Master of Science

Demand Forecasting of a First-Tier Supplier in Automotive Industry Using Nonlinear Autoregressive Network with Parsimonious Variables

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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. Producing under 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 compare its forecasting performances with an autoregressive integrated moving average (ARIMA) model. A parsimonious set of external variables (provisional demand order and the 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 in the root mean square error (RMSE) of the proposed model being 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

CONTENT

CHAPTER 01

INTRODUCTION

1.1. Problem Statement

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

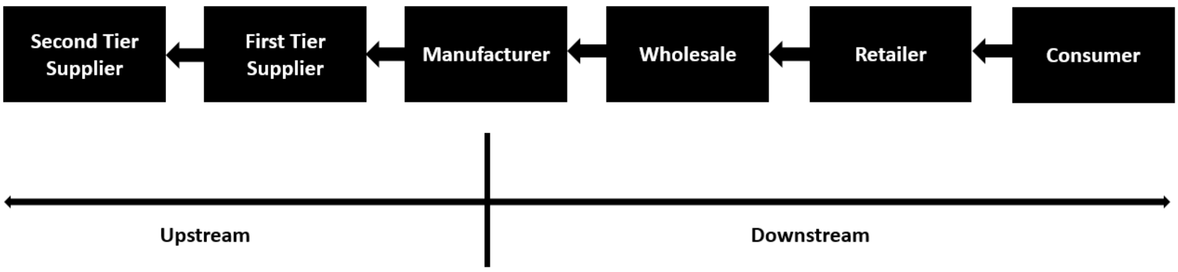

Figure 1. Supply chain flow (Adapted from Junior, Reche, and Estorilio, 2018)

Even where customer sales seem to be stable, there is significant inconsistency in supplier orders to wholesalers in a supply chain. Orders to the producer and the manufacturer's supply have increased even more. This is known as the "Bullwhip effect" which is an issue with misleading facts. The bullwhip effect occurs as a result of logical actions in the supply chain's system. Because of this crucial difference, businesses seeking to monitor the bullwhip effect must concentrate on changing the chain's infrastructure and associated procedures rather than the policymakers' actions. The bullwhip effect can be caused by human actions, such as misunderstandings regarding inventory and demand facts. Request prediction updating, order batching, market fluctuation, rationing, and scarcity cooperation are all established as causes of the bullwhip effect. The bullwhip effect is created by both of these powers working together, as well as the chain's technology and order managers' sound decision-making. Managers will design and build methods to combat it by first identifying the triggers.

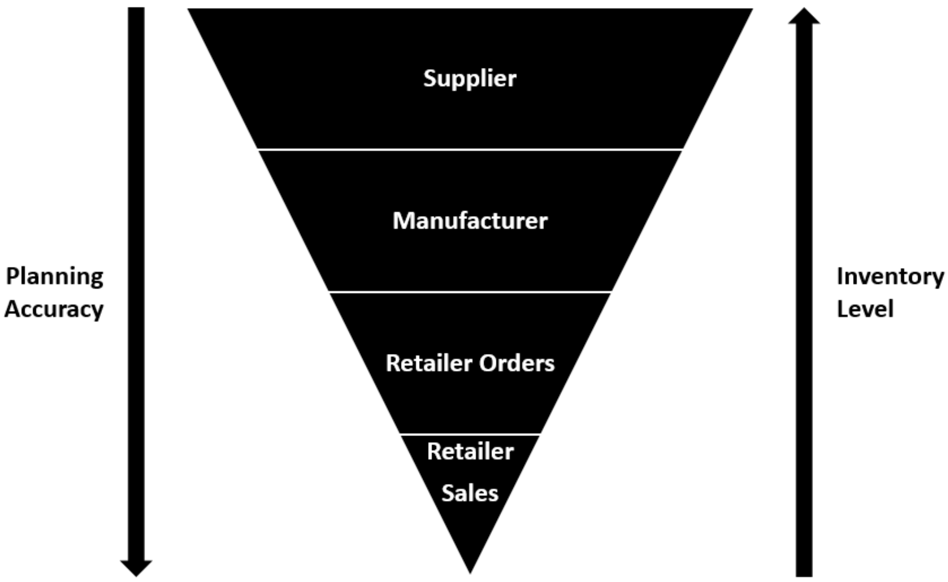

Figure 2. Bullwhip effect of supply chain (Adapted from Rabe, Jäkel, and Weinaug, 2006)

Demand forecasting is used by about every organization in the supply chain for production management, capability preparation, inventory tracking, and commodity needs planning. Forecasting is frequently dependent on the company's recent customers' order experience. Many behavioral causes, such as the partners' expectations and distrust, result as a result of this. Each partner's thinking process in forecasting the demand trend depending on what one observes is a significant aspect. When a downstream process puts an order, the upstream manager interprets the data as a forecast of potential commodity demand. The upstream updates their market estimates and, as a result, the orders put with the upstream operation's suppliers based upon the signal. The bullwhip effect is thought to be exacerbated by demand signal processing. The dealer's instructions to the seller are often more variable than the demands of the customer. Since the volume of protection stock plays a role in the bullwhip effect, it stands to reason that while the lead times between replenishment of products together with the longer supply chain; the fluctuation would be much greater (Lee, Padmanabhan, and Whang, 1997). If each stage uses local uncoordinated predictions focused on incoming orders or demand, the bullwhip effect, or duplication of orders in the supply chain, occurs in all situations and policies. As a result, the bullwhip impact is verified to be caused by poorly coordinated local demand forecasting. The size of the bullwhip effect is influenced by the responsiveness of forecasts to demand, which is an expansion of this finding. The bullwhip impact is increased by forecasts that are strongly sensitive to changes in demand, whereas it is reduced by forecasts which are less responsive (Barlas and Gunduz, 2011).

To deal with the above challenge, the moving average (MA) is used to perform the daily task of prediction for production which is known as a traditional method. The inefficiency from the MA's prediction result with low accuracy is too limited to address the problems in this company condition. Alternating to a new method to approach as high accuracy as possible is a major requirement to stabilize the production line.

1.2. Exiting Studies

Since it is challenging to reach a better accuracy of demand prediction, several studies attempted to apply various methods including both traditional and state-of-the-art approaches. Through those existing approaches which are applied in different areas, applying them into this specific condition can be an approach to get insights in finding a suitable method for future implementation.

Auto regressive integrated moving average (ARIMA) was used to predict future data of time series with good performances. Since ARIMA is based on historical data in forecasting future values, it can efficiently forecast a short-term value (Box et al., 2015). Basically, ARIMA was formed by integrating auto regression (AR) and moving average (MA) to balance each other for a better prediction which is compared to only-MA model (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. For example, a study applied the ARIMA approach on a plastic manufacturing company's data to predict a demand of raw material (Siregar, Nababan, Yap, and Andayani, 2017). Two years of sales data was used to build the model which resulted in 74% and 68%

accuracy for the respective products, PP Trilence and PP Tintapro. The forecasting values were flattened because the ARIMA lost its ability to capture the independent variable (Input data) as predicting on only the near previous predicted values. In addition, in the same area of the plastic industry, a study of ARIMA was conducted to dive deeper to check the improvement of performance by comparing with other methods (Udom and Phumchusri, 2014). The data which was used as the input for model development was in a five years period of sales volume. With the study's measurement as Mean Absolute Percentage Error (MAPE), four different methods were used in comparison as Naive, MA, Winter Exponential, and ARIMA to predict a future sale volume for five individual products. As a result, one of the five products respectively showed a similar output as 43%, 39%, 48%, and 37% in which ARIMA presented as the lowest MAPE resulted model. Furthermore, another attempt was conducted in forecasting demand for food manufacturing industry which used a larger data as six years with ARIMA (Fattah, Ezzine, Aman, El Moussami, and Lachhab, 2018). To receive various outputs for comparison to distinguish model performances, this study used the parameter switching approach to measure model performance in standard error (SE), log likelihood, Schwarz Bayesian criterion (SBC), and Akaike criterion (AIC). Forecasting a future ten months period of the demand by using IBM SPSS application for changing the parameter resulted in the best fit in ARIMA(1, 0, 1) with 12% SE. Hence, these attempted studies proved that the ARIMA model has a better capability to forecast future demands which reduced error percentage compared to other traditional methods.

On the other hand, artificial neural networks (ANN) have been integrated for forecasting in most sectors including the manufacturing industry. The flexible and dynamic ANN algorithm is capable of dealing with big datasets which are in complex form of various data types (Hsu et al., 1995). Since forecasting using ANN resulted in 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. For instance, a study of comparative analysis on demand forecasting models using various ANN training methods showed distinctive outcomes. The goal of the study was to determine the best training approach for forecasting demand signals in the supply chain using the ANN method. By focusing on ANN and various training approaches, they established a comparative forecasting mechanism. The market forecasting problem was studied on new data from a real-world case to show the feasibility of the suggested technique. The TrainLM system outperforms other training approaches in estimating more accurate predictions in our case, according to the evaluation findings. Because of further on-time delivery, the potential to improve forecasting performance would result in reduced prices and better customer loyalty. In terms of predicting consumer needs, the proposed approach is a positive attempt with a less Mean Absolute Error (MAE) percentage of 5% in MLP – TRAINLM which was compared to 12% in MLP – TRAINGD, 15% in MLP – TRAINGDA, and 11% in MLP – TRAINCGF (Kumar, Herbert, and Rao2014). Moreover, in the field of renewable energy, ANN was applied to forecast electricity demand of smart grid technology. This research aimed to see how well Artificial Neural Networks performed when it came to load forecasting in a real microgrid. Afyon Kocatepe University's ANS campus area is used as a micro grid for this purpose. The region's first load data is obtained on an hourly basis. This data was then divided into train and test data. Next, the neural network is used to forecast hourly load values. It is concluded that load forecasting is critical for micro grid preparation in order to reduce losses and improve output unit performance. It is proposed to build a 1 MW solar power plant in the city. The findings showed that ANNs are capable of making accurate predictions. However, increasing the number of input parameters relevant to the loads, such as general human activities in the field, temperature, humidity, and other meteorological parameters, is expected to improve forecast accuracy (Akarslan and Hocaoglu, 2018). In addition, in the area of water supply, the HLSALOA provided the highest degree of precision, according to the results of the applied ANN algorithms. Residential end-use demand forecasting models were developed by the HLSALOA, with R2 ranging from 21% for bath demand forecasting to 60% for shower demand forecasting. But for the dishwasher and bath demand forecasting models, all of the models' root mean standard errors (RMSEs) were less than half. The validation collection yielded comparable results when the models were added. Except for the bath demand forecasting models, the HLSALOA was able to estimate the means and medians of observed demand frequency distributions (Bennett, Stewart, and Beal, 2013).

1.3. Methodology

Nonlinear autoregressive exogenous networks (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, it is only dependent on the pattern of its own historical data.

Specifically, NARX can additionally consider external variables along with ARIMA does not. Thus, many studies have attempted to apply NARX for future value predictions in several fields. For example, in environmental surveillance for health risks, accurate peak measurement of ozone concentration data is critical. This research focuses on using nonlinear black-box regression models to model and forecast these types of data, which is a difficult problem due to the insufficient knowledge provided by the existing data and the high pulse variability of the concentration data. The use of a recent modelling framework for ozone forecasting (polynomial NARX models), a consistency comparison between such models and neural networks, and the use of alternate cost functions for model recognition are among the study's key contributions. Polynomial NARX models deliver outcomes that are comparable to NN-based NARX models (which are usually assumed the state-of-the-art models for predictive ozone forecasting), and they often include details about the best regressors for a certain nonlinear phenomenon.

The study further demonstrates the advantages of amplitude weighting of the identity cost function in spike estimation accuracy (independent of the model class used). It is shown, in particular, that such weighting can improve peak estimation reliability, allowing for further assured model utilization in the monitoring phase (Pisoni, Farina, Carnevale, and Piroddi, 2009). Also, using the NARX technique, a study developed a model that predicts wind speed one step forward. The Mahalanobis distance was used to find outliers in the multivariable sample, and the Granger test was used to decide which variables could be included in the model.

Finally, the NARX model was compared to the one-variable NAR and the persistence model to assess the contribution of the variables used in the NARX model to the forecast. Apart from wind direction, solar radiation was the most important factor. 22 outliers were identified in the raw dataset, deleted, and replaced using the one-point linear tendency. The descriptive mathematical measurements, which were compared with the processed data and the clean sample, confirmed that the sample data had not been significantly altered. The Granger test in La Mata, Oaxaca, revealed that solar radiation is the only element that influences wind speed production, making its configuration as the entry vector in the NARX model crucial. The test data and the error prediction measurements: MSE, MAE, and MAPE were used to compare the NARX, NAR, and persistence models for each technique. The NARX outperformed the NAR by 4% and outperformed the longevity model by 11%, according to the findings (Cadenas, Rivera, Campos-Amezcua, and Heard, 2016). Furthermore, NARX was successfully designed for flood simulation and prediction. Training data was used to improve the model, and testing data was used to evaluate its accuracy. The data used for model construction was in meters and ran from November 18, 2010 at 8:20 to November 21, 2010 at 18:20 in 10-minute intervals. The water peaks condition at time steps 60-80 and 250-275, where estimation was unsuccessful, contributes the most errors. Other regions have close to zero errors, indicating strong estimation. The NARX model's prediction outputs are defined as showing good results with errors close to zero and a Best Fit of 87 percent. The flood water level at the downstream channel, also known as the flood site, was successfully forecast 10.83 hours in advance, with excellent results. In this analysis, the effects of physiographic factors such as basin area, mainstream volume, and mean slope were ignored (Ruslan, Zain, and Adnan, 2014). In addition, on a horizontal layer, a NARX neural network model for predicting direct solar radiation. The key result of this research is that the neural network's training process is conducted on a regular basis, considering a variety of factors such as solar characteristics, sailboat mobility, and cloud cover. The built predictor is useful for calculating direct solar radiation on a mobile horizontal surface, but it ignores the two tilt angles used to account for sailboat pitch and roll motions. Furthermore, the sails' shadow is not considered. As a result, the built predictor will be enhanced to take into account these new constraints. The developed predictor will be built as part of the previously discussed project for a 100 percent renewable race sailboat, first to forecast direct solar radiation on a sloped and theoretically shady surface, and then the amount of usable power from the boat's PV arrays. The energy control scheme of the boat will use this new indicator. MSE and DMPE failures are used to test some models that were run with various assessment parameters. The best findings (0.00279 for MSE and 24.0584 W/m2 for DMPE) were obtained using the following parameters: a 10-day dataset with a MA of 30 minutes over one-hour cycles, a NARX model with 15 nodes on the input and hidden layers, a sigmoid function input and hidden layer, a tansig function output layer, and a randomized initialization of weights (Boussaada, Curea, Remaci, Camblong, and Mrabet Bellaaj, 2018). Moreover, internal and external faults in distillation columns were investigated using a NARX network-based fault detection system. The simulation of a pilot size distillation column in both steady-state and dynamic modes has been presented. Since the NARX approach is a data-driven technique, it can only detect past faults. The intelligent detection system can also be used in real-world industrial distillation column applications where noise and disturbances are present. This tracking technique can be used to track multiple faults as well as detect them in real time. This approach may be applied to a diagnostics device for identifying defective plant parts. Co-simulation of the APD-MATLAB interface produced the results. The input signals were produced using random perturbations. Many of the measurements were subjected to a simulation of sensor noise, which included zero mean normal distributed noise. The data collected was used to train a neural network model. The network's accuracy was validated using error autocorrelation. Based on these findings, it can be inferred that the evolved model is suitable for representing machine behavior and, as a result, for fault detection. This soft computing approach yields a viable outcome for a distillation column fault detection system that is both accurate and stable. The MDR is used to assess the algorithm's reliability, which is important when using fault detection and diagnosis methods in real-time processes (Taqvi, Tufa, Zabiri, Maulud, and Uddin, 2020).

However, very limited studies were conducted to develop the NARX method to predict the demand of a first-tier supplier in the automotive industry even though several external factors may influence its actual demand. For instance, Diagonal Feeding had been introduced as a method for predicting Build-To-Order goods. When future delivery dates are known, it aids in improving precision. Domain expertise, comprehensive feature engineering, or specialized technological skills are not needed for this approach. Many studies demonstrate that there is no one-size-fits-all technique for time series prediction. Furthermore, this study made a highly important and unique data collection accessible. The lack of publicly available data sets presents a problem in designing strategies for predicting demand for BTO goods. It is also worth looking into the effect of transforming the goal variable on Diagonal Feeding, as it has been shown that some transformations do better than others. From an algorithmic aspect, the approach can be improved with non-parametric pre-processing methods to filter out anomalies, such as multichannel anomaly detection, online aggregation of diverse forecasting models through long-term aggregation strategies, and techniques to model quasi-periodic data and trend detection in the presence of non-stationary nodes, among other things. With a SMAPE of 0.17, Adaboost was the best model. The Ensemble of Random Forests came in second with 0.18. However, it was worth noting that these models underwent comprehensive feature engineering, with over 300 features produced. The best approach for Diagonal Feeding was a random forest with log transform fitted on the entire data collection. It received a score of 0.34. This was slightly greater than the SMAPE of 0.42 achieved by the average of methods educated on the data set of function engineering (Rivera-Castro, Nazarov, Xiang, Pletneev, Maksimov, and Burnaev, 2019). In addition, a manufacturing demand forecasting was studied in a setting with only partly accurate details. Request, which is based on three independent variables: price, efficiency, and lead time, was considered in an unpredictable setting. Partial knowledge characterizes the demand climate. As a result, Z-numbers are used to characterize input and output data for demand forecasting. On the basis of historical Z-information, the problem is to create a relationship among the demand variable and the variables price, cost, and lead time. The forecasting model is a Z-regression model, with demand as the dependent variable (represented by a Z-number) and price, cost, and lead time as independent variables (represented by Z-numbers). The proposed Z-regression model has been tested and found to be accurate (Aliyeva, 2017). In this sense, a study is needed to develop a NARX model for prediction of demand considering the characteristics of a first-tier supplier in the automotive industry.

1.4. Purpose of Study

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 minimize errors in training and validation sets. This study used an actual one-year data set obtained from a first-tier supplier in the automotive industry.

CHAPTER 02

DATA ANALYSIS AND PROPOSED METHOD

2.1. Data Sets

This study used an actual data for one year which was obtained from a first-tier supplier, manufactures automotive supplies such as parts and wires, in automotive industry in Korea. A production company (main contractor) delivered the daily demand to this supplier along with preorder amount (provisional demand) for upcoming 12 days. The preorder was subject to change according to the main contractor's production schedule. This study divided the data into three subsets 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. Hence, the first-tier supplier's actual demand is considered as the target variable which is preprocessed to be a summation of the 14 values in a time step.

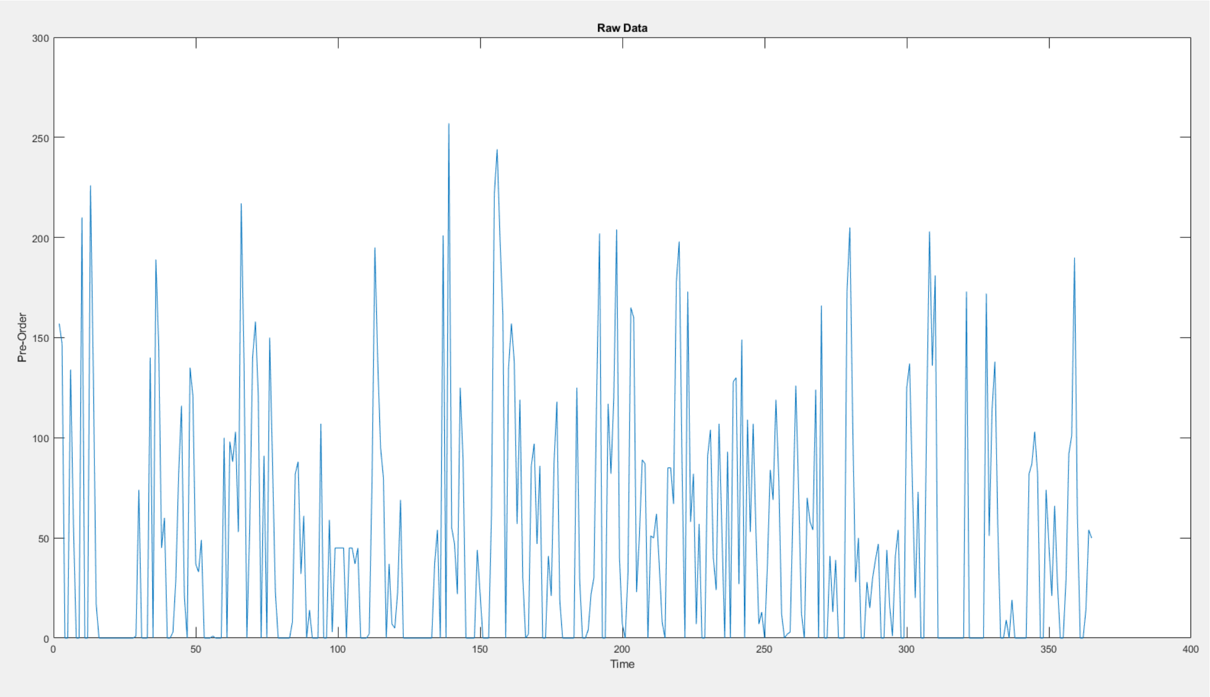

Figure 3. The plot of the preorder data

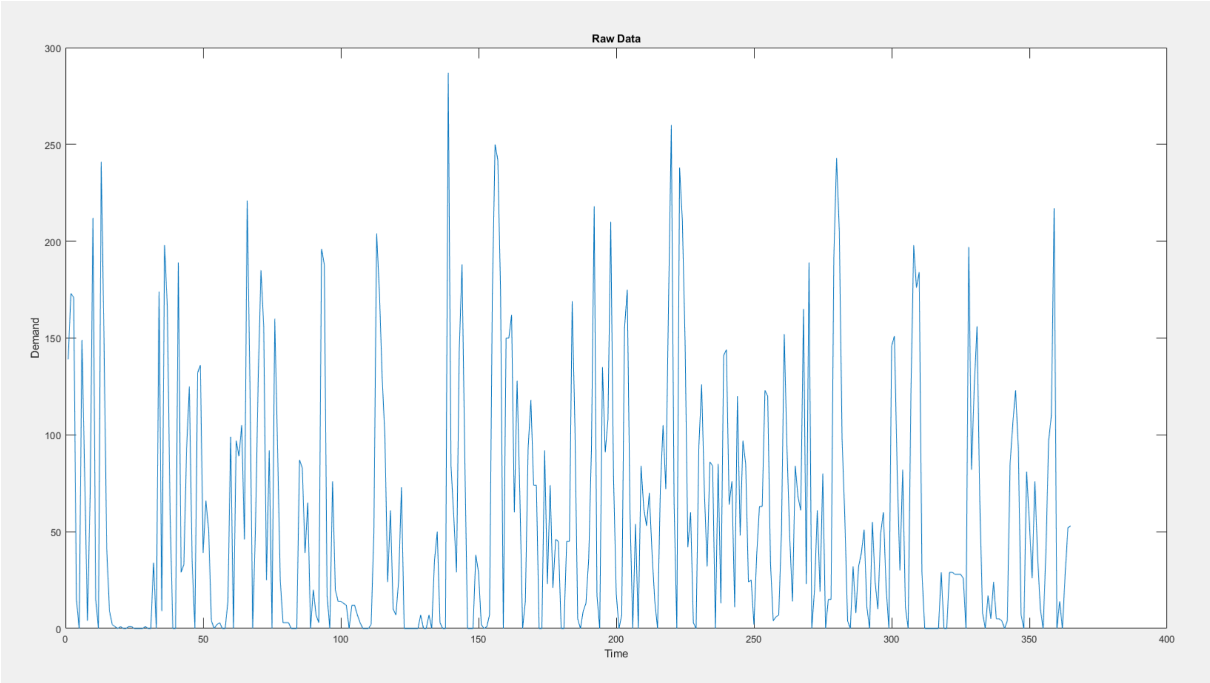

Figure 4. The plot of the actual demand

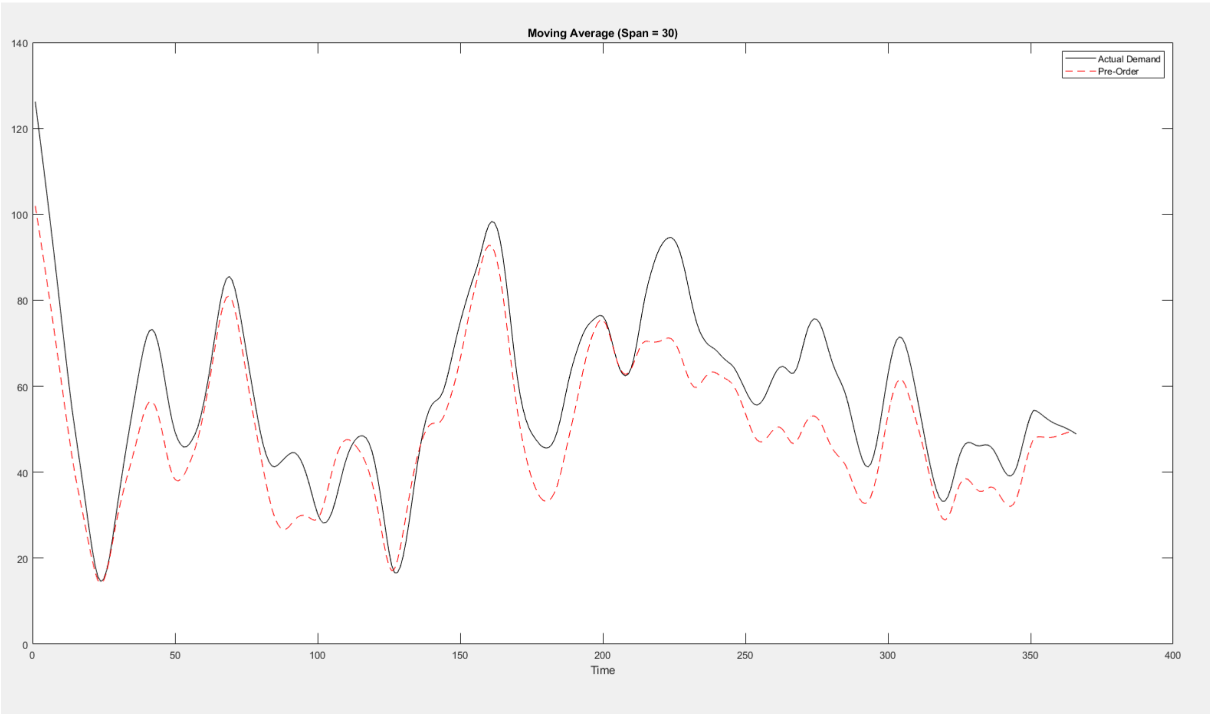

Figure 5. The plot of Moving average (span = 30) of the preorder and actual demand

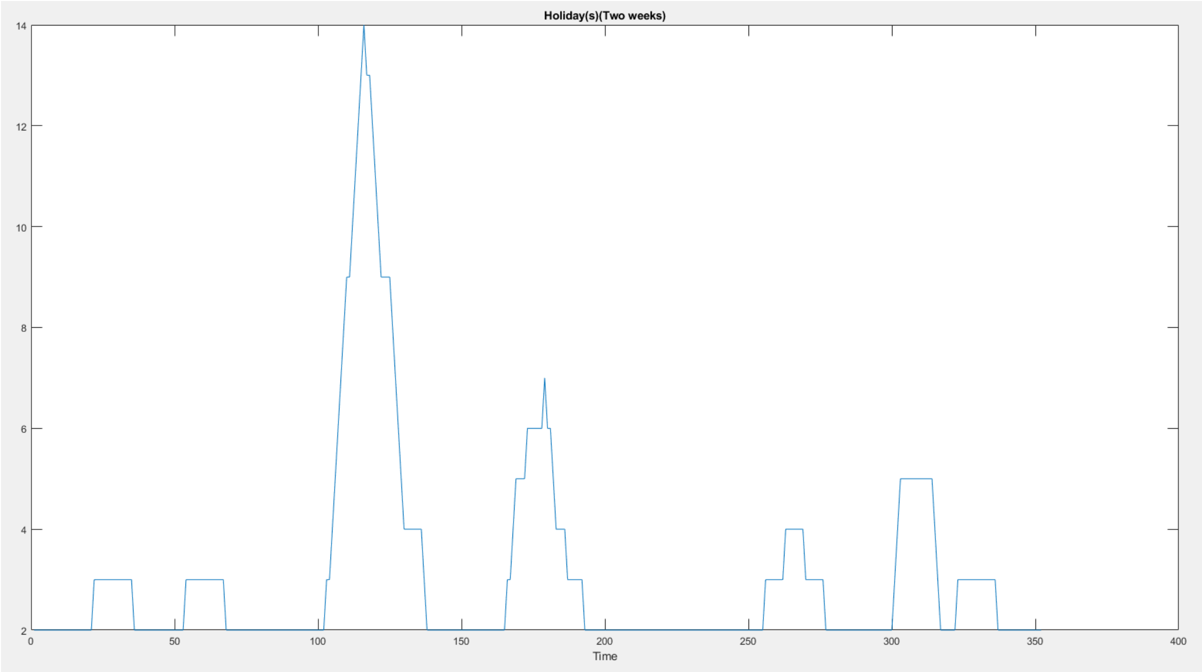

Figure 6. The plot of the holiday data

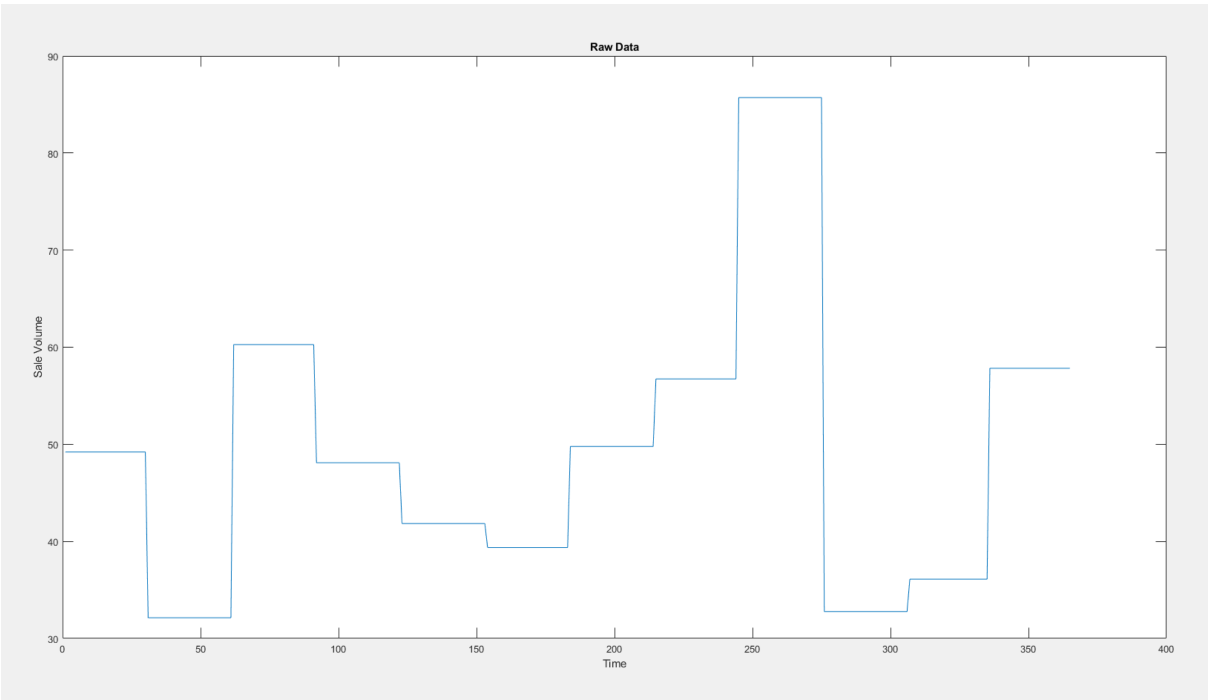

Figure 7. The plot of the sale volume data

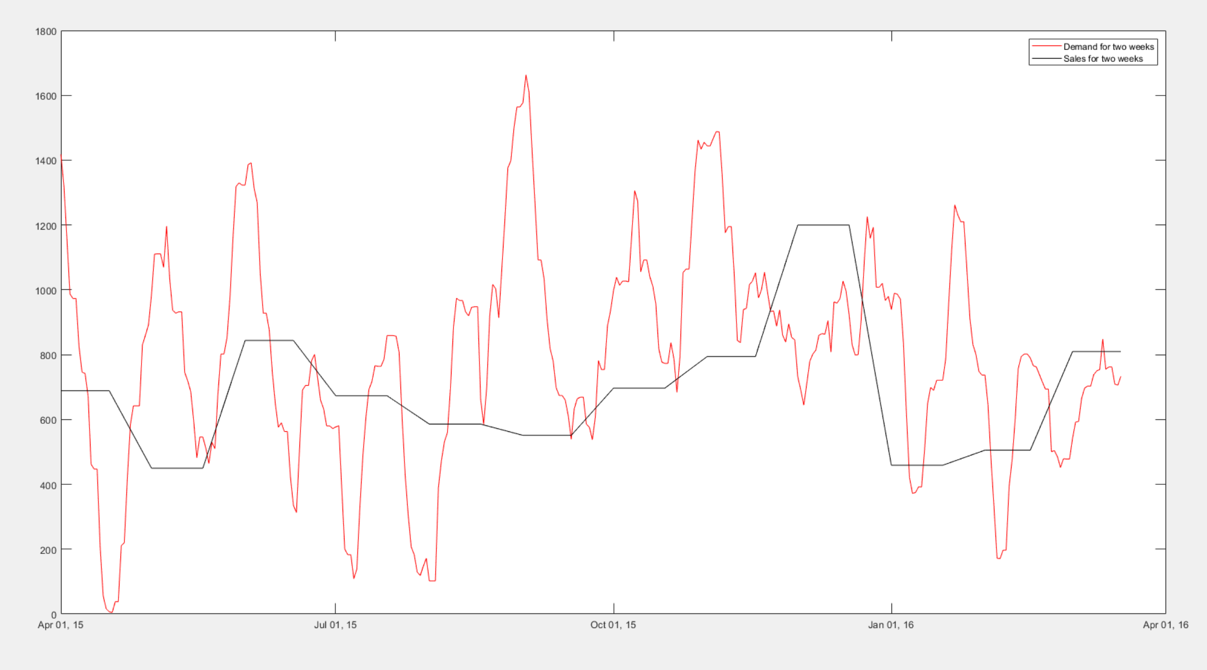

Figure 8. The plot of the actual demand and sale volume in two weeks

2.2. Parsimonious Variables Selection

This study considered three external variables (preorder amount, holiday number, and sale volume of the car) that may be related to the demand of automotive parts. Firstly, preorder amount is rough demand for a designated period (e.g., 12 days) estimated from an automotive company. An automotive company generally provides a preorder amount to a first-tier supplier in order for facilitating its supply chain. As shown in Figure 9, an automotive company shares their estimated demand for upcoming 12 days; however, this preorder 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. Besides, the sale volume data is firstly divided daily in each month's values since it is available monthly. The external variables are the summation of 14 values in a time step, the same as the target variable, which are used as feature variables to together feed into the proposed network.

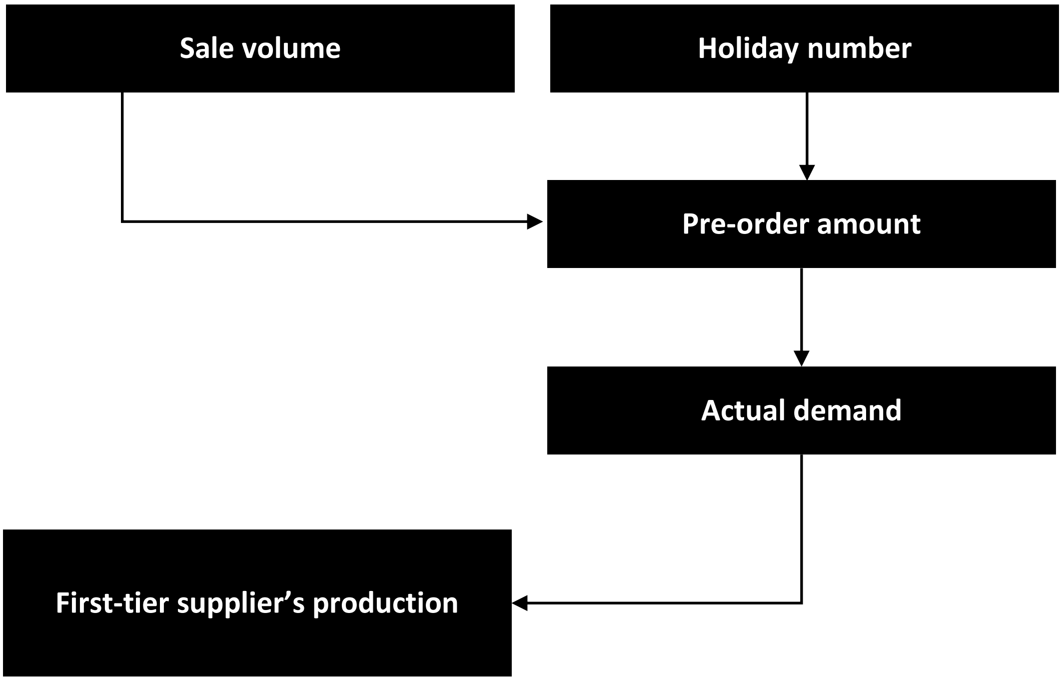

Figure 9. Relationship of each external variable with the actual demand

Two key variables (preorder amount and holiday number) out of the three external variables were chosen to avoid multicollinearity problems in a prediction model. High correlation among external variables may cause multicollinearity problems 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 preorder 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 preorder amount (0.813 to 0.780) and holiday number (0.734 to 0.725). It implies that preorder amount and holiday number without the sale volume can properly predict the demand since the two have high correlation with sale volume.

2.3. 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 10 and 11. Correlations for the preorder amount (0.81 to 0.72) gradually decreased as time-lag increased. On the other hand, correlations for holiday numbers (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.

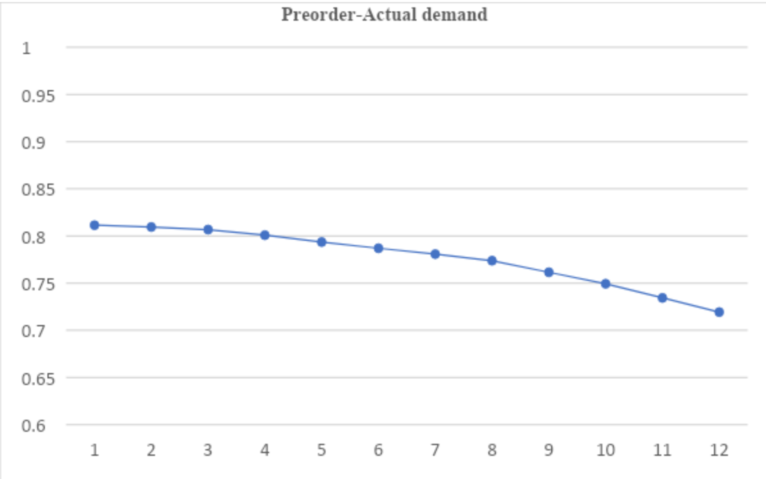

Figure 10. Cross-correlation coefficients of Preorder with Actual demand (y-axis) in time lags (x-axis; unit: time)

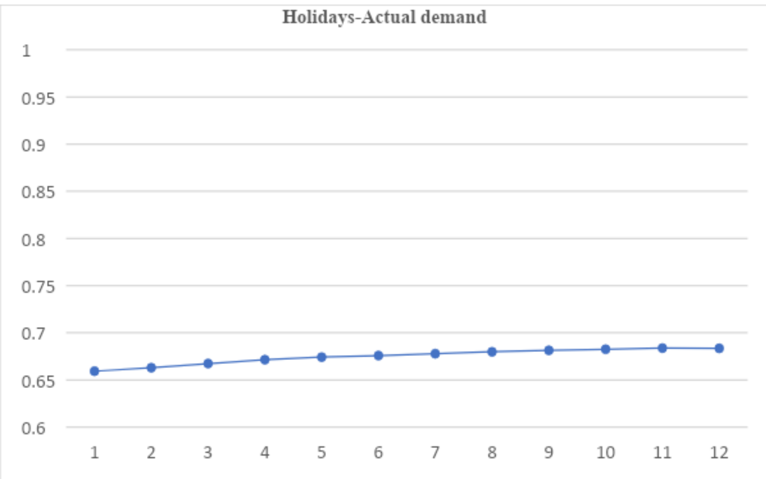

Figure 11. Cross-correlation coefficients of Holiday with Actual demand (y-axis) in time lags (x-axis; unit: time)

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 12 and 13, 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 delays in this study was determined as 2.

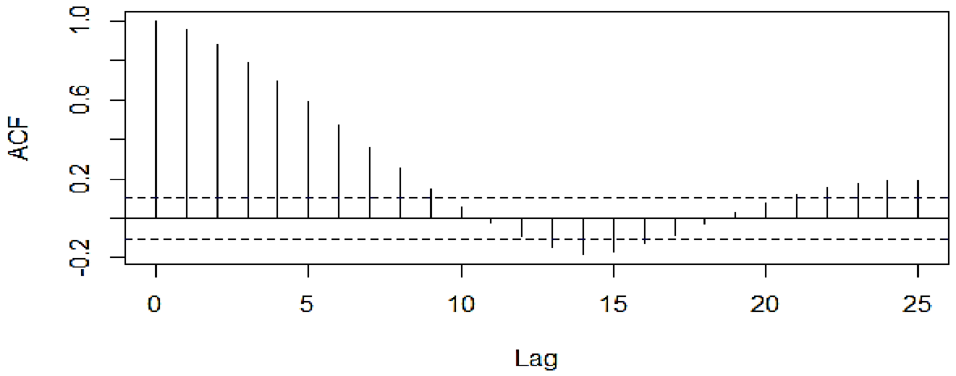

Figure 12. ACF of the actual demand

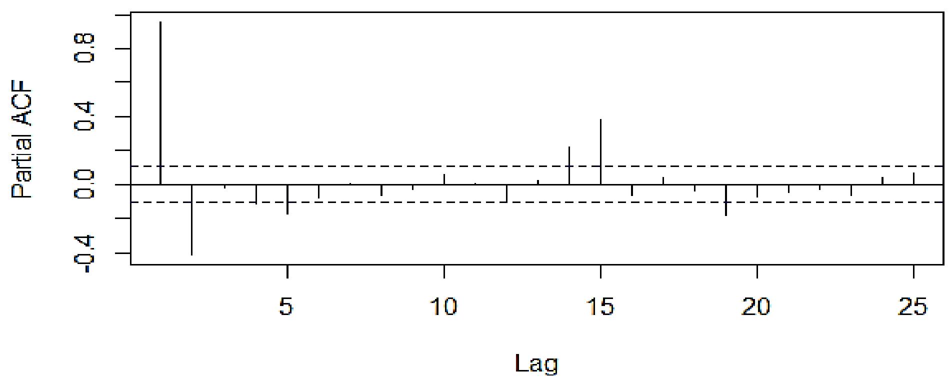

Figure 13. PACF of the actual demand

CHAPTER 03

METHOD

3.1. Autoregressive

Autoregressive models are highly adaptable when it comes to dealing with a variety of time series trends. The following two series illustrate series from an AR(1) and an AR(2) model, respectively.

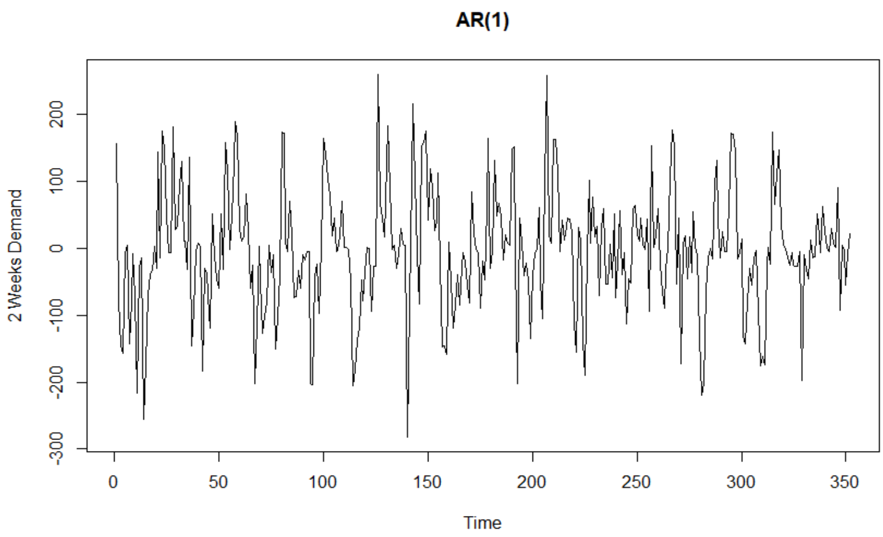

Figure 14. Autoregressive models, AR(1), on the actual demand

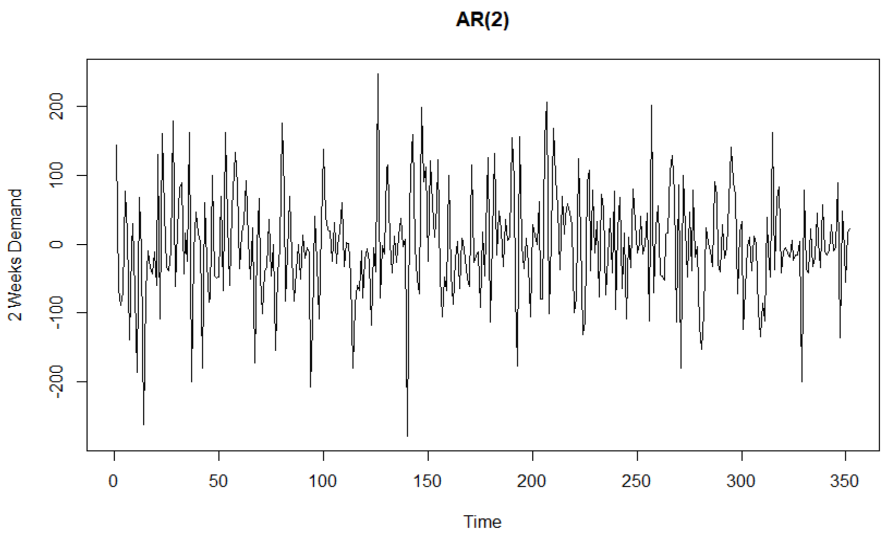

Figure 15. Autoregressive models, AR(2), on the actual demand

The variable of interest is forecasted using a linear combination of past values in an autoregression model. The word autoregression means that the variable is being regressed against itself. As a result, a p-order autoregressive model can be written as

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

where is white noise as ε_t,

$-1 < \phi_1 < 1$ for the AR(1)

$-1 < \phi_2 < 1$, $\phi_1 + \phi_2 < 1$, $\phi_2 - \phi_1 < 1$ for the AR(2).

In the case of AR(1):

- yt is equal to white noise: $\phi_1 = 0$
- yt is equal to a random walk: $\phi_1 = 1$, $c = 0$
- yt is equal to a random walk with drift: $\phi_1 = 1$, $c \neq 0$,
- yt tends to fluctuate around the mean: $\phi_1 < 0$.

This is similar to multiple regression, except the predictors are lagged y values. This is known as an AR(p) model, which stands for autoregressive model of order p. Changing the parameters $\phi_1,\ldots,\phi_p$ causes the time series dynamics to change. The error term ε_t's variation would only affect the size of the sequence, not the trends.

When it comes to $p \geq 3$, the constraints are far more complex. When estimating a model, R considers these constraints. Usually, autoregressive models are limited to stationary data, which necessitates certain restrictions on parameter values (Hyndman, and Athanasopoulos, 2018). By changing the regression coefficients ϕ_p, the Autoregressive model will predict a broad range of time series. The distinction between Autoregressive models and other traditional regression models is that the error term is assumed to be independent. The assumption of uncorrelated error is usually generated since the predictors are time-lagged values for the explanatory variables (Zhai, 2005).

3.2. Moving Average

The formula of Moving Average is present as:

$$Y_t = w_0 + \varepsilon_t - w_1\varepsilon_{t-1} - w_2\varepsilon_{t-2} - \dots - w_q\varepsilon_{t-q}$$

where:

- Y_t : the series value at time t
- $w_0, w_1, w_2, \dots, w_q$: the weights used to account $\varepsilon_{t-1}, \varepsilon_{t-q}, \dots, \varepsilon_{t-q}$ for prior prediction errors
- ε_t the residual error.

To determine a Moving Average, the number and value of the q moving average parameters w_1 to w_q must be determined while keeping in mind some value limits in order for the procedure to be stationary. The Moving-Average model performs well with stationary results, which is a type of time series that does not have a pattern or seasonality.

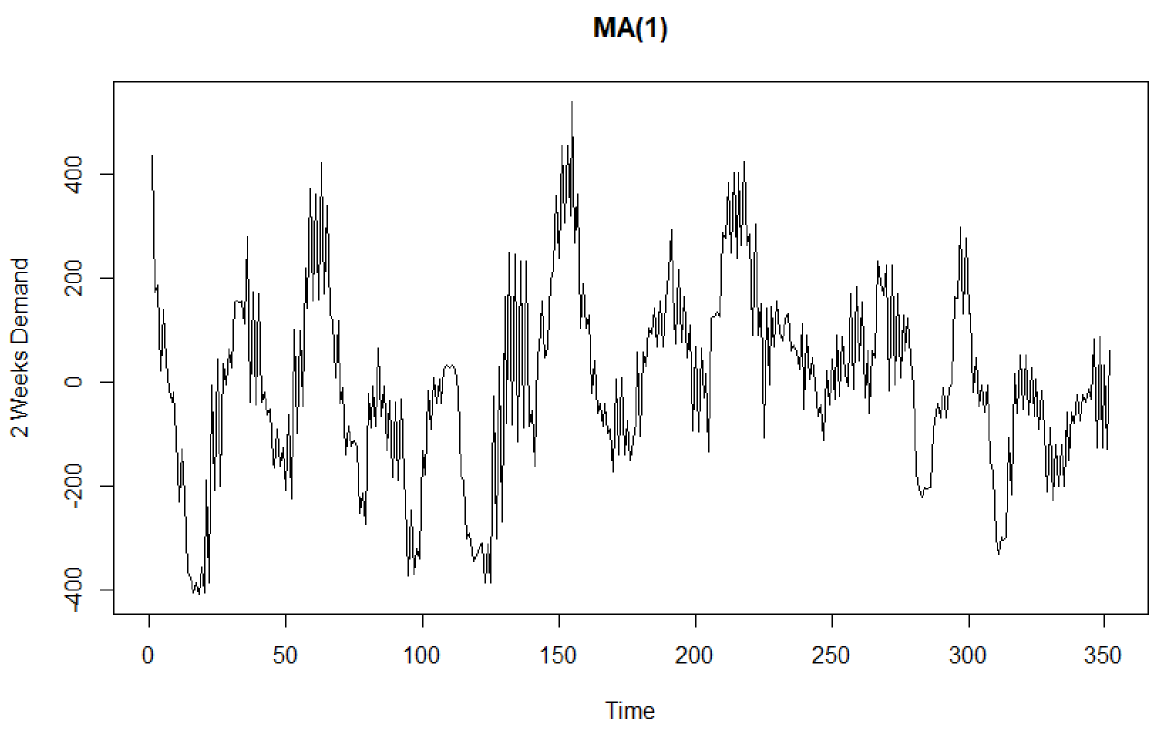

Figure 16. MA(1) of the actual demand

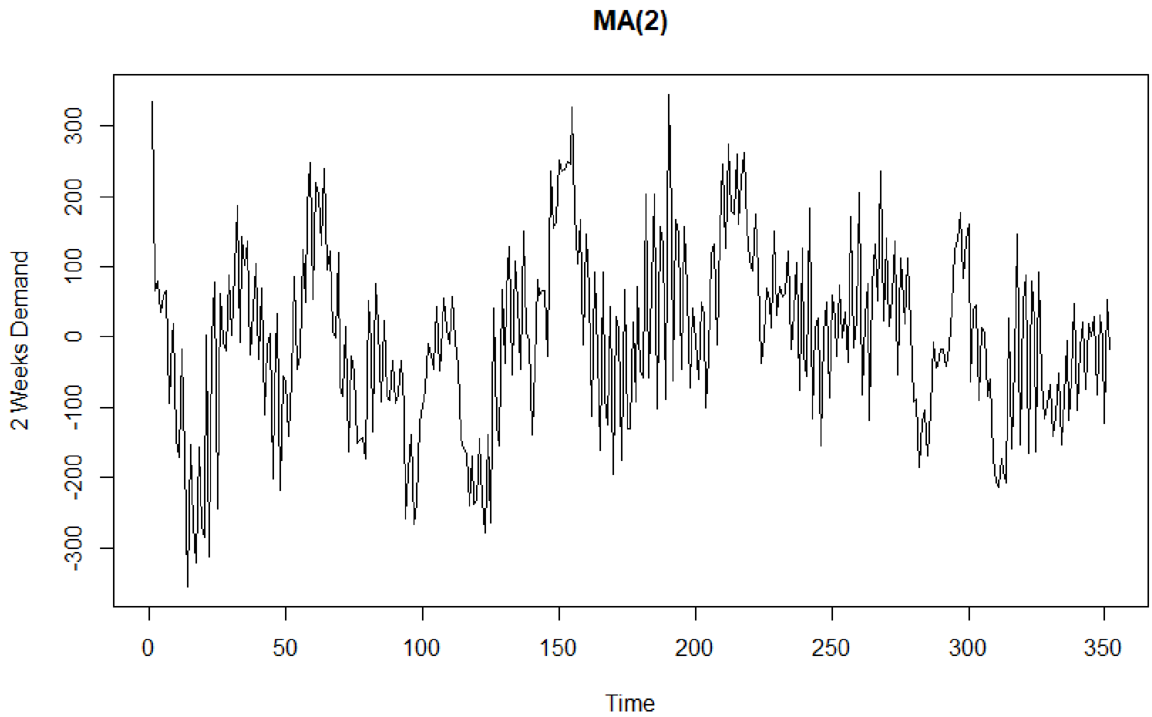

Figure 17. MA(2) of the actual demand

The fundamental theory behind the Moving-Average model is to first find the mean for a series of values, then use that mean to predict the next time while adjusting for any errors made in previous forecasts (Zhai, 2005).

In a regression-like algorithm, a moving average model uses historical prediction errors rather than previous values of the forecast component. Moving average smoothing is used to estimate the trend-cycle of past values when a moving average model is used to predict future values. The variance of the error term ε_t, like that of autoregressive models, can only shift the size of the sequence, not the trends (Hyndman and Athanasopoulos, 2018).

3.3. Autoregressive Integrated Moving Average

Time series forecasting can also be done using ARIMA models. The two most commonly used methods to time series prediction are exponential smoothing and ARIMA models, which offer alternative approaches to the challenge. If exponential smoothing models attempt to identify the data's pattern and seasonality, ARIMA models attempt to explore the data's autocorrelations (Hyndman and Athanasopoulos, 2018).

The ARIMA equation as:

$$Y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - w_1\varepsilon_{t-1} + w_2\varepsilon_{t-2} - \ldots - w_q\varepsilon_{t-q}$$

where:

- p : the number of autoregressive terms
- d : the number of non-seasonal differences
- q : the number of lagged prediction errors

The AR and MA models can be combined to form a third class of general models known as ARMA, which is a specific ARIMA(p, 0, q) model. With the addition of non-seasonal variations d to the formula, the ARIMA(p, d, q) model can handle a wide range of time series prediction problems. The ARIMA(p, d, q) model uses a mixture of previous values and past prediction errors to suit models that would otherwise be difficult to fit using an AR or an MA model alone.

Besides that, the differencing reduces the majority of non-stationarity in the sequence. The Akaike Information Criterion (AIC) is used by the Best ARIMA function in R to select the p, d, q, value and define the best ARIMA model. The ARIMA approach differs from previous approaches in that it makes no claims regarding the number of terms or the relative weights that should be applied to the terms. To define the formula, the analyst first chooses the required model, including the number of p, d, and q terms; then, using a nonlinear least squares procedure, determines the coefficients and provides a refined suggestion of the parameters of the model (Hyndman, and Athanasopoulos, 2018).

3.3.1. Non-seasonal ARIMA

A non-seasonal ARIMA model is created by combining differencing with autoregression and a moving average model. ARIMA stands for AutoRegressive Integrated Moving Average (integration is the inverse of differencing in this sense), which describe as:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q} + \varepsilon_t,$$

ARIMA models must meet the same stationarity and invertibility requirements as autoregressive and moving average models. The scale of the prediction intervals is also affected by the value of d; the greater the value of d, the larger the prediction intervals become. When d = 0, the long-term forecast standard deviation is equal to the standard deviation of the historical results, resulting in exactly the same prediction intervals (Hyndman, and Athanasopoulos, 2018).

3.3.2. Seasonal ARIMA

ARIMA models may also be used to model a variety of seasonal data. Additional seasonal words are added to ARIMA models to create a seasonal ARIMA model. The seasonal portion of the model consists of concepts that are identical to the non-seasonal elements but include seasonal backshifts.

The formula is described as:

$\text{ARIMA}(p, d, q)(P, D, Q)_m$

where:

- (p, d, q) : Non-seasonal part
- (P, D, Q)m : Seasonal part
- m : Observations number per year.

For $\text{ARIMA}(1,1,1)(1,1,1)_4$ model

- Without a constant
- m = 4 : Data is collected every three months.

Simply multiply the non-seasonal terms by the extra seasonal terms on the following equation (Hyndman and Athanasopoulos, 2018):

$$(1 - \phi_1 B)(1 - \Phi_1 B^4)(1 - B)(1 - B^4)y_t = (1 + \theta_1 B)(1 + \Theta_1 B^4)\varepsilon_t$$

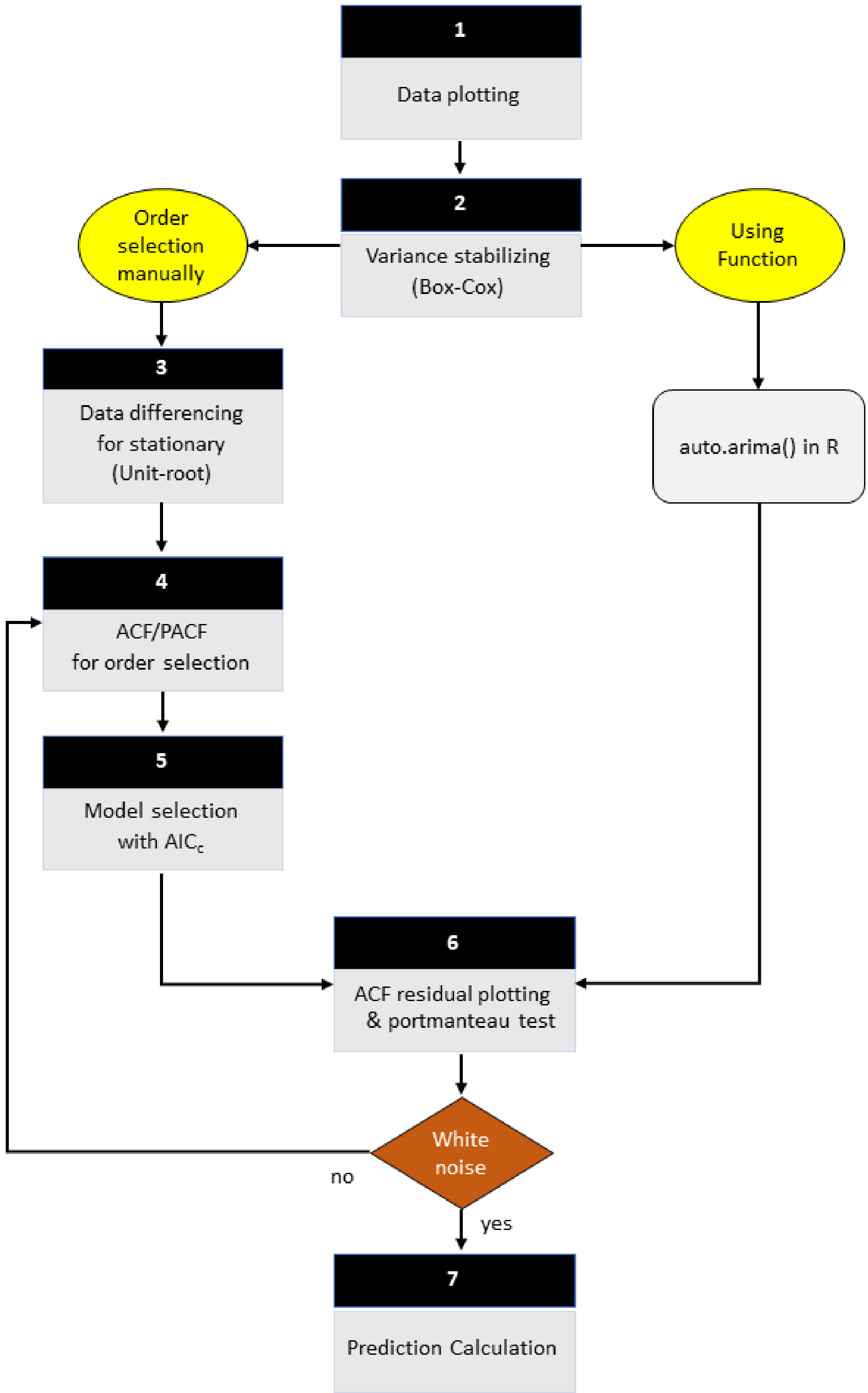

Figure 18. ARIMA model building flow (Adapted from Hyndman and Athanasopoulos, 2018)

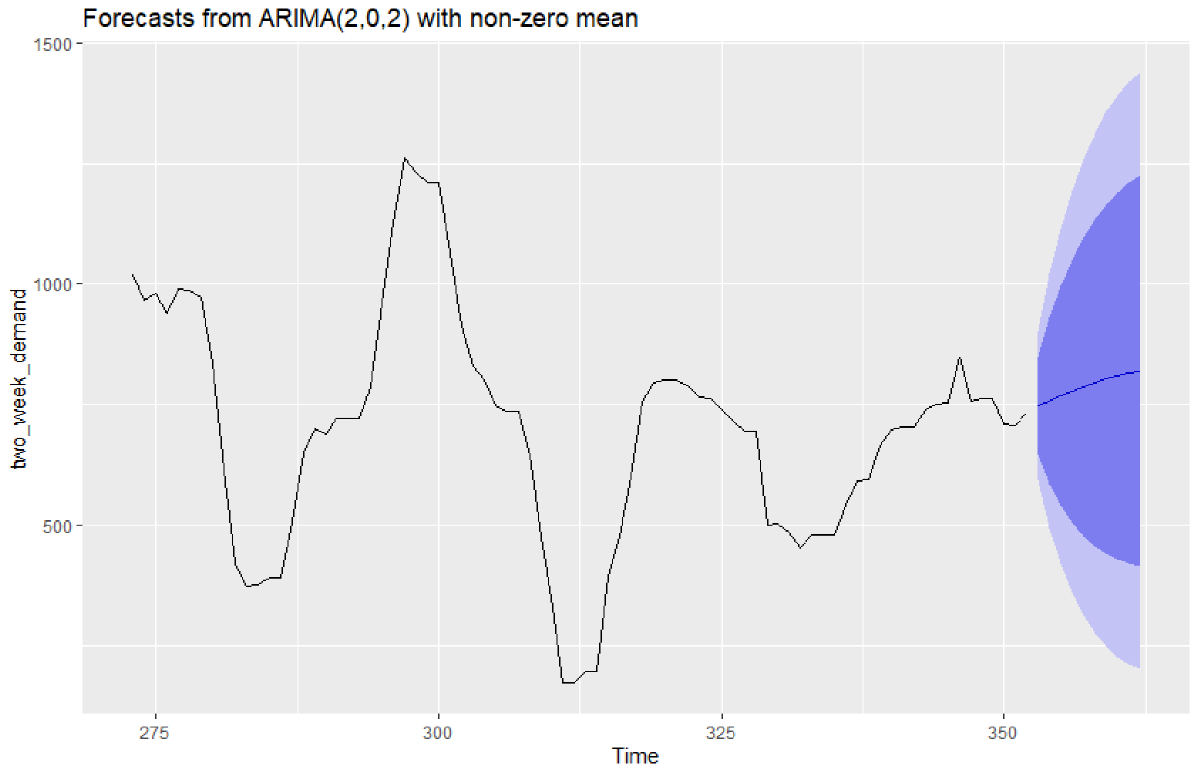

Figure 19. Forecasting plot using ARIMA model on the actual demand

3.4. Time Series Using Shallow Networks

Easy components acting in parallel make up neural networks. The biological nervous system stimulated these components. The network structure is primarily determined by the relations between elements, just as it is in nature. By changing the values of the correlations (weights) between components, a neural network can be trained to perform a specific role. Neural networks are usually tweaked, or practiced, such that a specific input contributes to a specific output. A scenario like this is shown in the next diagram. Based on a calculation of the performance and the target, the network is balanced so the network output meets the target. To train a network, several such input or target pairs are usually required. In addition, neural networks may be programmed to solve problems that are impossible for traditional computers or humans to solve. It has been programmed to carry out complicated tasks in a variety of areas, including pattern recognition, naming, grouping, voice, vision, and process control (Shallow Networks for Pattern Recognition, Clustering and Time Series - MATLAB & Simulink, 2019).

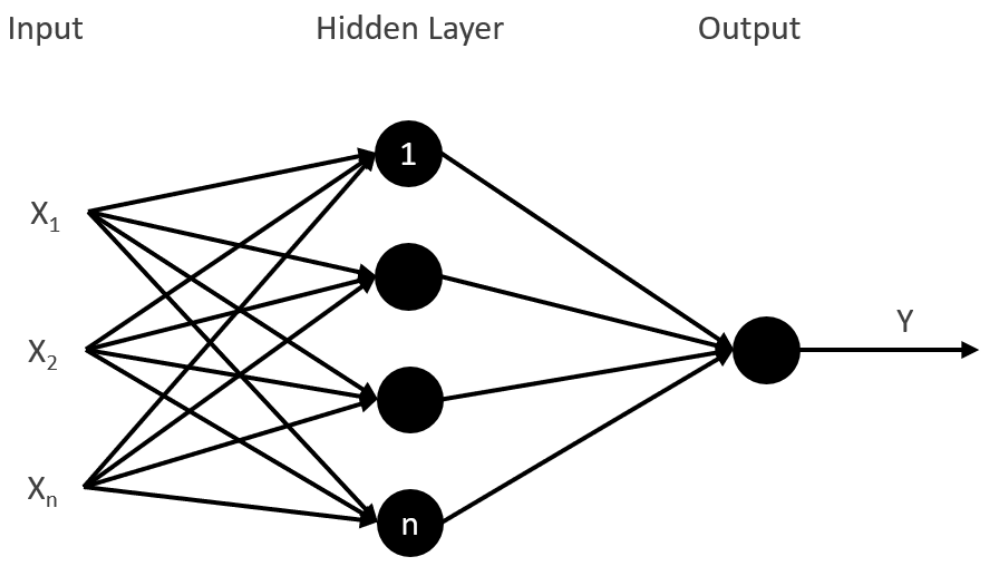

Figure 20. A neural networks structure (Adapted from Yılmaz, Aci, and Aydin, 2015)

Neural networks have both static and dynamic characteristics. Static networks are well-known for their lack of feedback and delays. The static system's output is determined directly from the current inputs. Static networks are based on the assumption that data is continuous and that they have no sense of time, resulting in random actions. Though dynamic systems are more difficult to train than static networks, they are proven to be more efficient. Dynamic networks provide a kind of memory in terms of delays, which can be used to teach them to recognize sequence data or time series patterns (Primasiwi, Sarno, Sungkono, and Wahyuni, 2019).

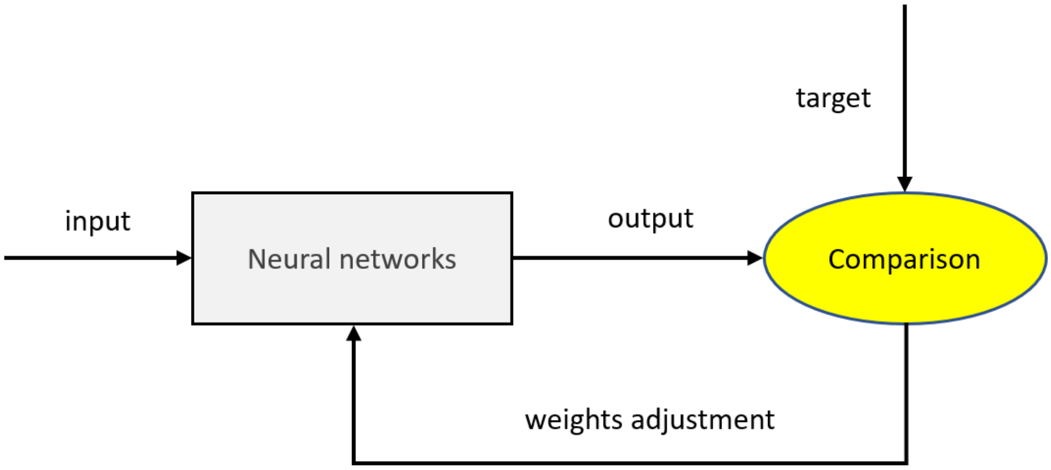

Figure 21. A neural networks architecture (Adapted from, MATLAB & Simulink, 2019)

3.5. Proposing Nonlinear Autoregressive with External (Exogenous) Input (NARX) Network

The NARX network has a wide range of implementations. It could be used as an indicator to forecast the input signal's next value. It could also be used for nonlinear filtering with a noise-free variant of the input signal as the target output. Another essential use of the NARX network would be in the simulation of nonlinear dynamic systems.

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:

$y_t = f\,(y_{t-1}, y_{t-2}, u_{t-1}, u_{t-2}, u'_{t-1}, u'_{t-2})$

where: y : output of the network,

u, u' : external input of the network, and

f : NARX function of the network.

Previous values of the output signal and previous values of an isolated (exogenous) input signal are used to regress the next value of a target variable output signal y_t. To estimate the function f, the NARX model could be applied using a feedforward neural network. The resulting network is shown in the diagram below, with the approximation performed using a two-layer feedforward network. This implementation also allows for a vector ARX model of multidimensional input and output. The NARX network's performance can be thought of as a guess at the output of a nonlinear dynamic system attempting to model.

As part of the traditional NARX architecture, as Parallel architecture, the output is passed back to the feedforward neural network's data. Since the true output is usable during the network's training, a series-parallel architecture may be created, in which the true output is used rather than the approximate output being fed back. This has two benefits. One is that the feedforward network's feedback is more precise. The second benefit is that the resulting network has a strictly feedforward design which can be trained using static backpropagation (Design Time Series NARX Feedback Neural Networks - MATLAB & Simulink, 2019).

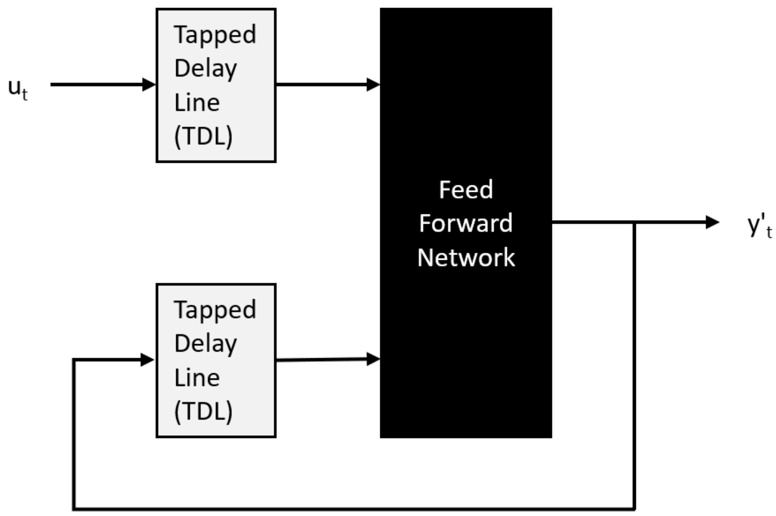

Figure 22. Parallel architecture (Adapted from MathWorks, Inc.)

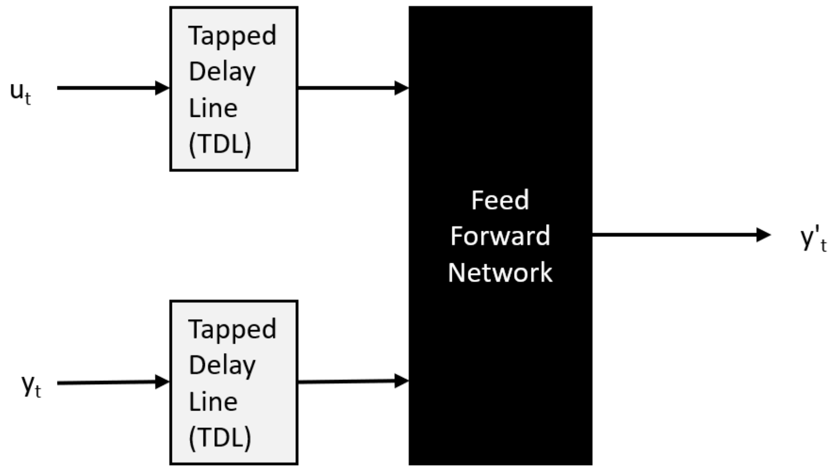

Figure 23. Series-Parallel architecture (Adapted from MathWorks, Inc.)

The NARX network has a better learning with a faster generalized convergence in neural networks by using gradient descent 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 the Levenberg-Marquardt learning algorithm which is a standard technique for converging nonlinear least squares selection (Lourakis, 2005).

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

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

where: t_i : target,

y : predicted value

γ : performance ratio.

The proposed network consisted of three layers (input, hidden, and output layers) as shown in Figure 24. The input layer had 2 inputs (preorder 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 numbers of nodes (1 to 20 with step size = 1). As shown in Figure 25, the training error kept decreasing as the number of nodes; however, the training error for validation data was decreasing and started 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.

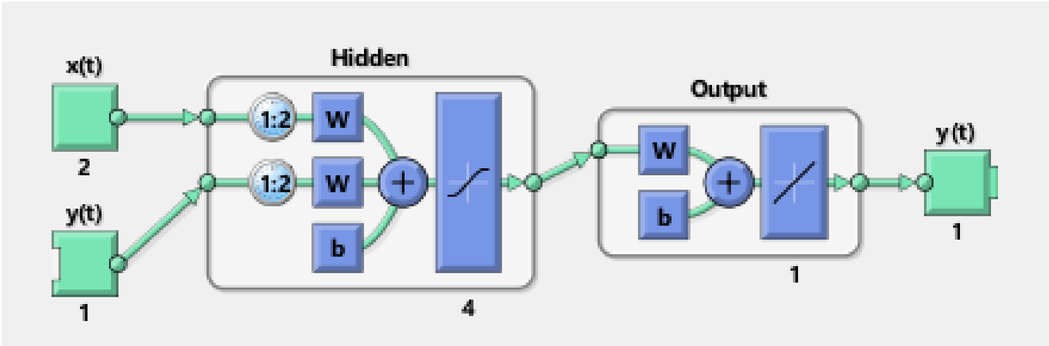

Figure 24. Artificial neural network with parsimonious variables (Adapted from MathWorks, Inc.)

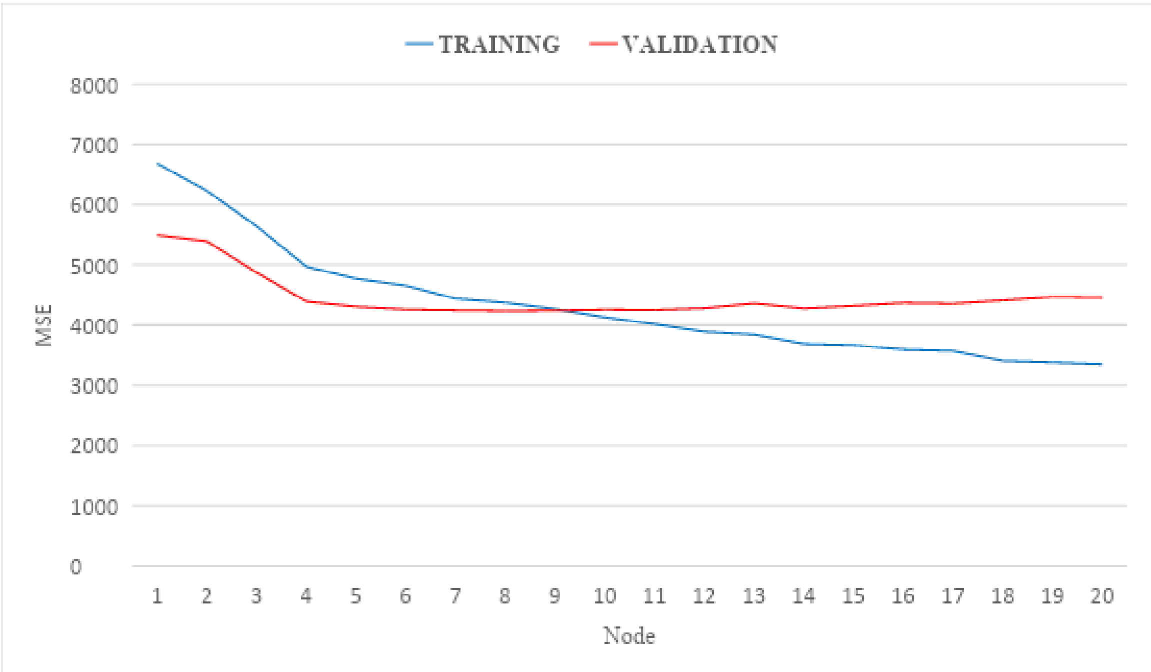

Figure 25. Training and validation performance according to the number of nodes in the network

CHAPTER 04

RESULTS

4.1. Loss and Accuracy Comparison

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 R2 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. The RMSE of the NARX model (RMSE = 70) was sufficiently smaller for the training data set than ARIMA (85). Similarly, RMSE of NARX was better than that of ARIMA for the testing data set. Lastly, R2 between actual and predicted values was better in NARX (training = 96% and testing 94%) than ARIMA (training = 95% and testing 92%) for both data sets.

4.2. Predicted Value Comparison

The proposed NARX showed slightly better performance than an ARIMA as shown in Figure 26. 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 a tremendous spike in RMSE which was higher than the proposed NARX. For example, in Figure 27, the points 3, 14, 17, and 31 showed relatively higher error in ARIMA than the proposed NARX.

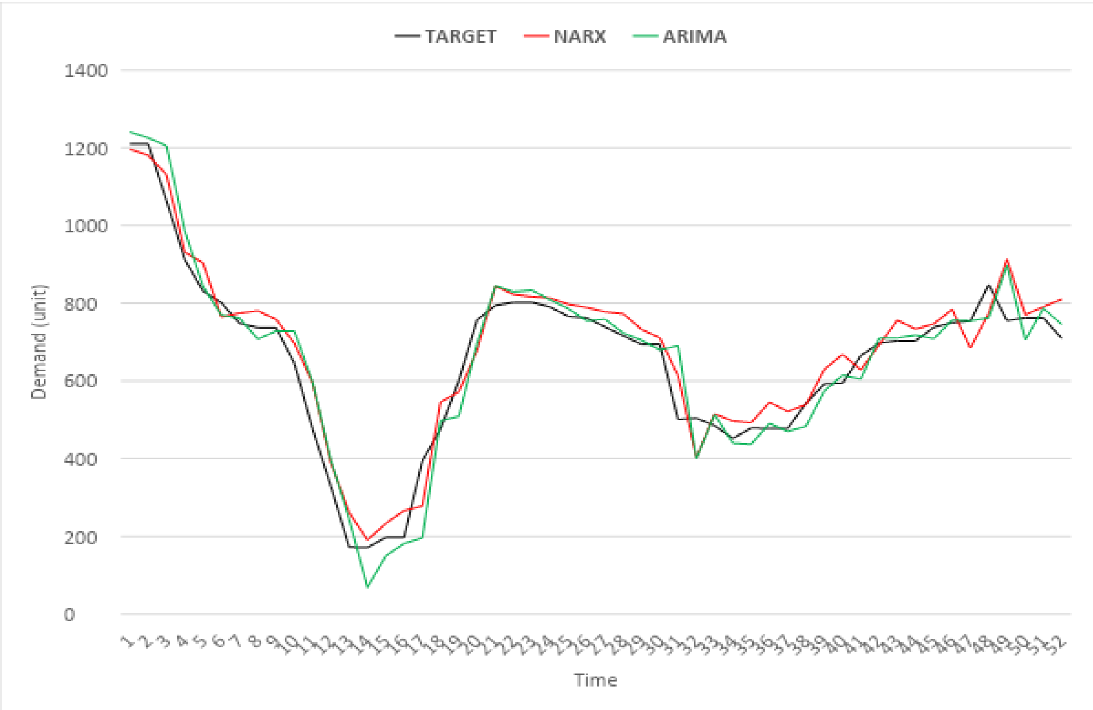

Figure 26. Predicted values of NARX and ARIMA

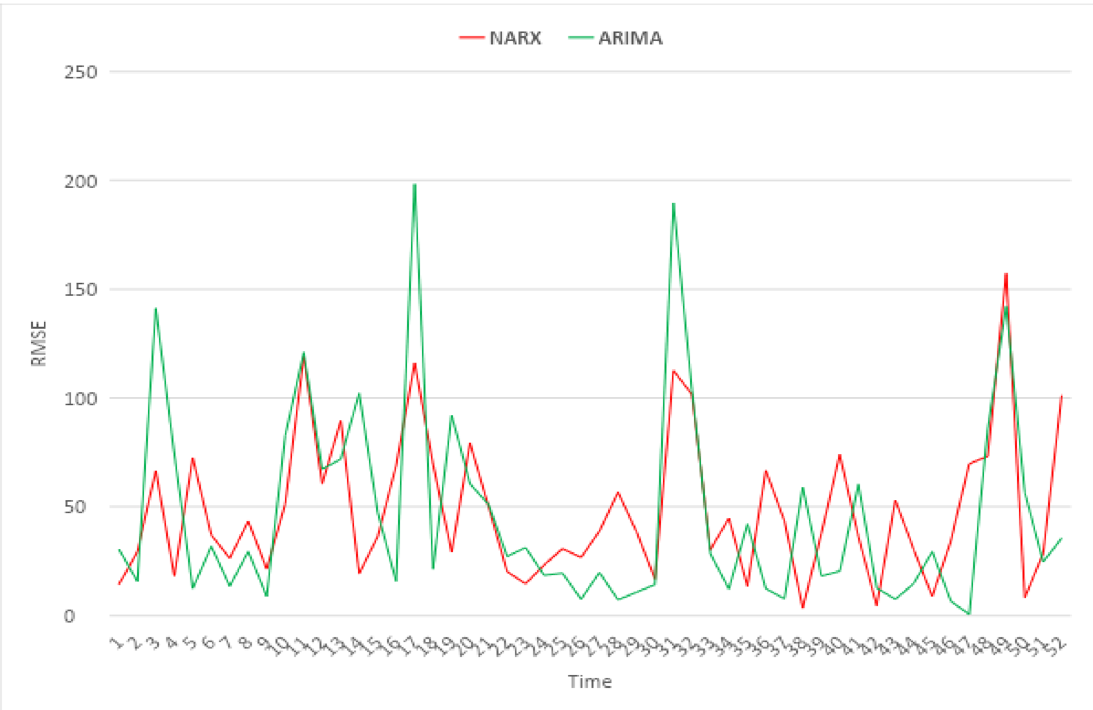

Figure 27. RMSE of the predicted value of NARX and ARIMA

CHAPTER 05

DISCUSSION AND CONCLUSION

5.1. Discussion

This study determined the inputs and parameters of proposed NARX in a systematic way. Three external variables (preorder amount, holiday number, and sale volume) were considered at first, and then two parsimonious variables were selected to avoid multicollinearity because one external variable (sale volume) had high dependency to the others. In addition, the number of input-out delays 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 numbers 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.

5.2. Conclusion

The NARX developed in this study resulted in a promising result since it employed near optimal parameters including number of input-output delays, node numbers, and parsimonious variables. The parsimonious variables showed the positive effect in boosting the 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.

The model’s improvement reflects a better performance for the company’s production. Approaching higher accuracy in forecasting the actual demand placed by the main contractor of the automotive industry aims to relieve uncertainty in managing inventory. Efficient inventory management mainly affects the dilemma of profitable supply chain management which is whether to keep low inventory level in order to keep the cost under control or high inventory level in order to assure the availability of products for actual demand. The supplier tends to eliminate waste and unnecessary processes to minimize safety stock which costs in maintenance and expiration of the individual product, while the high inventory level can guarantee to satisfy the order. So, the significant loss will be used to address the decision by stabilizing the inventory level. Furthermore, the forecasting also impacts the dilemma of the supply chain system in positioning factories and warehouses. An optimal distance between the first-tier supplier’s upstream suppliers and the main contractor can be confidently considered with a known demand of individual raw material. The precise distance strongly contributes to a profitable production planning by providing particular capacity preparation for human resource management and commodity for product categorizing in procurement.

Since the model was built based on a specific dataset in the certain scenario of a first-tier supplier, adapting this study result in other companies, parameters will be required to alter based on the various complexity and characteristics of the respective dataset. As the availability of data depends on shared information between the company and partner, different methods will be applied. For further study, other approaches such as deep learning and hybrid models can be applied to study alternative insight and performance.

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