DEMAND FORECASTING OF A FIRST-TIER SUPPLIER IN AUTOMOTIVE INDUSTRY USING NONLINEAR AUTOREGRESSIVE NETWORK WITH PARSIMONIOUS VARIABLES

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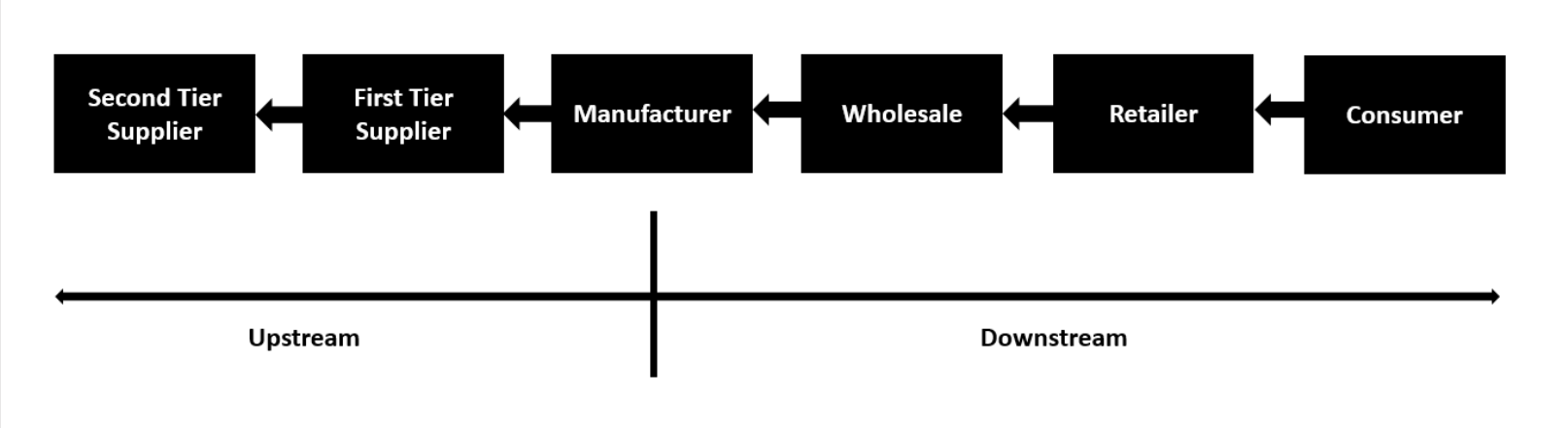
CONTENTS

1. PROBLEM STATEMENT

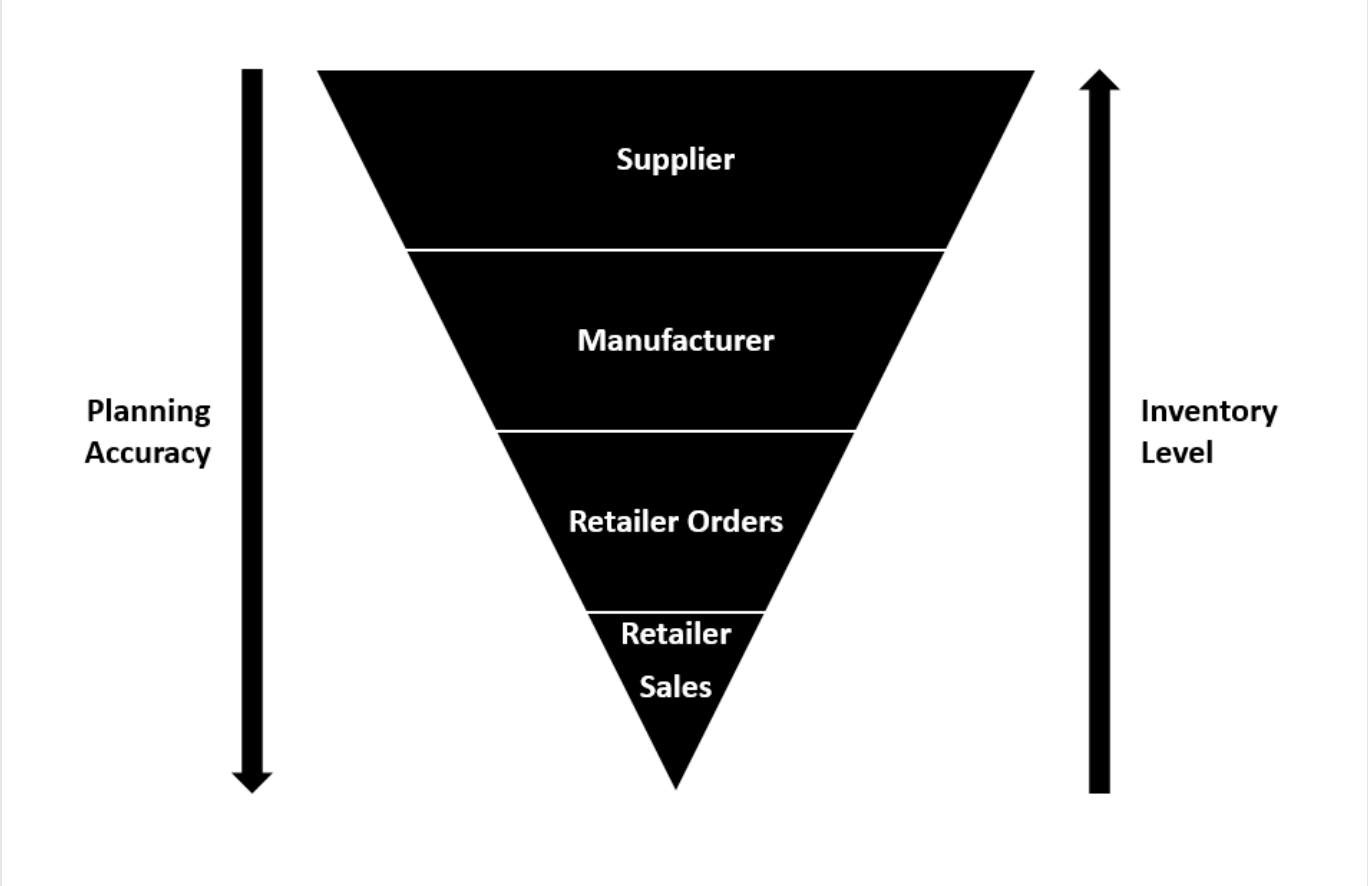
- Facing an issue in predicting future demands



- Dealing with a burden of inventory management
  - Carrying cost
  - direct and indirect cost

1. PROBLEM STATEMENT

- Inconsistency orders causing "Bullwhip effect"



1. PROBLEM STATEMENT

- Design and build a Demand Forecasting model (planning)
  - Production management
  - Capability preparation
  - Inventory tracking
  - Commodity

- Prevent partners' distrust
- Narrow fluctuation interval

2. EXITING STUDIES AND METHODS

- A traditional method (Auto regressive integrated moving average (ARIMA) has been applied with a good performances *(Box et al., 2015)*.

Previous Studies	Method	MAPE
Fattah et al., 2018	ARIMA (1, 0, 1)	13%
Sen et al., 2016	ARIMA (1,0,0) × (0,1,1)	22%
Udom and Phumchusri, 2014	ARIMA (1,0,1)	24%

- Artificial neural network (ANN) has been integrated for forecasting in most sectors to deal with big datasets *(Hsu et al., 1995).*
  - ***Ex.*** Kochak and Sharma (2015) studied the demand forecasting by applying ANN, and the forecasting resulted an effective performance and accuracy as 6% of MAPE

3. METHOD TRENDS AND IMPORTANCE OF THE STUDY

- Nonlinear autoregressive exogenous network (NARX)
  - Historical data
  - External variables

- Many studies have attempted using NARX (Cadenas et al., 2016; Pisoni et al., 2009; Ruslan et al., 2014; Boussaada et al., 2018; Taqvi et al., 2020)
  - Wind speed,
  - Air pollution level,
  - Flood water level,
  - Solar radiation, and
  - Fault detection
- Lacking studies in applying NARX in first-tier supplier in automotive industry

4. PURPOSE OF THE STUDY

- Build models
  - ARIMA
  - NARX
- Determine optimal parameters
- Analyze time-lag effects of the external variables and historical demands
- Selection parsimonious external variables
- Compare model performances

5. DATA ANALYZING

- Data sets in three sub-sets
  - Train (70%),
  - Validate (15%)
  - Test (15%)

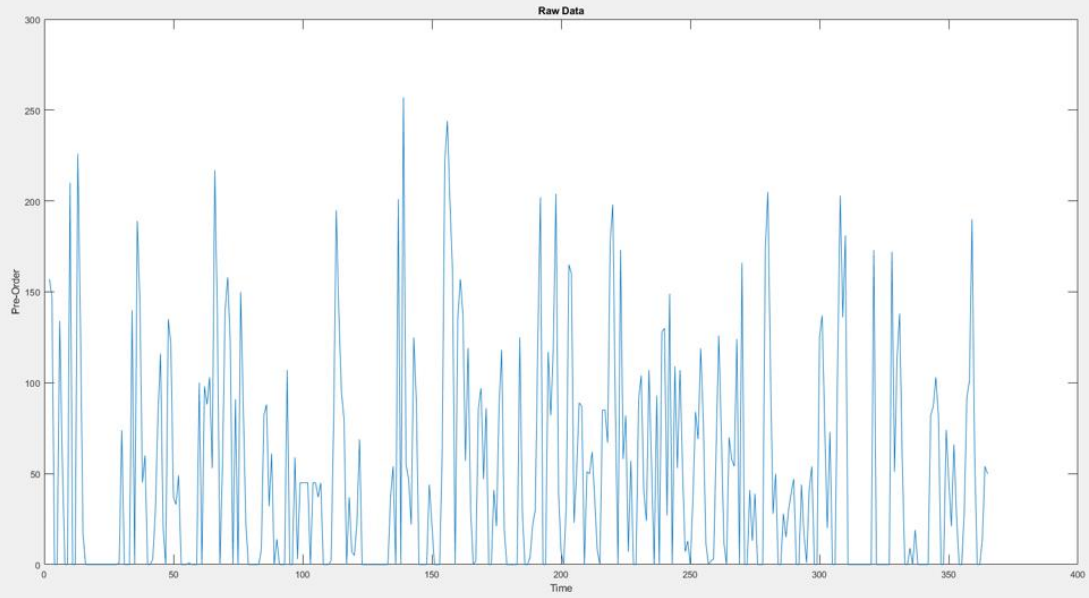


Figure.3. The plot of the pre-order data

5. DATA ANALYZING

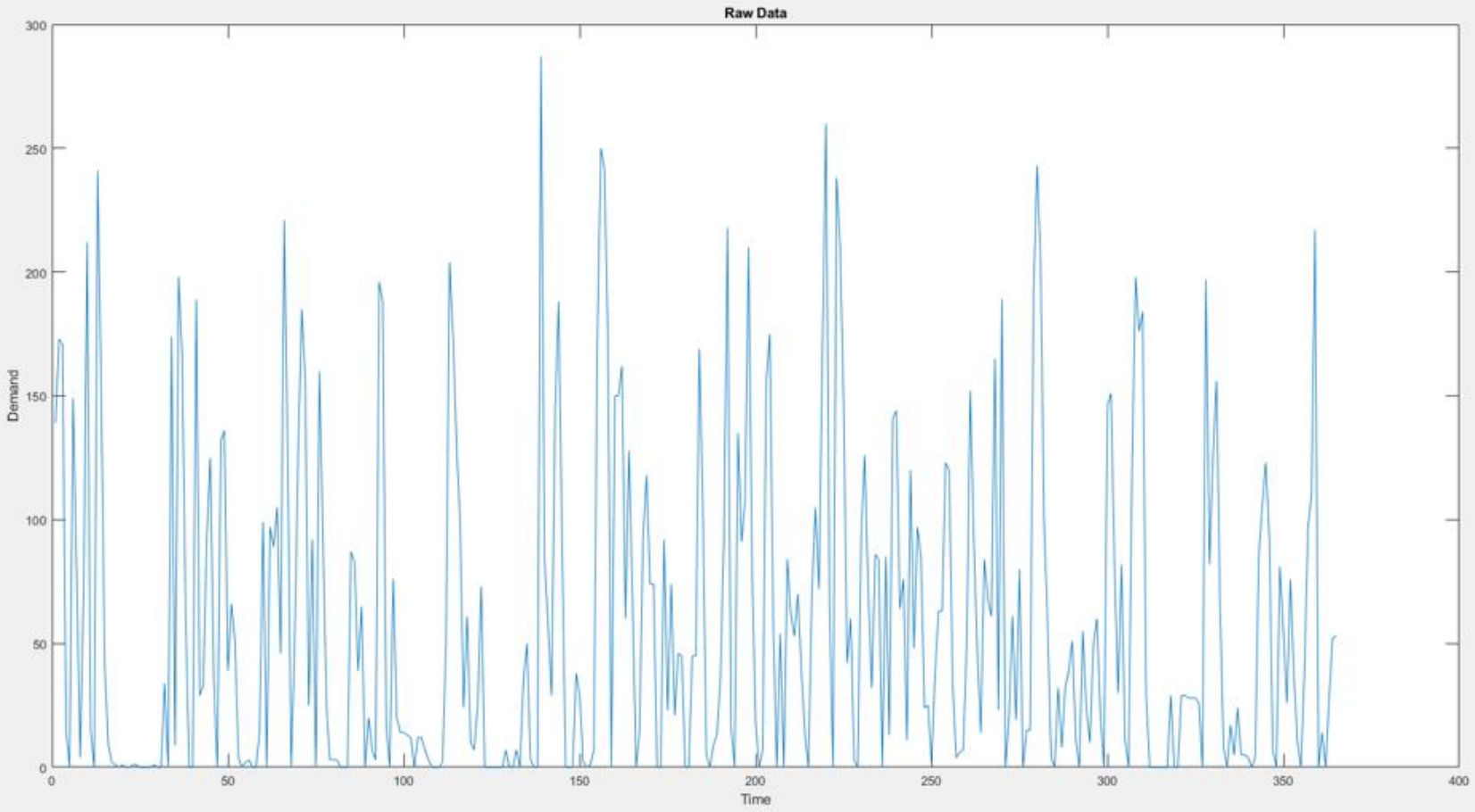


Figure.4. The plot of the actual demand

5. DATA ANALYZING

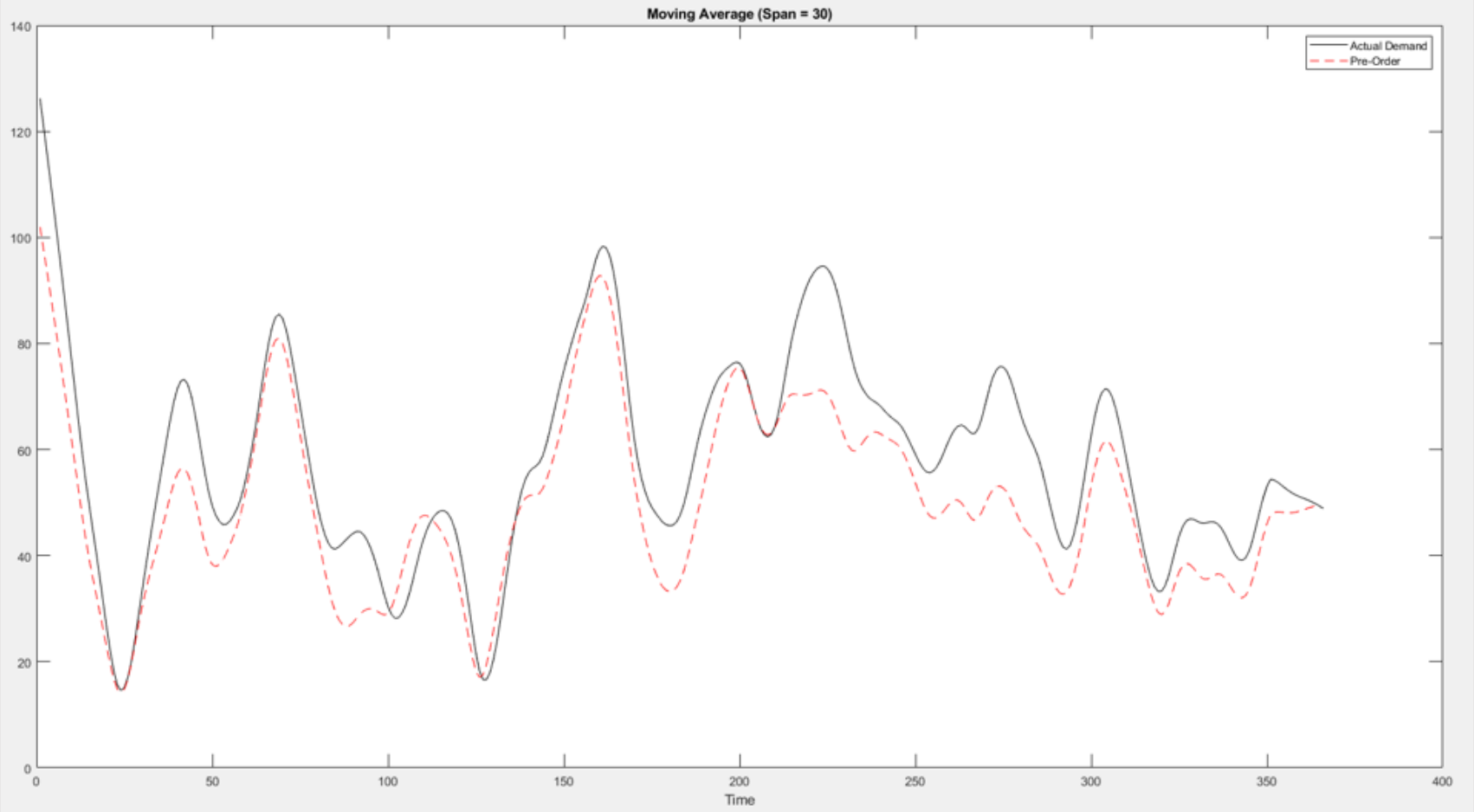


Figure.5. The plot of Moving average (span = 30) of the pre-order and actual demand

5. DATA ANALYZING

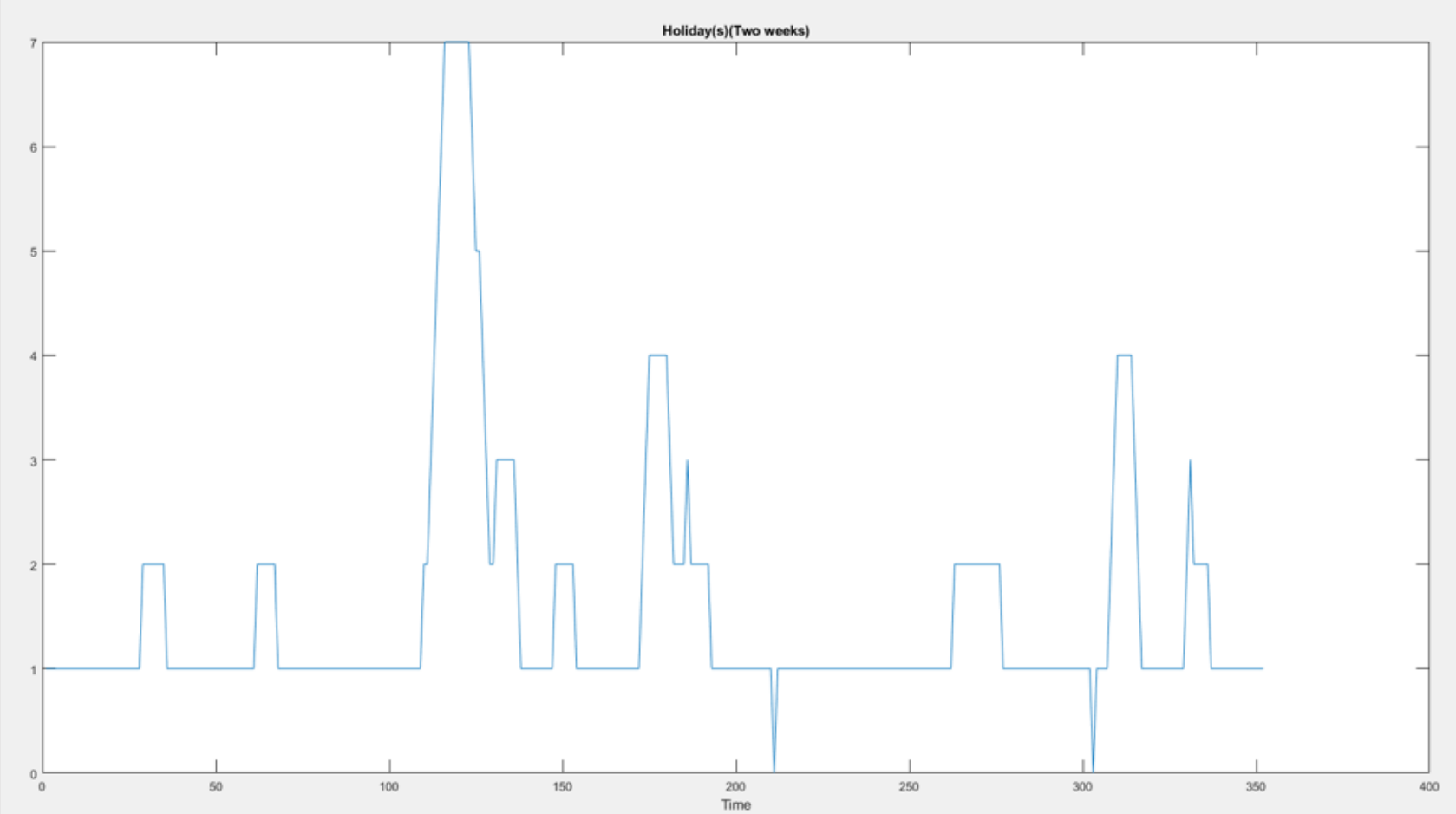


Figure.6. The plot of the holiday data

5. DATA ANALYZING

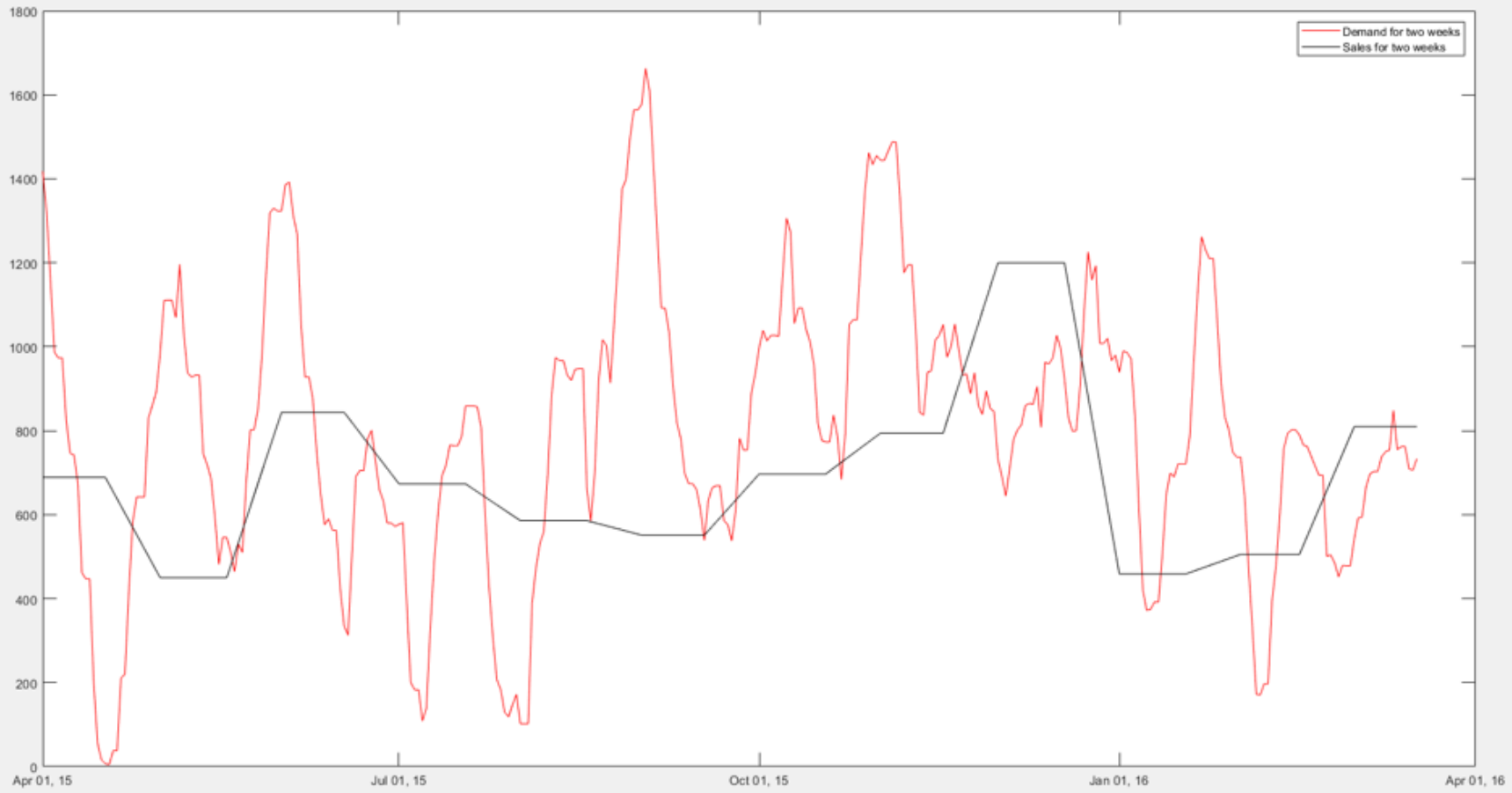


Figure.8. The plot of the actual demand and sale volume in two weeks

6. PARSIMONIOUS VARIABLES SELECTION

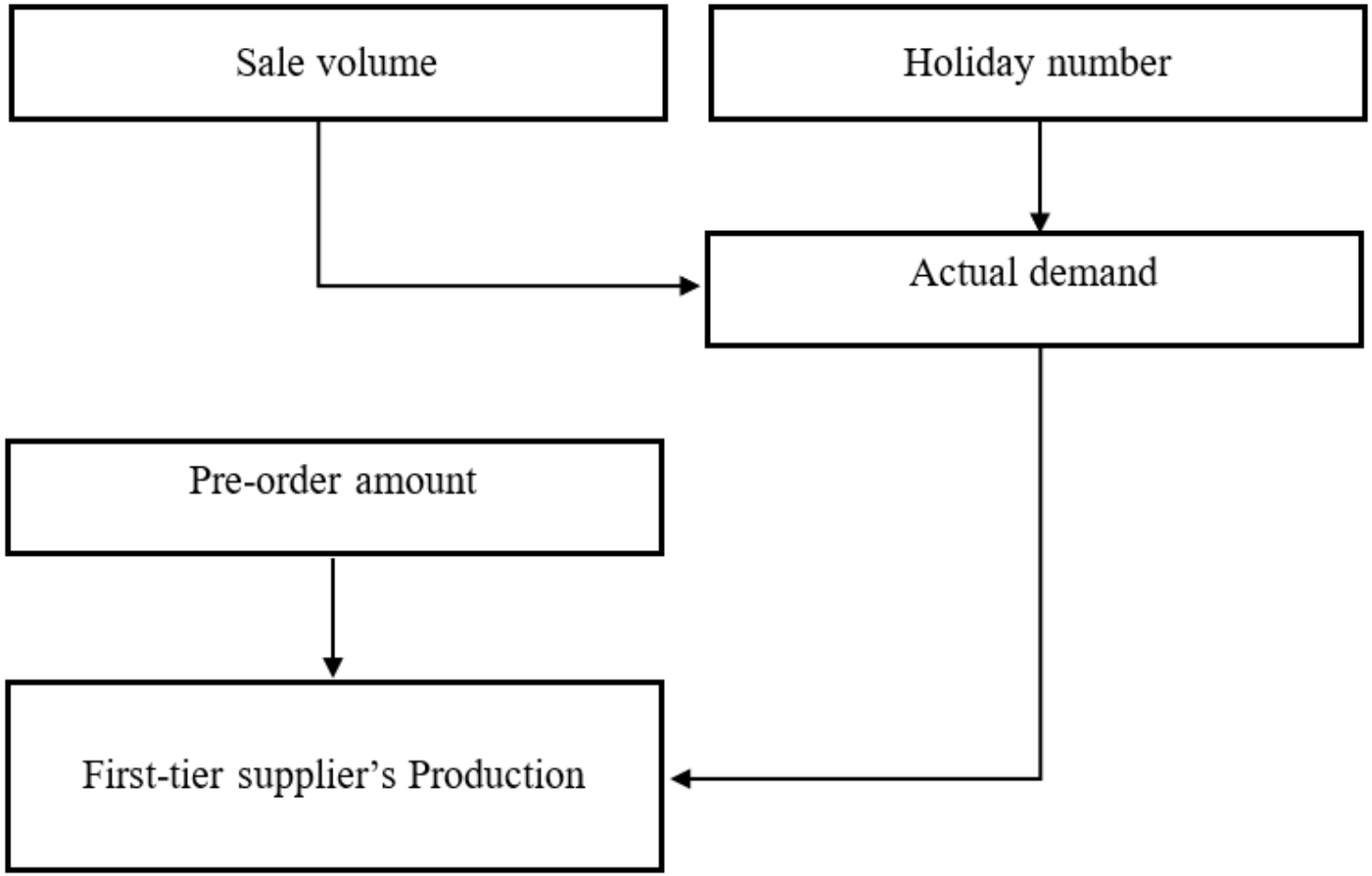


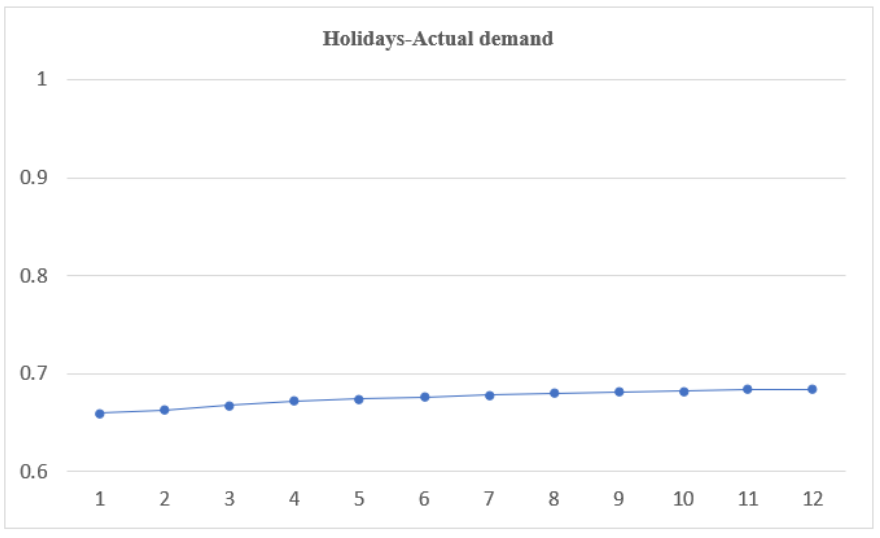
Figure.9. Relationship of each external variable with the actual demand

6. PARSIMONIOUS VARIABLES SELECTION

- Parsimonious Variables Selection
  - Stepwise regression
    - holiday number: $p < 0.001$
    - pre-order amount: $p < 0.001$
  - Correlation analysis
    - holiday number : 0.734 to 0.725
    - pre-order amount: 0.813 to 0.780

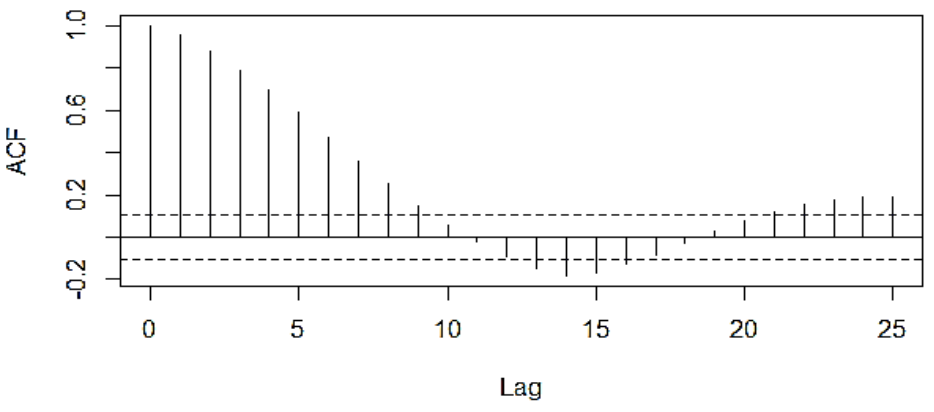
6. PARSIMONIOUS VARIABLES SELECTION

- Correlation analysis

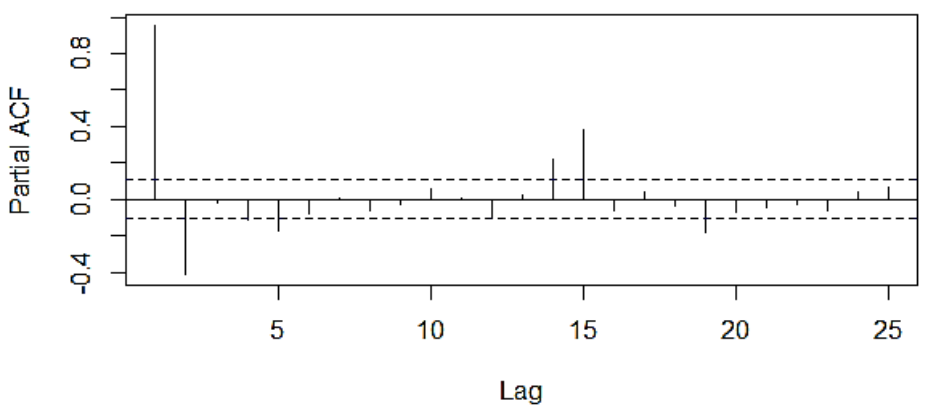


6. PARSIMONIOUS VARIABLES SELECTION

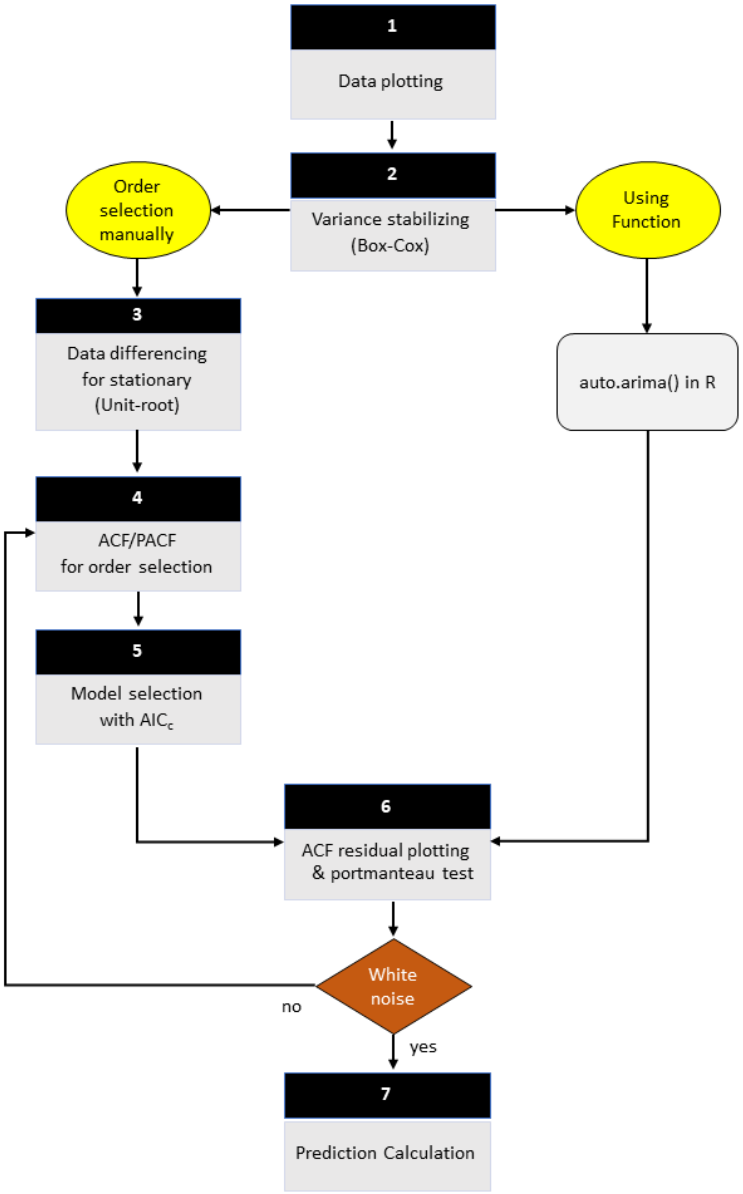
- autocorrelation function (ACF)



- partial autocorrelation function (PACF)



7. METHOD



- Auto Regression Integrated Moving Average (ARIMA)

7. METHOD

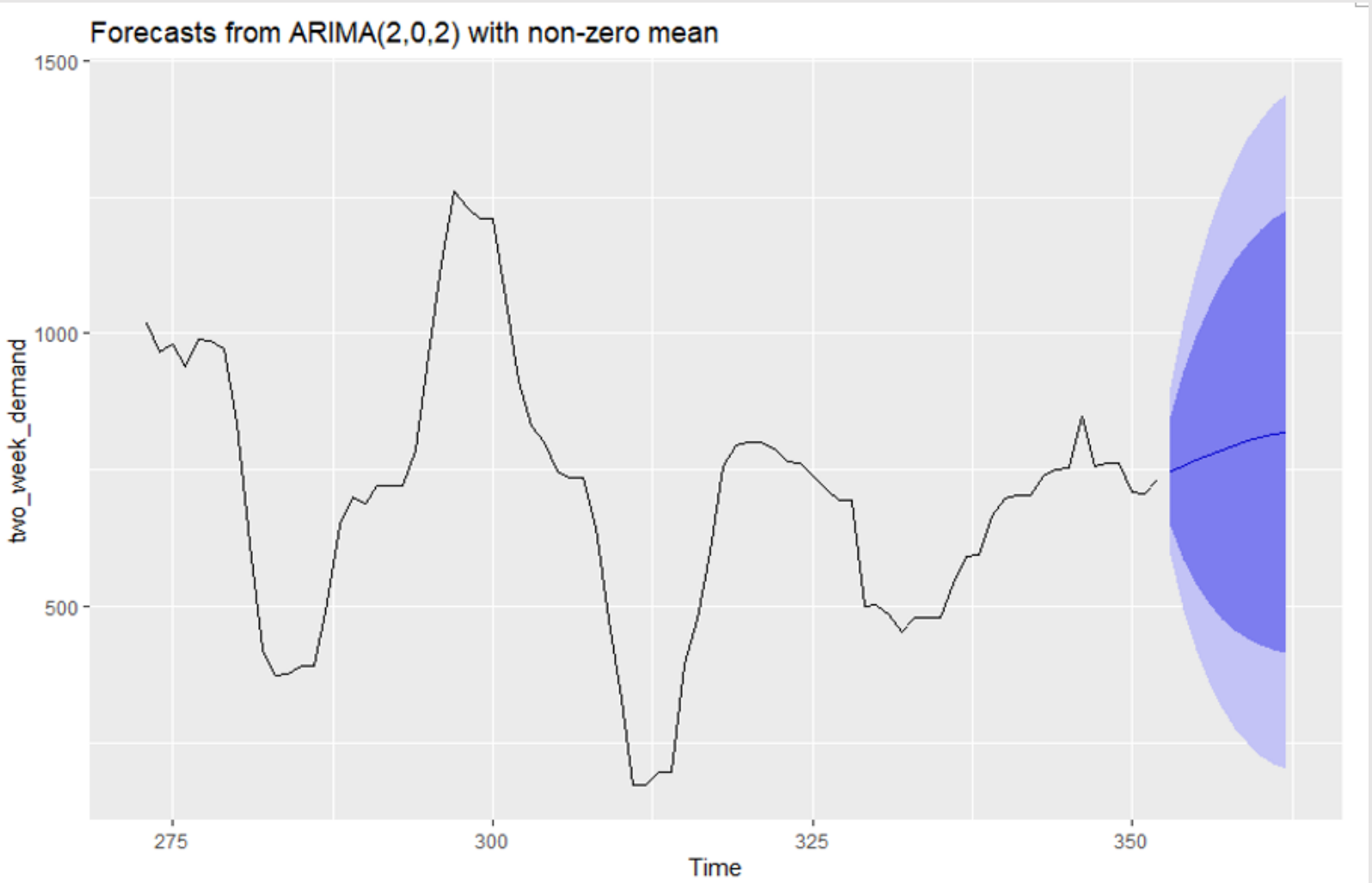
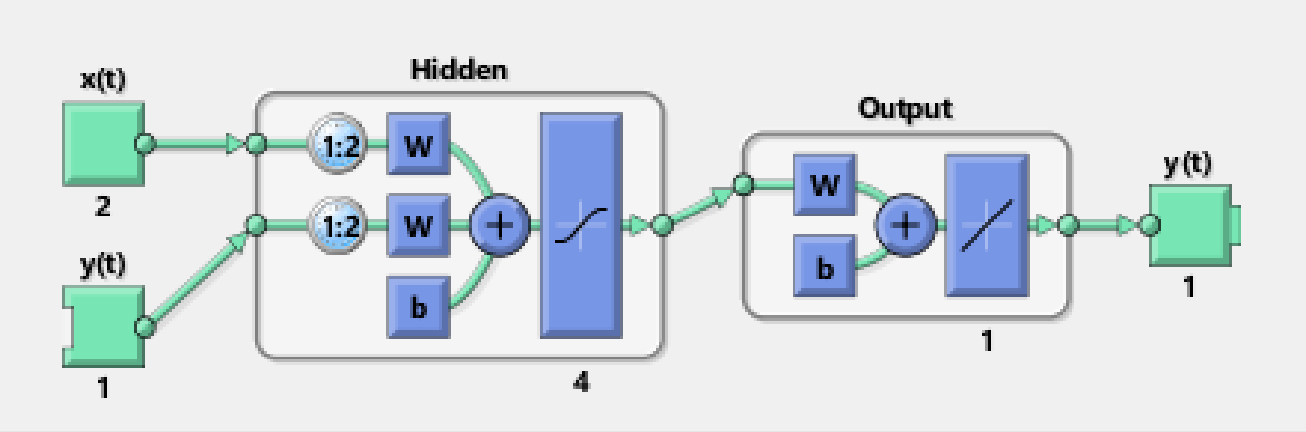


Figure.15. Forecasting plot using ARIMA model on the actual demand

- Proposing NARX Network
  - 3 layers (input, hidden, and output)
  - 2 inputs (pre-order amount and holiday number) with 2 time-lags
  - 4 nodes in the hidden layers



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

- Neural network

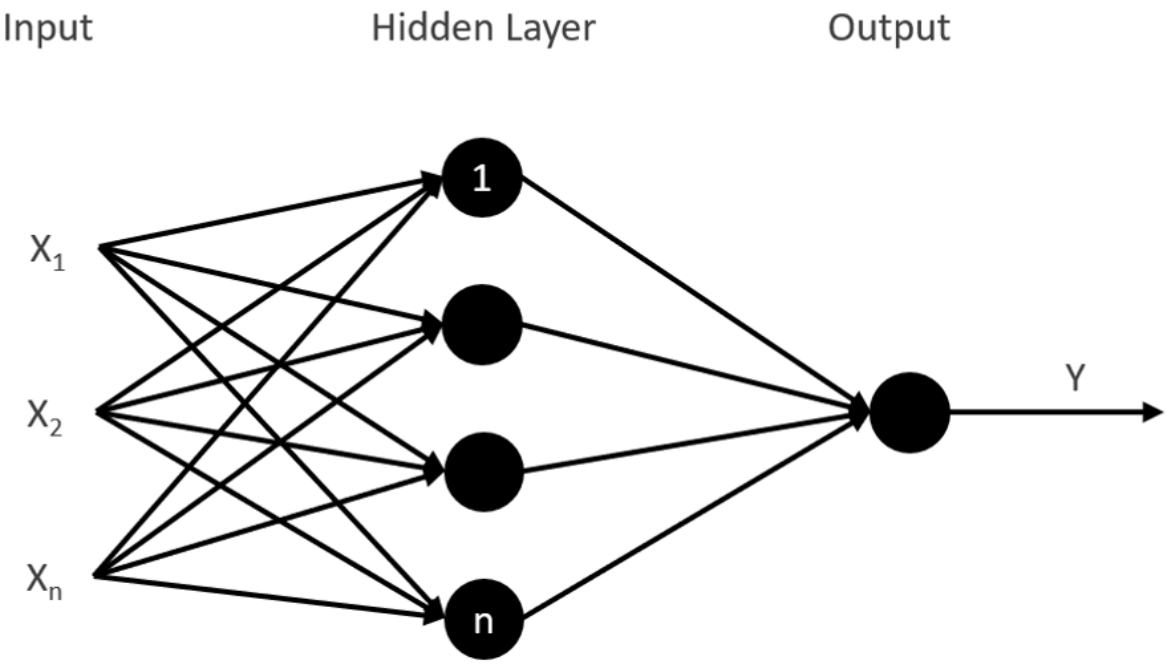


Figure.16. A neural networks structure (Adapted from Yılmaz, Aci, and Aydin, 2015)

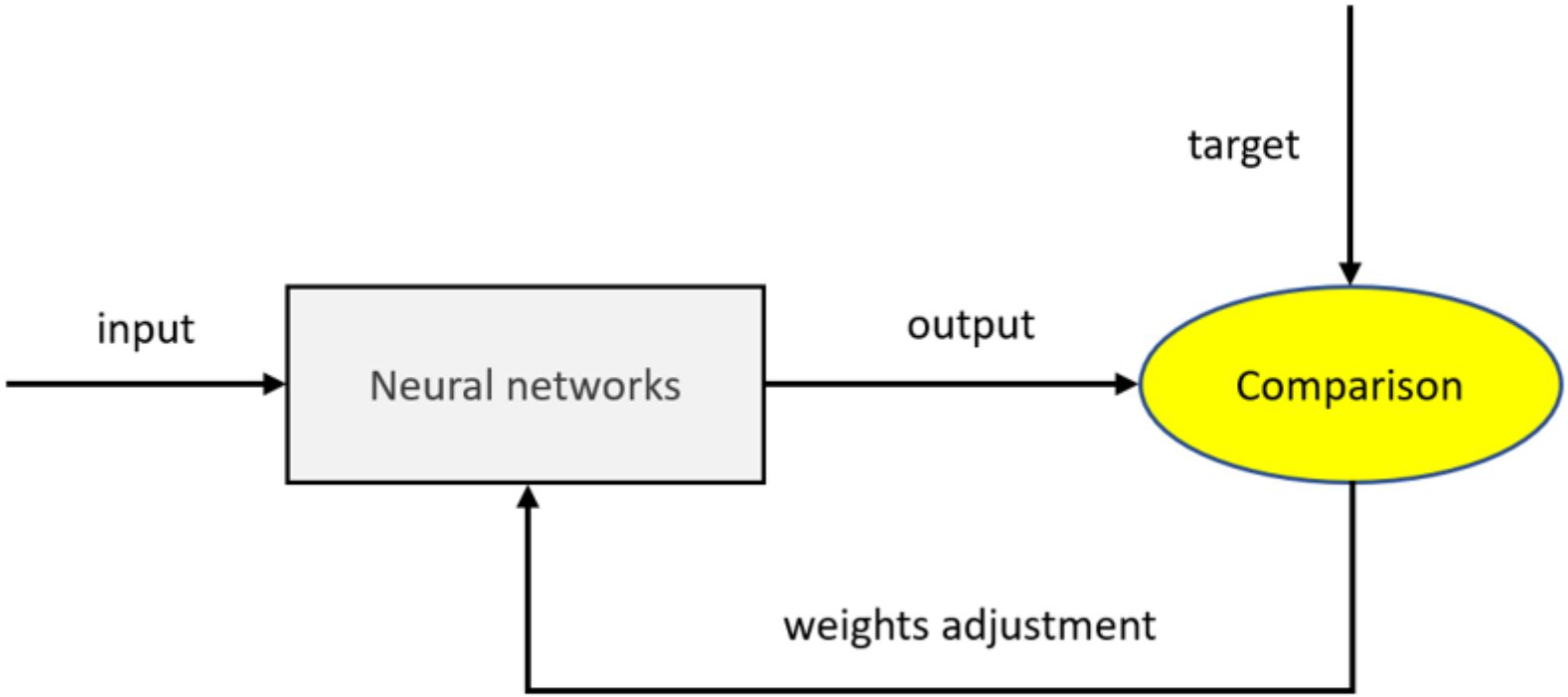


Figure.17. A neural networks architecture (Adapted from, MATLAB & Simulink, 2019)

7. METHOD

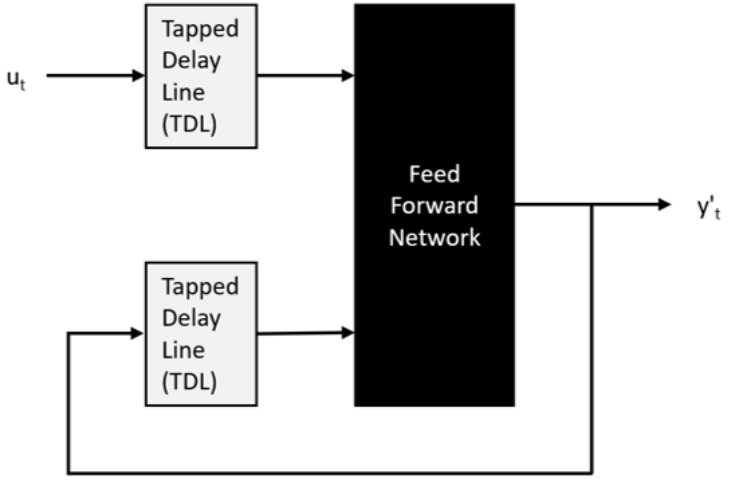


Figure.18. Parallel architecture (Adapted from MathWorks, Inc.)

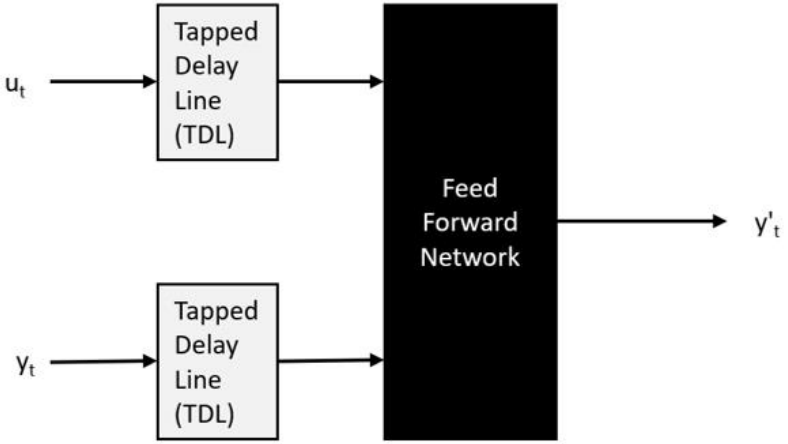
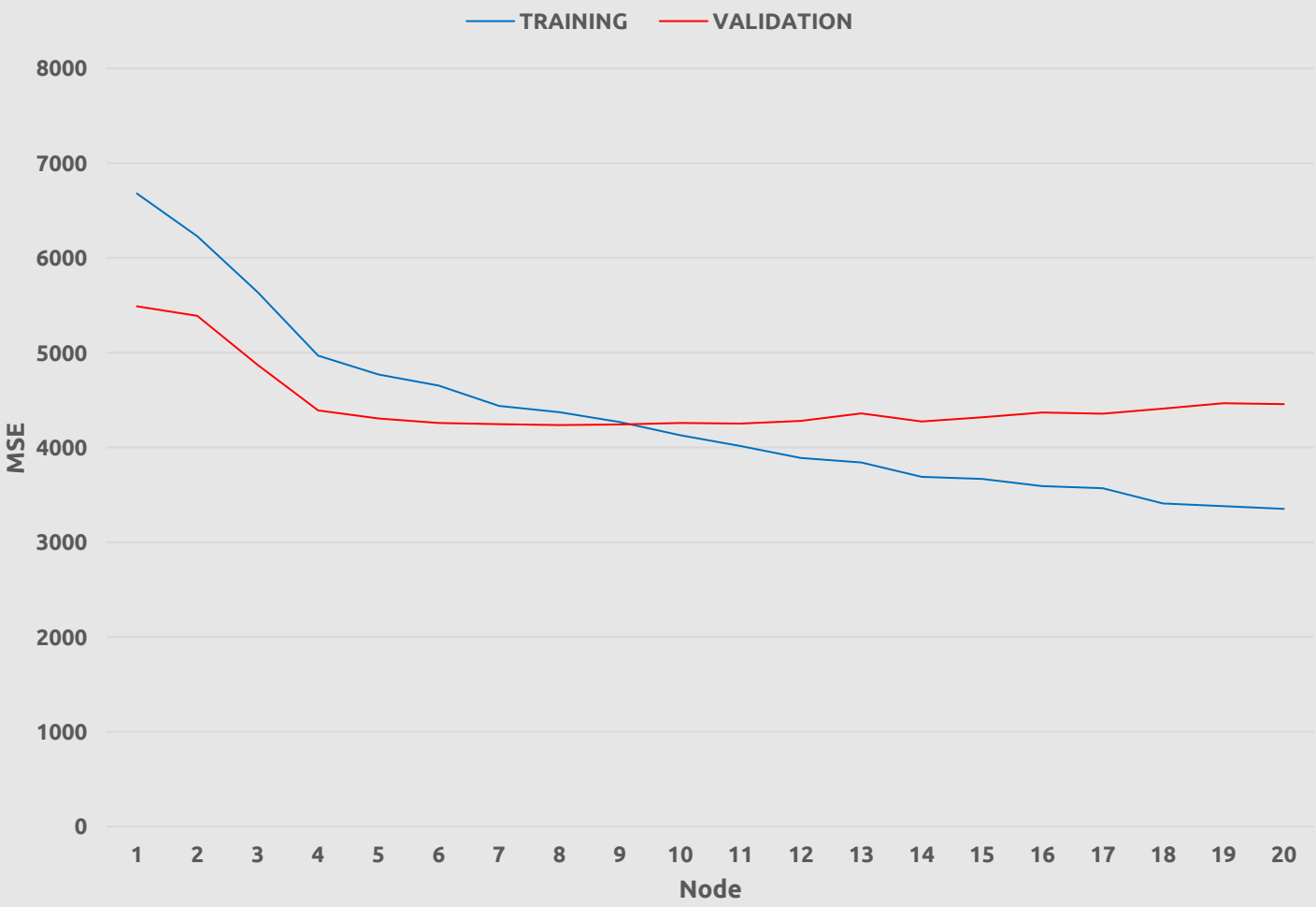


Figure.19. Series-Parallel architecture (Adapted from MathWorks, Inc.)

- Training and validation performance



8. RESULTS

- RMSE of the proposed model was better than an ARIMA model in both training (18%) and testing (15%) sets

- R2 between the predicted demands and actual demands was 96% and 94% for the training and testing sets

	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%

8. RESULTS

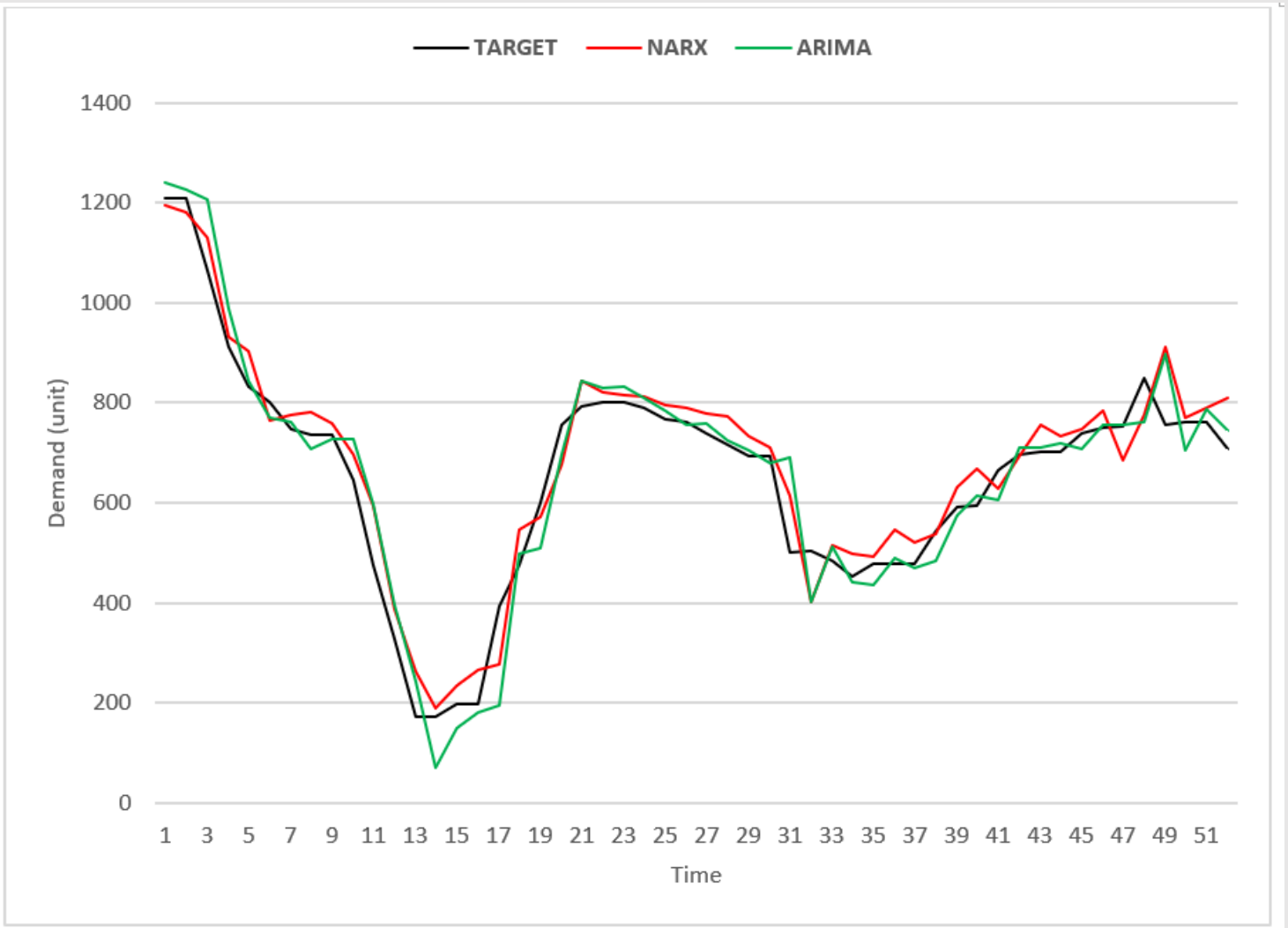


Figure.22. Predicted values of NARX and ARIMA

8. RESULTS

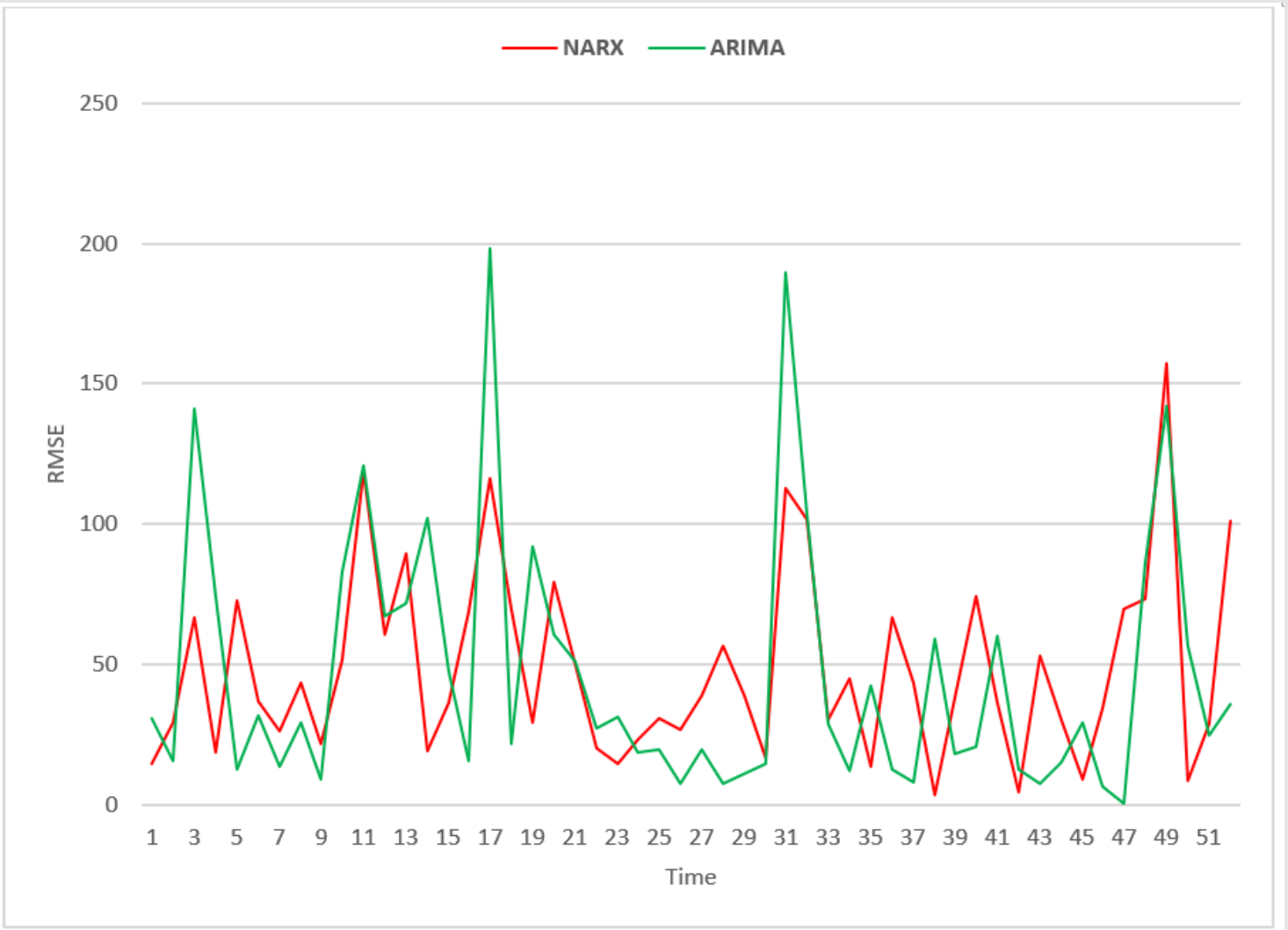


Figure.23. RMSE of the predicted value of NARX and ARIMA

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9. CONCLUSION

- Determined the inputs and parameters of proposed NARX in a systematical way
- Selected two parsimonious variables in order to avoid multi-collinearity
- Decided the number of input-out delay as 2 based on ACF and PACF
- Determined the node number for the hidden layer as 4 by analyzing the learning performance
- Further study:
  - Transfer learning to adapt data characteristics
  - Alternation of availability of data sets

Q & A