/2LGw1z5)

Abstract

Accurate demand forecasting is compulsory for a first-tier supplier to determine an optimal amount of parts to produce in order to minimize safety stock after supplying to the manufacturer. Under producing than an actual order will negatively impact relationships with the industry, while overproducing will face unnecessary carrying costs. This study was to develop a nonlinear autoregressive exogenous network (NARX) model to predict part demands of a first-tier supplier and compared its forecasting performances with an autoregressive integrated moving average (ARIMA) model. A parsimonious set of external variables (provisional demand order and number of non-working days) were considered in the NARX model. The time-lags for each variable and demand for the previous period were determined by analyzing autocorrelation functions. The dataset was obtained from a first-tier supplier for a year and divided into 70% training, 15% validation, and 15% testing sets. The performance evaluation resulted that root mean square error (RMSE) of the proposed model was better than an ARIMA model in both training (18%) and testing (15%) sets. The promising results of the proposed NARX model could be crucial for improving manufacturing planning to efficiently reduce carrying costs and prevent stock out.

Keywords: demand forecasting, automotive industry, neural network, parsimonious variable, ARIMA

1. Introduction

A first-tier supplier of upstream supply chain needs to predict future demands of a production company (main contractor). For an example of automotive industry, a first-tier supplier (e.g., part manufacturing company) is responsible for supplying the amount of automotive parts ordered from an automotive company on time. However, its demands keep fluctuating because of several relevant factors such as sale volumes, national holidays, and unexpected events. Therefore, to respond its demand fluctuation, a first-tier supplier should accurately predict to supply on time for lean or just-in-time manufacturing. Overproduction due to inaccurate prediction cause a carrying cost by holding unnecessary stock in inventory. Meanwhile, underproduction cause stock out that probably causes additional direct and indirect costs.

Auto regressive integrated moving average (ARIMA) has been used to predict future data of time series with good performances (Box et al., 2015). Since ARIMA is based on historical data in forecasting future values, it can efficiently forecast a short-term value. In addition, ARIMA was formed by integrating auto regression (AR) and moving average (MA) to balance each other for a better prediction (Ariyo et al., 2014; Sun et al., 2019). Many existing studies showed that ARIMA responded with better mean absolute percentage error (MAPE) and mean squared error (MSE) among other traditional methods such as Holt's and Winter exponential (Udom and Phumchusri, 2014; Fattah et al., 2018; Sen et al., 2016; Babai et al., 2013). For example, Fattah et al. (2018) formed ARIMA (1, 0, 1) model for the IBM SPSS forecasting and showed an acceptable MAPE of 13% (Udom and Phumchusri, 2014).

On the other hand, artificial neural network (ANN) has been integrated for forecasting in most sectors including manufacturing industry. The flexible and dynamic ANN algorithm is capable in dealing with big datasets which are in complex form of various data types (Hsu et al., 1995). Since forecasting using ANN resulted better error values and was suitable in both short-term and long-term demand forecasting (Al-Saba and El-Amin, 1999), ANN is considered as a precise model in the automotive parts manufacturing company too. Kochak and Sharma (2015) studied the demand forecasting by applying ANN without considering any external variables, the forecasting resulted an effective performance and accuracy as 6% of MAPE.

Nonlinear autoregressive exogenous network (NARX) can predict more accurately since it can consider the pattern of historical data as well as external variables that may help a better prediction. Although ARIMA and ANN showed an acceptable prediction, but it is only depending on the pattern of its own historical data. On the other hand, NARX can additionally consider external variables along with

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ARIMA does. Thus, many studies have attempted to apply NARX for future value predictions in several fields such as wind speed, air pollution level, flood water level, solar radiation, and fault detection (Cadenas et al., 2016; Pisoni et al., 2009; Ruslan et al., 2014; Boussaada et al., 2018; Taqvi et al., 2020). However, no study has been conducted to develop a NARX to predict the demand of a first-tier supplier in automotive industry even though several external factors may influence its actual demand (Vargas and Cortés, 2017; Boussaada et al., 2018). Therefore, a study is needed to develop a NARX model for prediction of demand considering the characteristics of a first-tier supplier in automotive industry.

This study focuses on building a demand forecasting model using NARX using parsimonious variables and optimal parameters for the network (input and output delays, nodes). The external variables of NARX were determined by correlation analysis between them and demands of a first-tier supplier company. The delay of input and output of the network were also decided by analyzing time-lag effects of the external variables and historical demands on future demands. The optimal number of nodes for the network was determined to minimizing errors in training and validation sets. This study used an actual one-year data set obtained from a first-tier supplier in automotive industry.

2. Proposed NARX Model

Data Sets

This study used an actual data for 1 year obtained from a first-tier supplier in automotive industry. A production company (main contractor) delivered the daily demand to this supplier along with pre-order amount (provisional demand) for upcoming 12 days. The pre-order was subject to change according to the main contractor's production schedule. This study divided the data into three sub sets in order to train (70%), validate (15%), and test (15%) a proposed NARX. The prediction period in this study was set to 14 days since this supplier need to spend about 14 days in procurement, production, and delivering.

Parsimonious External Variables Selection

This study considered three external variables (pre-order amount, holiday number, and sale volume of the car) that may be related to the demand of automotive parts as shown in Figure 1. First, pre-order amount is rough demand for a designated period (e.g., 12 days) estimated from an automotive company. An automotive company generally provides a pre-order amount to a first-tier supplier in order for facilitating its supply chain. As shown in Figure 1.a, an automotive company shares their estimated demand for upcoming 12 days; however, this pre-order amount is subject to change depending on the production schedule of an automotive company. Second, holiday number is the number of holidays (non-business days) during a prediction period. Since an automotive company is not working on holidays, its demand may be affected by the number of non-business days during a prediction period. Lastly, sale volume of the car (obtained from http://m.auto.danawa.com/newcar/?Work=record&Brand=303&Month=2016-12-00&MonthTo=) is also affecting to the demand since more or less parts are required depending on sale volume.

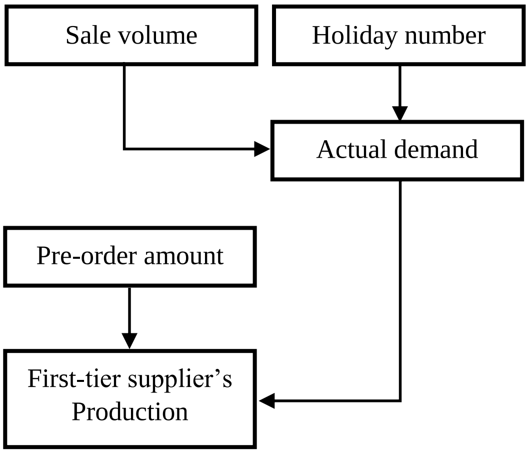

Figure 1. Relationship of each external variable with the actual demand

Two key variables (pre-order amount and holiday number) out of the three external variables were chosen to avoid multi-collinearity problem in a prediction model. High correlation among external variables may cause multi-collinearity problem that may degrade the accuracy of a prediction model. First of all, stepwise regression analysis was performed and resulted that holiday number ($p < 0.001$) and pre-order amount ($p < 0.001$) were included in the model; but rejected sale volume. In addition, this study analyzed correlation among variables and found that sale volume is highly correlated with pre-order amount (0.813 to 0.780) and holiday number amount (0.734 to 0.725). It implies that pre-order amount and holiday number without the sale volume can properly predict the demand since the two have high correlation with sale volume.

Time-lag Analysis

The number of time lag for the two key variables was determined as 2 by analyzing the correlations with actual demand as shown in Figure 3. Correlations for the pre-order amount (0.81 to 0.72) gradually decreasing as time-lag increased. On the other hand, correlations for holiday number (0.66 to 0.68) were relatively consistent regardless of time-lag. There were significant effects of time-lag; however, it was generally decreasing or sustained. Thus, this study chooses 2 for time-lag.

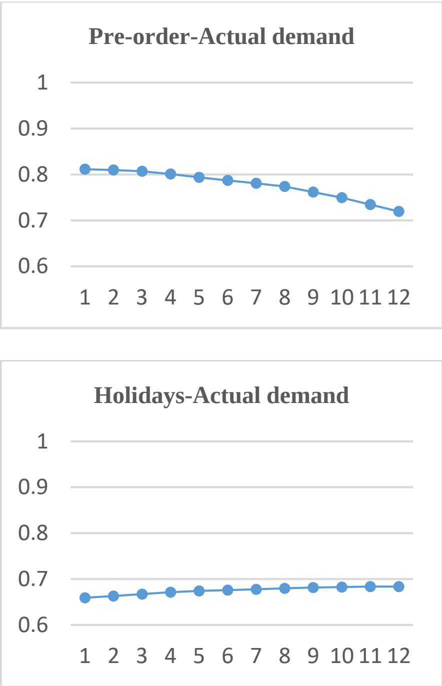

Figure 3. Cross-correlation coefficients with Actual demand (y-axis) in time lags (x-axis; unit: time)

The number of input-output delay for the network was determined by autocorrelation function (ACF) and partial autocorrelation function (PACF) (Box et al., 1994). Based on the Figure 4, the coefficients of AFC gradually decrease to 0 as "tails off", and PACF shows that, after the high correlation in lag 1 (0.96) and 2 (-0.48), the others' correlation sharply decreases as "cuts off" below and close to the confidence interval. Thus, the number of input-output delay in this study was determined as 2.

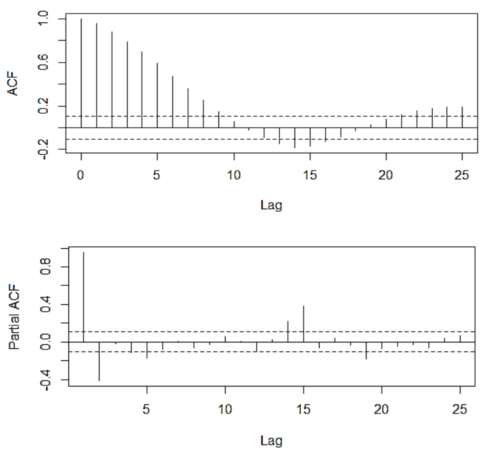

Figure 4. ACF and PACF of the actual demand

Proposed NARX Network

The proposed network consisted of three layers (input, hidden, and output layers) as shown in Figure 5. The input layer had 2 inputs (pre-order amount and holiday number) with 2 time-lags, which was determined from correlation analysis between the two variables and the actual demand. The hidden layer had 4 nodes. The optimal number of nodes was decided by analyzing network performance for training and validation data sets according to different number of nodes (1 to 20 with step size = 1). As shown in Figure 6, the training error kept decreasing as the number of nodes; however, the training error for validation data was decreasing and start to increase after 8. Thus, this study selected 4 as the optimal number of nodes for our prediction problem. The output layer is the predicted demand for a designated period (12 days in this study). In addition, the demand is recurrent to the input in order to reflect its historical patterns.

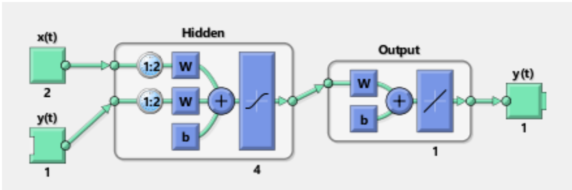

Figure 5. Artificial neural network with parsimonious variables (the image adapted from MathWorks, Inc.)

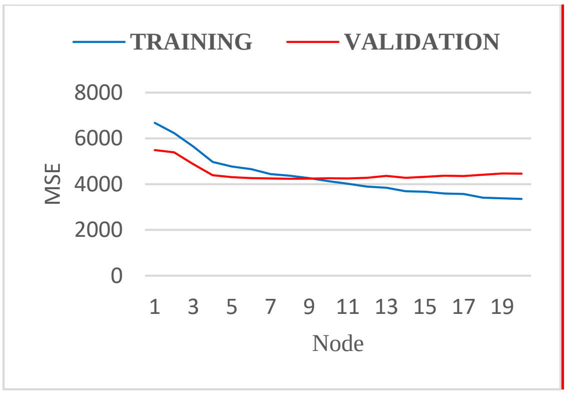

Figure 6. Training and validation performance according to the number of nodes in the network

The NARX was used to employ a feature of external variables as the input and the historical data on demand. Thus, this study used NARX with time-lag following by:

$$y(t) = f\,(y(t-1), y(t-2), u(t-1), u(t-2), u'(t-1), u'(t-2)) \quad (1)$$

where: y = output of the network,
u and u' = external input of the network, and
f: NARX function of the network.

The NARX network has a better learning with a faster generalized convergence in neural networks by using gradient descendent getting from external variables to reduce estimation's parameter numbers

(Pisoni et al., 2009). Mean squared error (MSE) was used in the learning algorithm as the performance function to select optimal weights and bias (Equation 2; Cadenas et al., 2016). This study used Levenberg-Marquardt learning algorithm which is a standard technique for converging nonlinear least squares selection (Lourakis, 2005).

$$\mathrm{MSE_{reg}} = \gamma\mathrm{MSE} + (1-\gamma) \times \mathrm{MSW} \qquad (2)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(t_i - y_i)^2,\ \mathrm{MSW} = \frac{1}{n}\sum_{j=1}^{n}(w_i)^2$$

where: t_i = target,
y = predicted value, and
γ: performance ratio.

3. Results

The proposed NARX showed good prediction performances as shown in Table 1. MSEs of the proposed NARX for the training and testing data sets were 4969 and 4081, respectively. In addition, RMSEs for both sets were 70 (9% of average demand for a prediction period) and 63 (8% of average demand). The R^2 between the predicted demands and actual demands was 96% and 94% for the training and testing sets.

Table 1. Result comparison between the methods

	TRAINING			TESTING		
	MSE	RMSE	R^2	MSE	RMSE	R^2
ARIMA	7155	85	95%	5663	75	92%
NARX (4 Nodes)	4969	70	96%	4081	64	94%

Based on the comparison between NARX and ARIMA from Table 1, the proposed NARX showed a promising result. RMSE of NARX model (RMSE = 70) was sufficiently smaller for training data set than ARIMA (85). Similarly, RMSE of NARX was better than that of ARIMA for the testing data set. Lastly, R^2 between actual and predicted values was better in NARX (training = 96% and testing 94%) than ARIMA (training = 95% and testing 92%) for the both data sets.

The proposed NARX showed slightly better performance than an ARIMA as shown in Figure 7. Both the proposed NARX and ARIMA fitted well to the target by following the patterns and trends for the testing data set. However, several points of ARIMA appeared to have tremendous spike in RMSE which was higher than the proposed NARX. For example, in Figure 8, the points 3, 14, 17, and 31 showed relatively high error in ARIMA than the proposed NARX.

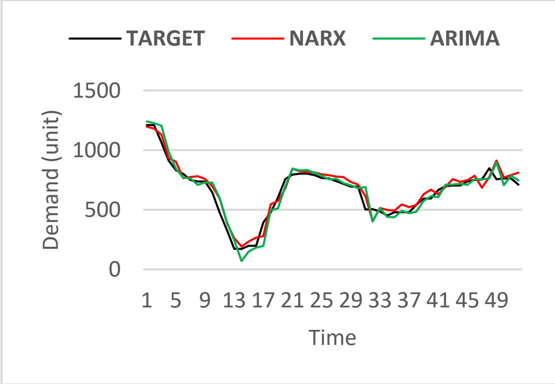

Figure 7. Predicted values of NARX and ARIMA

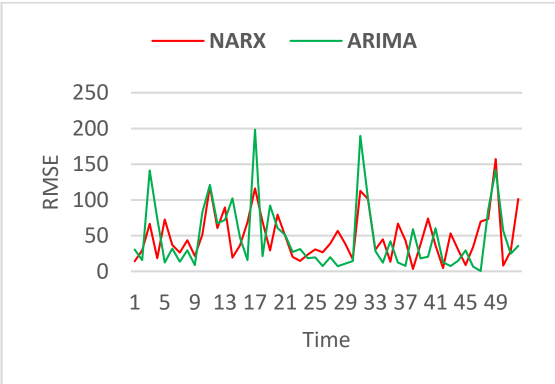

Figure 8. RMSE of the predicted value of NARX and ARIMA

4. Discussion and Conclusion

This study determined the inputs and parameters of proposed NARX in a systematical way. Three external variables (pre-order amount, holiday number, and sale volume) were considered at first and then two parsimonious variables were selected in order to avoid multi-collinearity because one external variable (sale volume) had high dependency to the others. In addition, the number of input-out delay was decided as 2 by ACF and PACF analysis. Furthermore, the node number for the hidden layer was determined as 4 by analyzing the learning performance for different node number of the network.

The best performance of learning in NARX is defined by the validation phrase when the validation error decays to the minimum value and then stops the training in order to optimize the network architecture (Larsen et al., 1996). Since the NARX used backpropagation algorithm for training, the number of hidden neurons is mandatory to determine to avoid under and overfitting with learning result (Kalogirou, 2013). We analyzed MSE by changing node number from 1 to 20 for the training and validation data sets. MSE for the training data set dramatically dropped from 1 node (6679) to 4 (4969) then gradually decreased until 20 (3351), while the validation data set sharply decreased from 2 nodes (5391) to 4 (4391) and then stop to improving performance. Hence, the node number for a best performance was suggested to be 4 in this study.

The NARX developed in this study resulted a promising result since it employed near optimal parameters including number of input-output delays, node number, and parsimonious variables. The parsimonious variables showed the positive effect in boosting network's learning process. Meanwhile, since there is no specific method to identify an exact optimal number of nodes for the network, the procedure used in study may be applied in determining a satisfying node number.

Acknowledgements

This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT; NRF-2019R1A2C4070310).

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