Supply Chain Management Project Report

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Demand Forcasting to reduce the Bullwhip effect

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Contents

1 Introduction **3**

2 Background **5**

2.0.1 Defining the Bull Whip effect 5
2.0.2 Naïve Forecasting: 5
2.0.3 Moving Average Forecast: 6
2.0.4 Exponential Smoothing: 6
2.0.5 Forecasting through AI and ML: 6

3 Literature Review **7**

4 Neural Networks Theoretical Concepts **8**

4.1 Background 8
4.2 Artificial Neural Networks (ANNs) 8
4.3 Nodes or Neurons and Node Layers 9
4.4 Node Weights and Threshold 9
4.5 Training of the Model 10
4.6 Working Principles of Neural Networks 10
4.7 Types of Neural Networks 12
4.7.1 Feedforward Neural Networks or Multi-Layer Perceptrons (MLPs). 12
4.7.2 Convolutional Neural Networks (CNNs) 12
4.7.3 Recurrent Neural Networks (RNNs) 12

5 Theoretical explanation **13**

5.1 Derivation for Back propagation 13
5.2 Bullwhip effects 15
5.2.1 Finding the amount of natural Gas required for electric production on forecast demand 16

6 Benefits **17**

7 Artificial Neural Network in Industries **18**
7.1 Walmart's use of AI to Make Smarter Substitutions in Online Grocery Shopping 18
7.2 Amazon's Personalized Product Recommendations 19

8 Traditional Forecasting Techniques and ANN **20**
8.1 Naive Forecasting Method 20
8.2 Moving Average Sum Forecasting Method 20
8.3 Exponential Smoothing Forecasting Method 20
8.4 Artificial Neural Network ANN Forecasting Method 21

9 Data Analysis and Comparison **22**
9.1 Data Source 22
9.2 Forecasting with Naive 23
9.3 Forecasting with Moving Average Sum 24
9.4 Forecasting with Exponential Smoothing 25
9.5 Forecasting with ANN 26
9.6 Comparison of Forecasting Techniques 29

10 Results and Conclusion **31**

Bibliography **32**

Introduction

A supply chain for power generation and distribution, also known as the power grid, consists of key stakeholders namely the suppliers of the primary sources of energy, manufacturers, distributors, retailers, and customers of energy. While encapsulating all the activities associated with the flow and transportation of relevant information and goods from the stage raw materials, such as coal, oil, gas, etc, are fetched till the end-user receives energy, the management of the supply chain in the power sector holds great significance in ensuring the uninterrupted transmission of energy (Bajor).

An important phenomenon that occurs in the supply chain is the bullwhip effect. It is the amplification in the prediction of demand by the stakeholders along upstream in the supply chain. This distortion in demand comes as a result of utilizing traditional forecasting techniques, creating collaboration barriers, and no explicit forecast information-sharing amongst the members of the supply chain (Pandey, 2014).

Although forecasting techniques do not ensure accurate demand predictions, the goal remains to minimize demand distortions. As such, in projecting long-term electricity demand, artificial intelligence methodologies, where machines demonstrate human intelligence in predicting long-term demand values, prove to be appropriate and efficient in mitigating the inefficiencies due to variability of demand in the supply chain (Pandey, 2014). One such methodology is the artificial neural network (ANN). It is an information replicating paradigm, similar to how human brains work, where predictions, pattern recognition, learning, and data mining are im-

plemented. This study focuses on improving forecast accuracy with the utilization of artificial neural network methodology in reducing the bullwhip effect in the power sector.

Background

2.0.1 Defining the Bull Whip effect

The bullwhip effect as described above can be defined as the phenomenon where demand changes at the end of a supply chain lead to inventory fluctuations along the chain. Consequently, this can result in excess inventory which might go to waste when obsolete or can lead to insufficient inventory which leads to reduced lead time, poor costumer experience and lost business. Such consequences call for effective measures by the organization as to prevent the bullwhip effect and the cost that comes with it. Inaccurate demand forecasting tops the list of potential causes of the bullwhip effect. Efficient methods of forecasting are an important resource for accurate predictions of demand and using better forecasting and visibility tools has been one of the approaches used to reduce the chances of the occurrence of such distortion in demand prediction and evaluation. Over the years various methods have been employed for demand forecasting that include exponential smoothing, Naïve Forecasting, moving average etc. Below lies a brief description of each of these methods traditionally used for forecasting:

2.0.2 Naïve Forecasting:

It is one of the simplest methods used to for estimation and forecasting. The actual values from the last period are directly assumed to be the forecast values of the current period.

2.0.3 Moving Average Forecast:

The moving average forecast uses the average of a defined number of previous periods to forecast the future demand. It gives the overall idea of the general trend of demand.

2.0.4 Exponential Smoothing:

Exponential Smoothing is a popular scheme to produce a smoothed Time Series. In Exponential Smoothing, exponentially decreasing weights are assigned as the observation gets older. To simplify, recent observations are given relatively more weight in forecasting than the older observations. This cancels out the effect of random variation and gives the general trend of the data set/time series.

2.0.5 Forecasting through AI and ML:

However with the advancement of technology, solutions and methods based on Machine Learning and AI can be employed to forecast demand through analyses of the general patterns and trends from the historic data available. These forecasting techniques based on AI can sufficiently reduce chances of error and increase accuracy which would be further discussed in this paper. Smart Grid Technology, Industry 4.0 and Demand Forecasting: With the increased dependence on electrical energy and the emergence of the fourth industrial revolution (Industry 4.0) were all factors in the increased need for smart, efficient and reliable energy systems. Qarabsh (2020). This introduced the concept of the Smart Grid (SG).The smart grid is a new paradigm that enables two-way communications between the electricity providers and consumers. Smart Grid makes power distribution more efficient and reliable as distribution of energy would be done on the basis of or in accordance to the demand. Therefore, for the implementation of smart grids, efficient demand management and accurate demand prediction is the key. Azad (2013).Demand forecasting comes into play here. As we plan to implement smart grids for reliable and sustainable use of energy, we rely on efficient demand forecasting techniques to predict demand with accuracy so that the distribution is efficient and as per the need. This area would be the main focus of our paper.

Literature Review

The bullwhip effect occurs when the demand variations in the supply chain magnify as we move upstream from the retailer to the manufacturer. The major causes behind this effect are forecasting, non-zero lead time, order batching, supply shortages, and price fluctuations. However, the most critical aspect among these is forecasting, as it directly affects the inventory system in the supply chain and, although sharing customer information reduces the bullwhip effect, it does not erase it.

In an electric supply system, electricity has to be supplied constantly to ensure that the system stays balanced and serviceable. This, however, can only be made possible if the power stations are functioning following the fluctuations in consumer demand. In a system where there is no storage facility for the power generated, the non-consumed energy is dissipated and the plant's capacity has to be set higher than the required daily maximum to accommodate for the wasted energy. In the Hungarian national grid, since there is no significant storage opportunity for energy that has been produced but not consumed, the capacity of the turbines is set at 8558MW, 33% higher than the required daily maximum of 6439MW to ensure stability and constant availability of electricity ZRt. (2017).

From this, it can be realized that the bullwhip effect in power generation and distribution does not occur in the conventional manner as the non-consumed electrical energy dissipates almost instantly, leaving no excess energy in stock. However, accurate demand prediction can help plant managers determine the amount of electricity needed throughout the day. They can then use this information to either ramp up the generation or slow it down. In such a scenario, artificial neural network forecasting is most suitable for accurately depicting the consumer demand based on the huge amounts of data collected and reducing production costs by limiting losses.

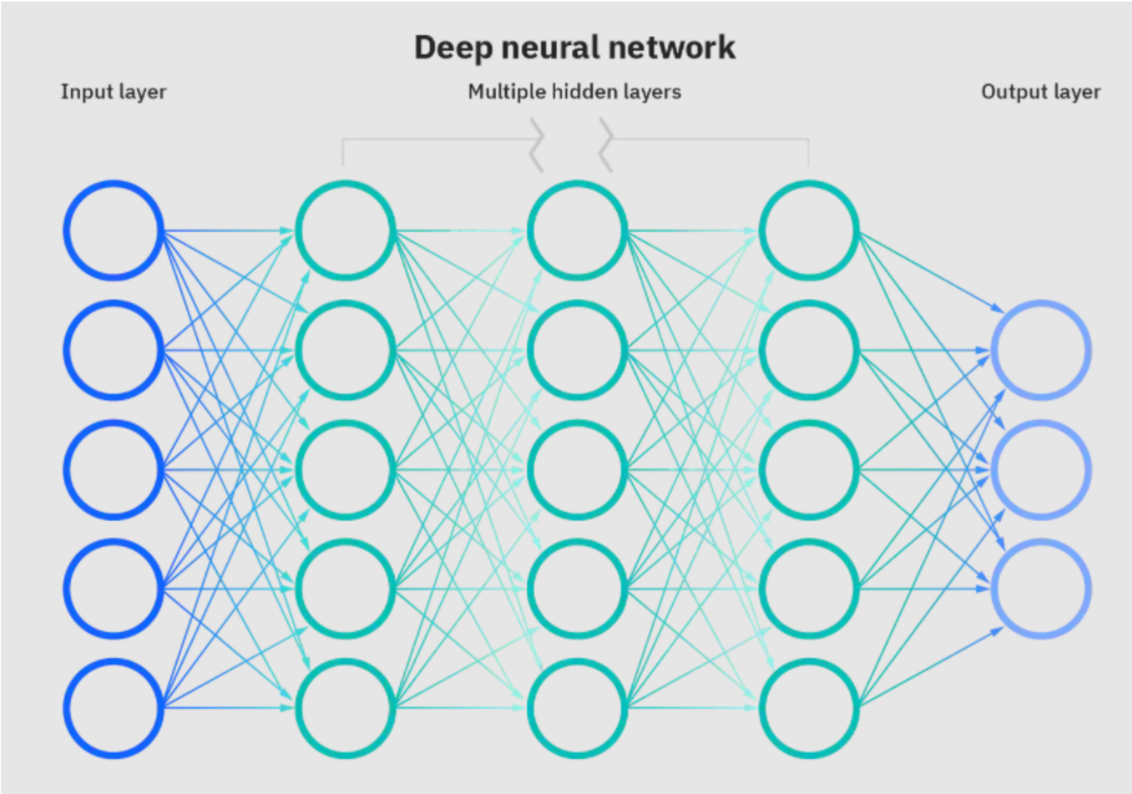
Neural Networks Theoretical Concepts

4.1 Background

A great effort has been put into the integration of modern technology with the traditional supply chain techniques, specifically focusing on overcoming the issues and bottlenecks occurring in this area in order to provide consistent and sustainable supplies of goods and materials. As mentioned above, we are going to use artificial intelligence, a prominent technological aspect in today's world, to reduce the most feared situation in supply chain, bullwhip effect. To further elaborate the process, we will be using a subset of AI called Artificial Neural Networks (ANN) that would accurately forecast the future demand and thus, mitigating the chances of bullwhip effect.

4.2 Artificial Neural Networks (ANNs)

Neural networks provide this capability to a computer to behave and mimic like a human brain. A human brain has the ability to store, process and generates results and conclusions based on the information. Thus, neural networks behave in a similar manner. They allow computer programs to interpret patterns and solve an analytical problem within the realm of AI and Machine Learning. Basically, as the name suggests, they reflect the functionality of biological neurons that send signals to one another for processing the data which makes humans behave intelligently in every situation IBM (2021).



4.3 Nodes or Neurons and Node Layers

Artificial Neural Networks (ANNs) are basically organized networks in a computer program that consist of nodes which are basically the neurons or the perceptrons, a computational unit connected to one or more nodes, forming a network of neurons. Together, these nodes form a layer and the combination or the connections among these layers constitute the Deep Neural Network. There are two primary layers: Input layer and the Output layer. Multiple hidden layers are programmed between the input and output layers that eventually process the data from the input layer, make the decision and send the data to output layer IBM (2021).

4.4 Node Weights and Threshold

As stated above, each node or artificial neuron is connected to another node, forming a layer. Every node is assigned a certain weight or threshold. This is similar to graphs data structure in which each edge has a certain weight or cost when moving from one vertex to another. The essence of these weights comes into play when the data is being transmitted from one layer to another. If the output of one specific node is not above the assigned weight or threshold, the node is not activated, and data is not sent to the next layer and vice versa IBM (2021).

4.5 Training of the Model

It is vital that the data provided for the training of the neural network algorithm should be large enough and accurate in the context of the application. ANNs rely on the training data to improve their efficiency of their output IBM (2021). Once programmed accurately and efficiently, they can outperform humans in most of the cases because of their high computational power.

4.6 Working Principles of Neural Networks

As it is mentioned above, the whole algorithm depends upon the efficiency of each node or neuron. The output of a specified node is transferred to the output layer at the end. Each node is designed on a linear regression model that is composed of input data, weights, bias or threshold and an output IBM (2021). The formula for an individual node is given as:

$$\sum_{i=1}^{m} w_i x_i + bias = w_1 x_1 + w_2 x_2 + w_3 x_3 + ...$$

The output is then defined by the activation function given as follows:
$Output = f(x) =$

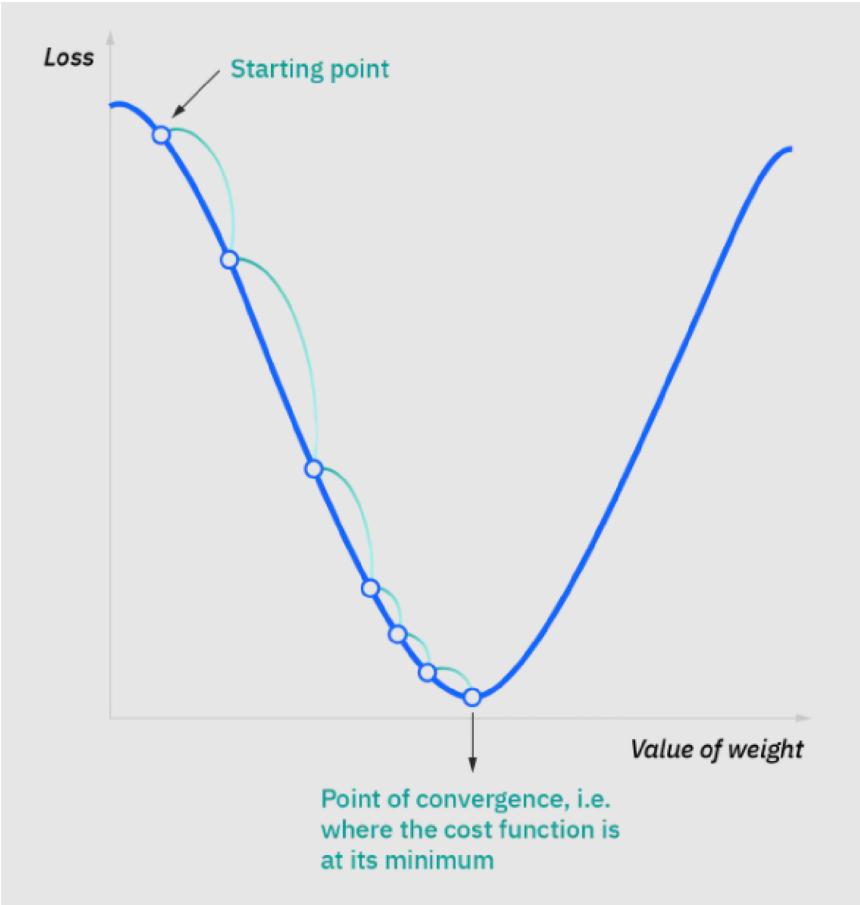
$$\begin{cases} 1 \sum_{i=1}^{m} w_i x_i + bias \geq 0 \\ 0 \sum_{i=1}^{m} w_i x_i + bias < 0 \end{cases}$$

After creating the input layer, weights are assigned that determine the output. Each input is multiplied with its weight and added with a bias or threshold which offsets the activation function as per the design of the problem. If the sum of the products is greater than the threshold, then the activation function activates the node which implies that the output of this node or neuron is high, and the data at will now serve as the input to another node. This process of passing data from one layer to another makes neural network a Feedforward network IBM (2021). In order to evaluate the accuracy or the efficiency of the ANN, we train the model and then define a cost or a loss function that estimates the performance of the neural network.

This is commonly referred to as the mean squared error (MSE).

$$Cost = MSE = \frac{1}{2m} * \sum_{i=1}^{m} (\hat{y} - y)^2$$

The main objective is to minimize the cost function to ensure correctness of the fit for a certain observation. More technically, the efficiency of the output is dependent upon the weights and the bias (threshold) value that the ANN selects for processing. Hence, during the training of the data, it follows the trial and error method. The algorithm adjusts the values of the weights and bias such that the cost function is minimum IBM (2021) . Thus, it is suggested to provide robust training data so that the values of weights and bias it adjusts are able to produce accurate results for any observation.



4.7 Types of Neural Networks

Artificial Neural Networks are classified into multiple types which are used for different purposes, however, three of the most popular kinds are following.

1. Feedforward Neural Networks or Multi-Layer Perceptrons (MLPs).
2. Convolutional Neural Networks (CNNs).
3. Recurrent Neural Networks (RNNs).

4.7.1 Feedforward Neural Networks or Multi-Layer Perceptrons (MLPs).

Feedforward or Multi-Layer Perceptrons have been explained above. They are composed of an input layer, a hidden layer and an output layer. Each layer sends the data to the next layer if the value is greater than the threshold value. Data is fed into these models to train them and adjust the values of bias and weights. Mostly used for Computer Vision and Natural Language Processing applications IBM (2021).

4.7.2 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) operates similar to MLPs, however, the difference comes into the applications. CNNs are primarily used for image recognition, pattern recognition, and/or Computer Vision. They are derived from the principles of linear algebra, specifically matrix multiplication, to identify patterns within an image IBM (2021).

4.7.3 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are recognized by their feedback loops. The output of the node may serve as the input to itself again in the next iteration. Hence, RNNs recognize data's sequential characteristics and use patterns to predict the next likely scenario. They are particularly used when analyzing time-series data to make predictions about future outcomes such as stock market prediction or demand forecasting IBM (2021).

Theoretical explanation

5.1 Derivation for Back propagation

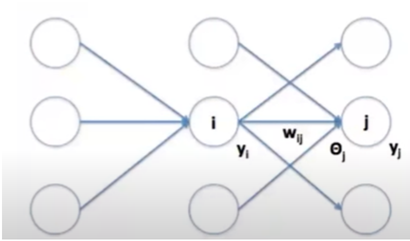


Figure 5.1: Back Propagation within hidddn layers

Our Analysis will be done in Matlab. Matlab Uses levenberg-marquardt algorithm as back propagation algorithm. The two main features of this algorithm is mean squared error and Gradient descent. Figure 5.1 shows two layers within a Neural Network. y_i and y_j are outputs from each layer, w_{ij} is the weight used, and Q is the active potential. The equation shown below derive the mathematics model behind back wards propagation Silva (2020).

The active potential consists of a Input(x), Weight(w) and Bias (b)

$$Q = xw + b \tag{5.1}$$

Choosing sigmod function as our activation function

$$y = \frac{1}{(1 + e^{-Q})} \tag{5.2}$$

$$MeanSquaredError(E) = \frac{1}{n} \sum \frac{1}{2} (y_{target} - y)^2 \tag{5.3}$$

There are three main equation to minimize the error, changing one derivative affect the rest of the equation

Change in Error as we change the Tranfer potential

$$\frac{\partial E}{\partial Q_i} = \frac{\partial E}{\partial y_i} \frac{\partial y_i}{\partial q_i} \tag{5.4}$$

Change in Error when we change the weight

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial Q_i} \frac{\partial Q_i}{\partial w_{ij}} \tag{5.5}$$

The change in Error when the first layer Output changes

$$\frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial Q_j} \frac{\partial Q_j}{\partial y_i} \tag{5.6}$$

The main objective is to minimize the expression (5.6). **Hence reducing the error across layers.**

5.2 Bullwhip effects

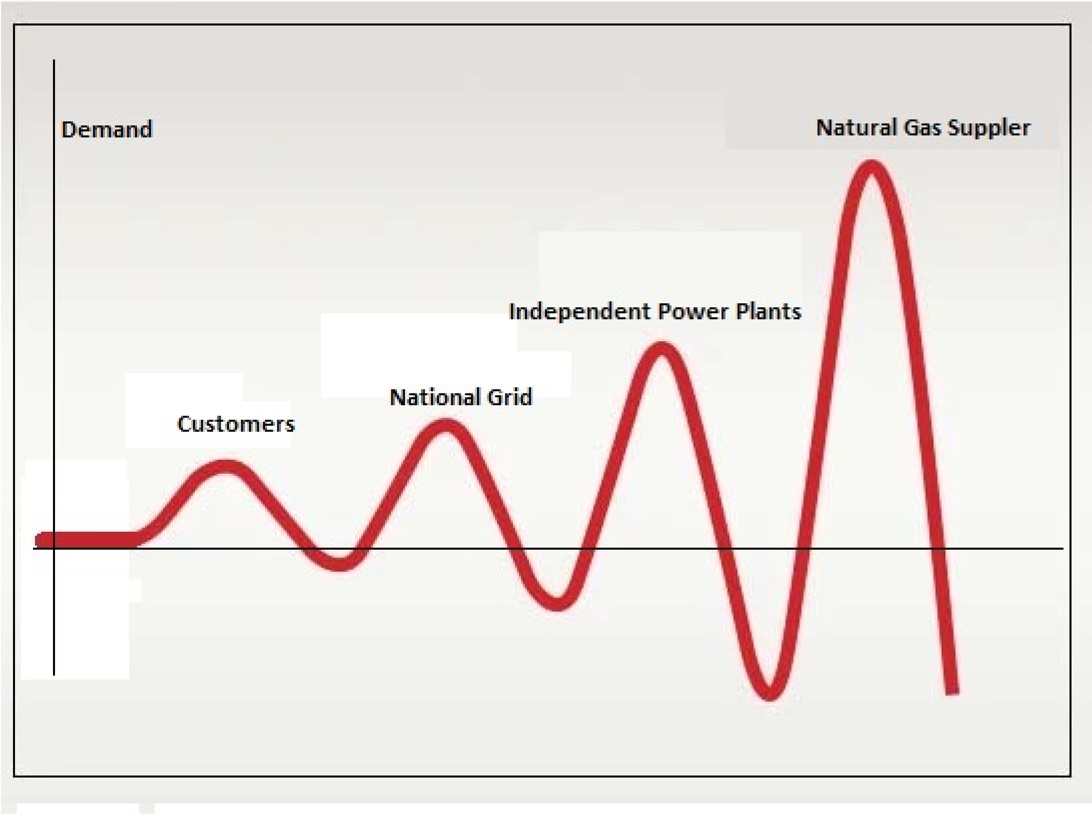


Figure 5.2: BullWhip effect of natural gas power plants

if we view the production within the energy sector, the thermal power plant produced the bulk of electricity in Pakistan. Considering the Natural Gas power plants, we can view the overall effect of bullwhip. Figure 5.2 shows how Natural Gas demand can fluctuate due to the Bull Whip which is not only bad for the energy sector but also for the general population who uses natural gas for cooking and heating purposes. The article discuss how demand can be affect due to lack of integration within the supply chain KianiPu (2021).

5.2.1 Finding the amount of natural Gas required for electric production on forecast demand

$$\text{Energy produced per kilogram} = 50MJ/kg \tag{5.7}$$

$$1MW/h * 3600sec = 3600MJ \tag{5.8}$$

$$efficiency = 50\% \tag{5.9}$$

$$Amount = \frac{3600}{(50 * 0.5)} = 144kg \tag{5.10}$$

$$1MW/h \rightarrow 144kg \tag{5.11}$$

$$xMW/h \rightarrow Tkg \tag{5.12}$$

$$Total = 144xMWkg/h \tag{5.13}$$

Benefits

The primary objective of our project is to study bullwhip effect and its causes and affects on supply chain. Furthermore, we introduced such an efficient technique that would help mitigate bullwhip effect. The most prominent benefit of using AI in this field is that it helps to accurately predict future demands based on the previous data. Every firm in supply chain would like to have accurate demand forecasts so that they do not become the victim of bullwhip effect because bullwhip can lead to tremendous inefficiencies such as excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation, and missed production schedules. Hence, by using ANNs to precisely predict the future demands, we can mitigate the effect of bullwhip effect, escaping the possibilities of the supply chain inefficiencies mentioned above.

Furthermore, there is no need for full integration among the supply chain partners that is usually required for keeping track of demand and measuring the extent of bullwhip effect, whether it is likely to occur or not. Hence, it is cost effective since it saves the expenditures of full integration and confidentiality is preserved since it would save a supply chain organization from revealing its goals and strategies to another organization required in full integration.

Artificial Neural Network in Industries

7.1 Walmart's use of AI to Make Smarter Substitutions in Online Grocery Shopping

Amidst the pandemic, there was a radical shift in customers' shopping behavior and a surge in online purchasing. As much as it boosted online stores' sales, it also posed a new set of challenges as retailers would struggle to meet the demand of both in-store shoppers and online orders as popular items would quickly sell out. Walmart tackled this by introducing AI to help both customers and personal shoppers choose the best substitute in case a product was found to be sold out.

There are many factors that go into picking out the best substitute for buyers who the personal shoppers know nothing about. This choice is dependent on aspects such as size, type, brand, price, aggregate shopper data, individual customer preference, current inventory, etc. Walmart's technology uses deep learning AI to consider hundreds of variables to determine the next best available item. It also asks the customer to approve or disapprove the substituted item so that this data may be fed back to the learning algorithm to improve the accuracy of future suggestions.

The deployment of this technology increased customer acceptance of substitutions by 95% Venkatesan (2021) and made the jobs of personal shoppers easier by letting them know precisely what the customer would prefer in case an order placed online became out of stock.

7.2 Amazon's Personalized Product Recommendations

Amazon's AI technology is deployed in multiple aspects of its operations which enables it to gain a competitive edge in the market share and increase customer satisfaction. One such area is the "Recommended for you" header on its online stores.

Amazon's recommendation algorithm uses user's previous purchases and matches them to similar products. It then compiles the similar products to generate a recommendation list that is more closely aligned with customer preferences compared to recommendation lists based on other similar customer's purchases.

According to a 2013 McKinsey & Company report, Amazon's personalized product recommendations drove 35% of purchases on Amazon Jarrell (2021)

Traditional Forecasting Techniques and ANN

8.1 Naive Forecasting Method

In Naive forecasting technique, the demand of the previous week or day is expected to be the demand for the next week/day. Basically, it chases the demand of the previous days. It is an estimating technique in which the last period's actuals are used as this period's forecast, without adjusting them or attempting to establish causal factors.

$$F_{t+1} = A_t$$

Where F_{t+1} = forecast for next period t+1 and A_t is the actual demand for period t

8.2 Moving Average Sum Forecasting Method

Simple Moving Average Sum is a time-series forecasting technique that uses historical data to predict the demand in future. It works well when the demand is stable over time. The formula for moving average sum is given below:

$$F_{t+1} = \frac{\sum_{i=t-n+1}^{t} A_i}{n}$$

8.3 Exponential Smoothing Forecasting Method

Exponential Smoothing forecasting model is an weighted moving average which predicts the demand of the next period by taking the sum of the previous period's forecast and the actual demand multiplied with a smoothing constant, α .

$$F_{t+1} = \alpha A_t + (1 - \alpha) F_t$$

8.4 Artificial Neural Network ANN Forecasting Method

Artificial neural networks work by altering the input to fit the output. This is done by processing the input through multiple layers. The Input received from different neuron is first multiplied by a weight which may be of a value that reduces the total error of the system. The bias added to it shifts the function to further improve the error. The activation function then controls how much a neuron would be expressed. The whole system works on back propagation which means that the output result compared to the target result influences the weight and bias added to each layer. Hence using a gradient decent algorithm we can minimize the error by finding the gradient decent. The equation below describe a neural network and back propagation in mathematical form.

$$Q = xw + b \tag{8.1}$$

$$y = \frac{1}{(1 + e^{-Q})} \tag{8.2}$$

$$\frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial Q_j} \frac{\partial Q_j}{\partial y_i} \tag{8.3}$$

Data Analysis and Comparison

9.1 Data Source

In order to acquire data for training the deep neural network and predicting demand, we used data from Power Data Reference Book issued by National Transmission and Despatch Company (NTDC) who are the custodians of wide range of data related to power system of Pakistan. The Power Data Reference book contains various important power system data such as historic demand, capability, load not served, annual generation mix, category-wise sales of electricity units etc. Volume 2 of the reference book contains power system operation data for years 2010-11 to 2016-17 that we used for our project as well Transmission and Company (2017)

9.2 Forecasting with Naive

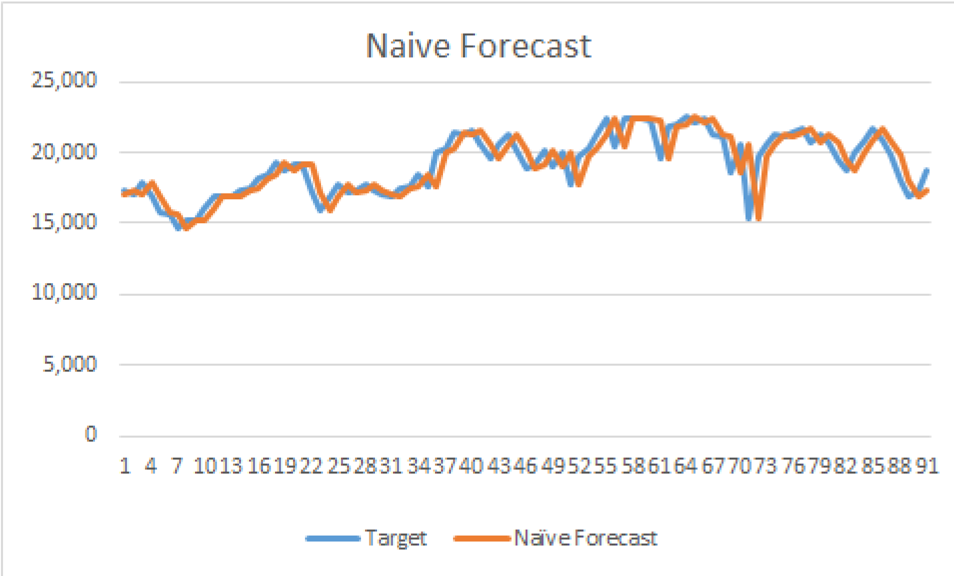


Figure 9.1: Forecast with Naive Model

Applying Naïve forecast technique to the demand of electricity, as indicated by figure 3.1, shows significant discrepancies between forecasted demand and the actual demand for the year 2017. For 10th June 2017, for instance, where the forecasted demand was around 21,000 kW, the actual demand turned out to be 15,000 kW. Figure 3.1 shows the actual and forecasted demand for power in the years 2014-2017. It can be seen that there is no noticeable difference between both the variables but, zooming in, that is during the year of 2017, the differences become significant enough to be considered damaging. Although this method is inexpensive to understand, develop, store data and operate, there is no consideration of causal relationships and the method does not produce accurate results.

9.3 Forecasting with Moving Average Sum

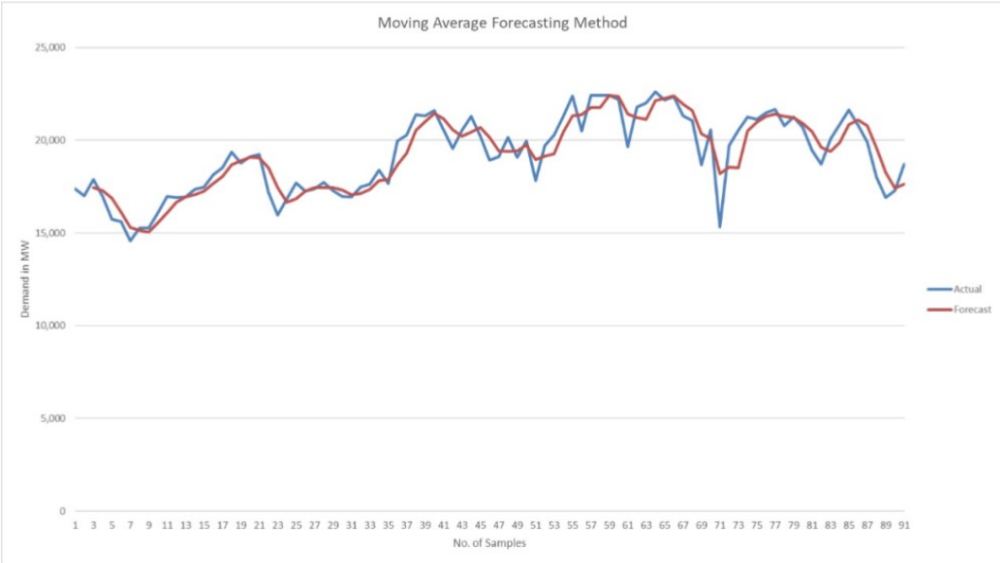


Figure 9.2: Forecast with Moving Average Model

The above figure shows the implementation of moving average sum technique on the data set to forecast demand alongside with the actual demand as a comparison to display accuracy of forecast. Moving Average Sum is calculated by adding up all the data points during a specific period and dividing the sum by the number of time periods. For its implementation, we are taking data sets from a few end months of 2017 and applying the MAS forecasting formula on the selected data. The results are quite accurate, however, it is not efficiently predicting the demand where there is drastic variation. As explained above, moving average sum works well when the demand is smooth and there is not a lot of variation. However, there is considerable variation in the power demand as shown by the actual demand curve. Hence, it fails to provide the required degree of demand forecasting accuracy.

9.4 Forecasting with Exponential Smoothing

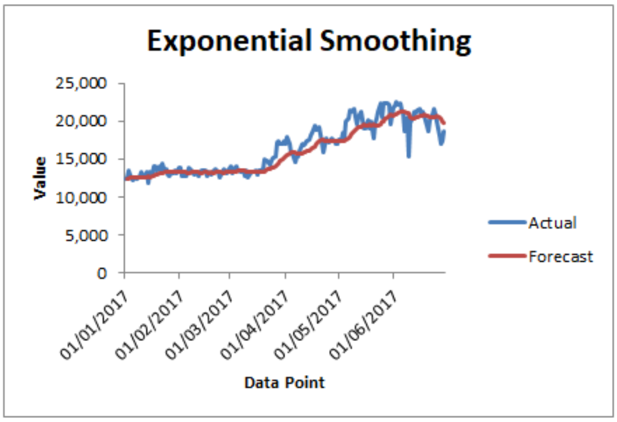


Figure 9.3: Forecast with Exponential Smoothing Model

The above figure shows the implementation of exponential smoothing technique on the data set to forecast demand alongside with the actual demand as a comparison to display accuracy of forecast. Exponential smoothing is a traditional forecasting technique that is essentially used to smooth or level the demand curve as to find the general trend of demand. For its implementation, exponentially decreasing weights are assigned to observations as they get older. This cancels out the effect of random variation and gives the general trend of the data set/time series. The exponential smoothed curve obtained for the above data set displays the trend quite accurately. However, it might not take into account all forms of variation that occur in between. Therefore, there is room for much accurate forecasting.

9.5 Forecasting with ANN

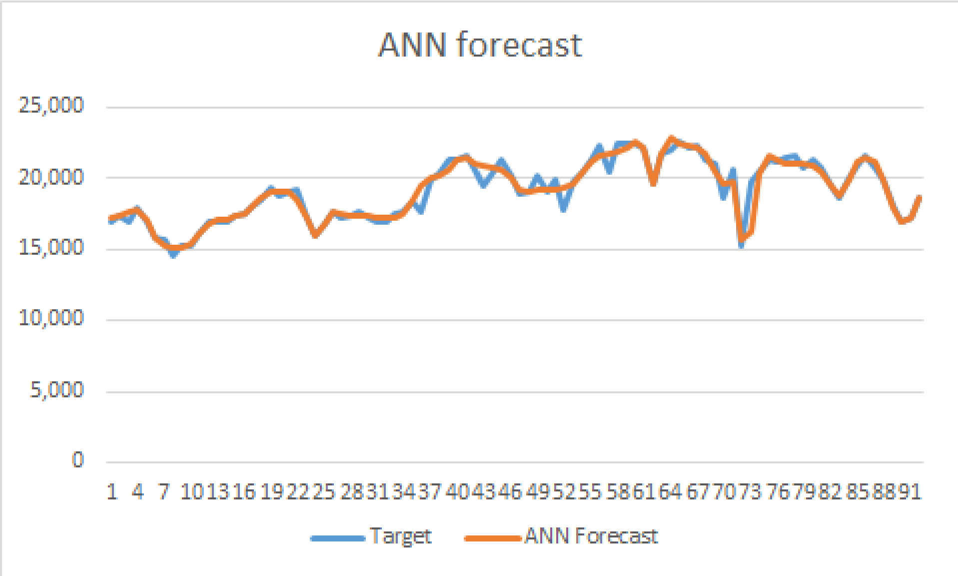
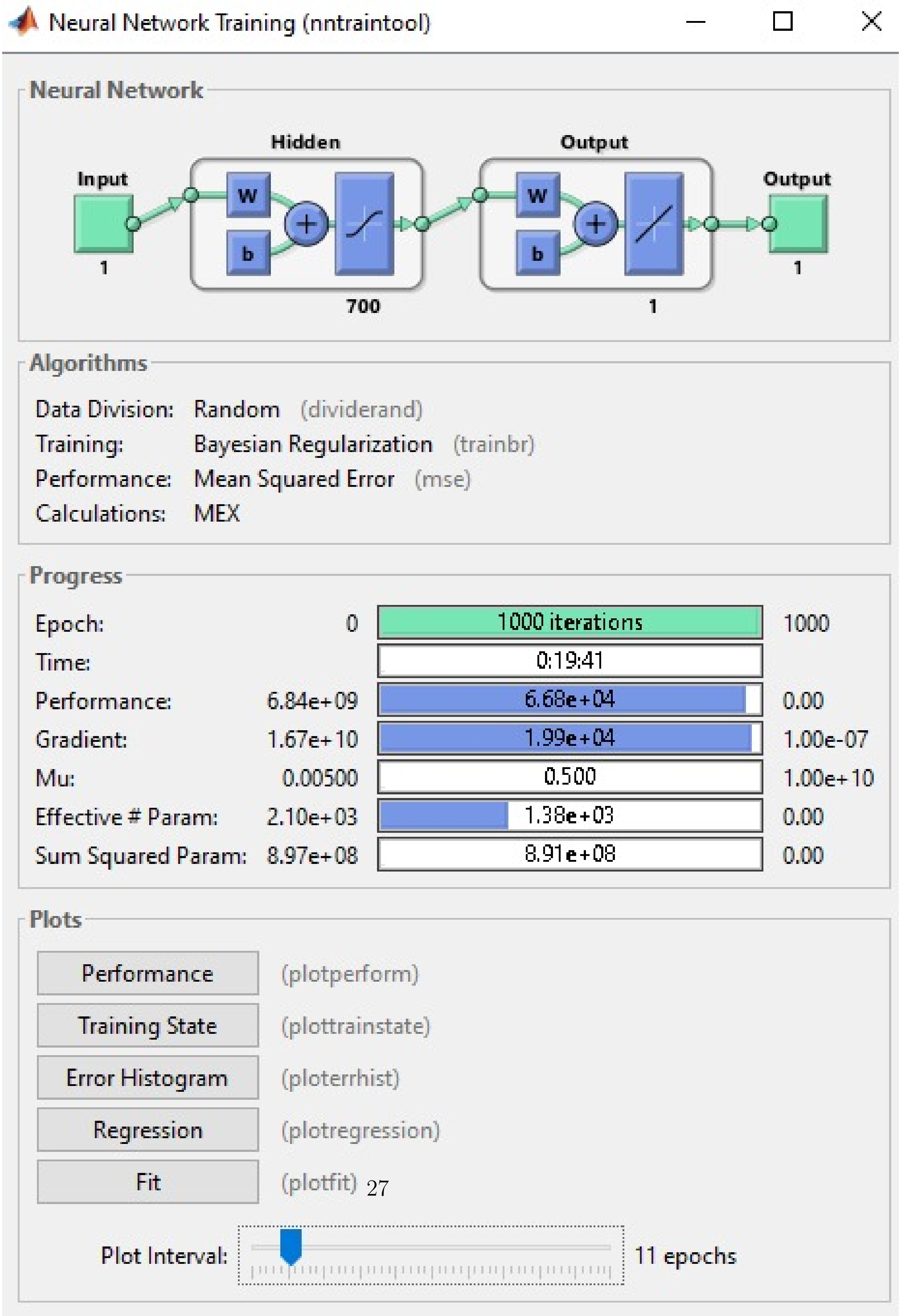


Figure 9.4: Forecast with ANN Model

Figure 9.4 shows the demand forecasting of electric power for the later part of 2017 along with the actual demand for the same period to show comparison:

The analysis is done using MATLAB's Artificial Neural networks library. The algorithm selected for this analysis was Bayesian Regularization. Number of neurons selected were 700. The figure below shows the specifications of the neural network created in MATLAB:


Neural Network Training (nntraintool)
Neural Network
Hidden
Output
Input
Output
W
b
W
b
1
700
1
1
Algorithms
Data Division: Random (dividerand)
Training: Bayesian Regularization (trainbr)
Performance: Mean Squared Error (mse)
Calculations: MEX
Progress
Epoch: 0 1000 iterations 1000
Time: 0:19:41
Performance: 6.84e+09 6.68e+04 0.00
Gradient: 1.67e+10 1.99e+04 1.00e-07
Mu: 0.00500 0.500 1.00e+10
Effective # Param: 2.10e+03 1.38e+03 0.00
Sum Squared Param: 8.97e+08 8.91e+08 0.00
Plots
Performance (plotperform)
Training State (plottrainstate)
Error Histogram (ploterrhist)
Regression (plotregression)
Fit (plotfit)
Plot Interval: 11 epochs

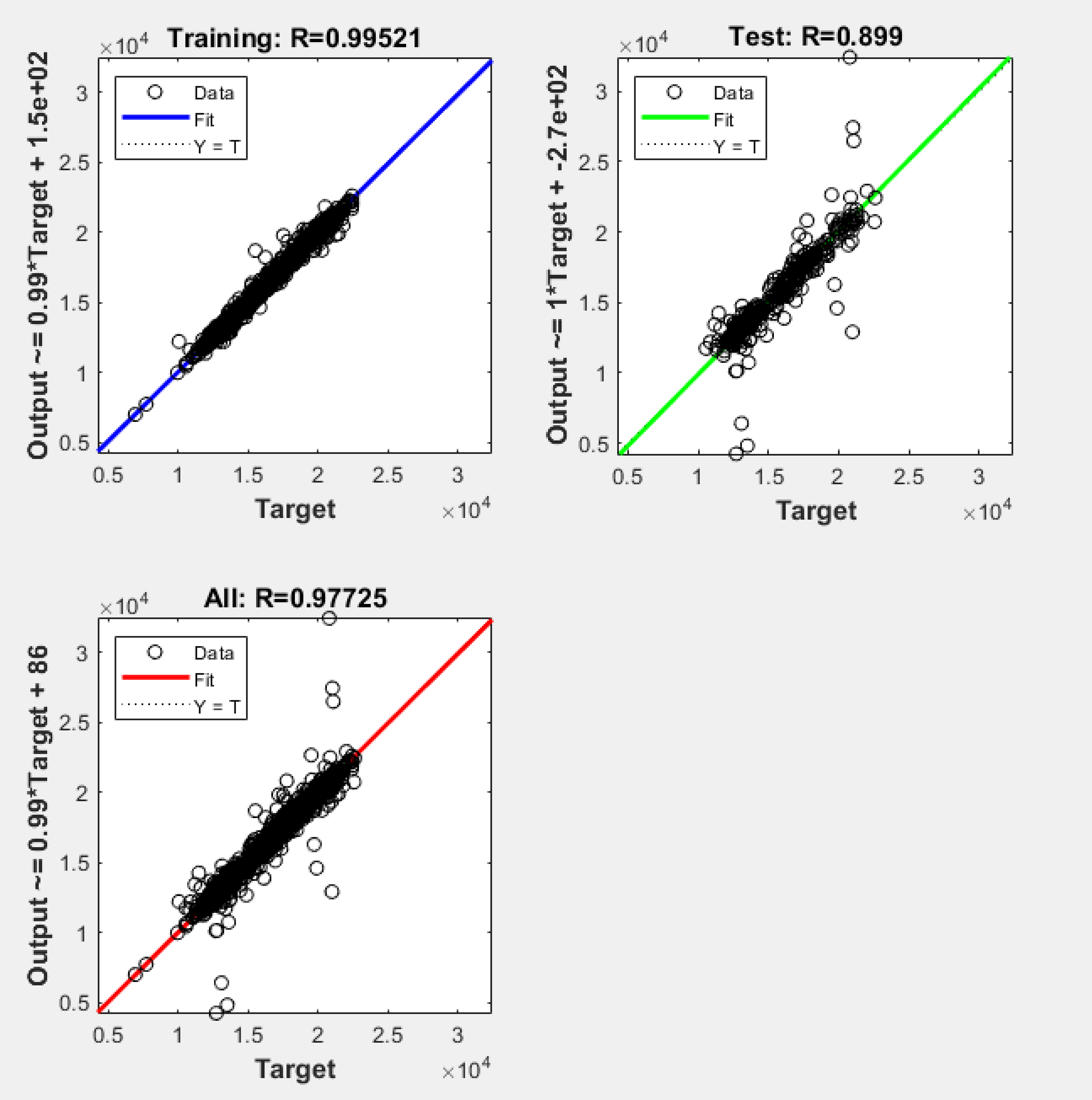


Figure 9.6: Regression Analysis of ANN

Figure 9.6 shows the regression analysis of the neural network. This shows that there is a positive correlation with our data for all categories. The Test shows that our data is not over fitting, hence

the model is very effective.

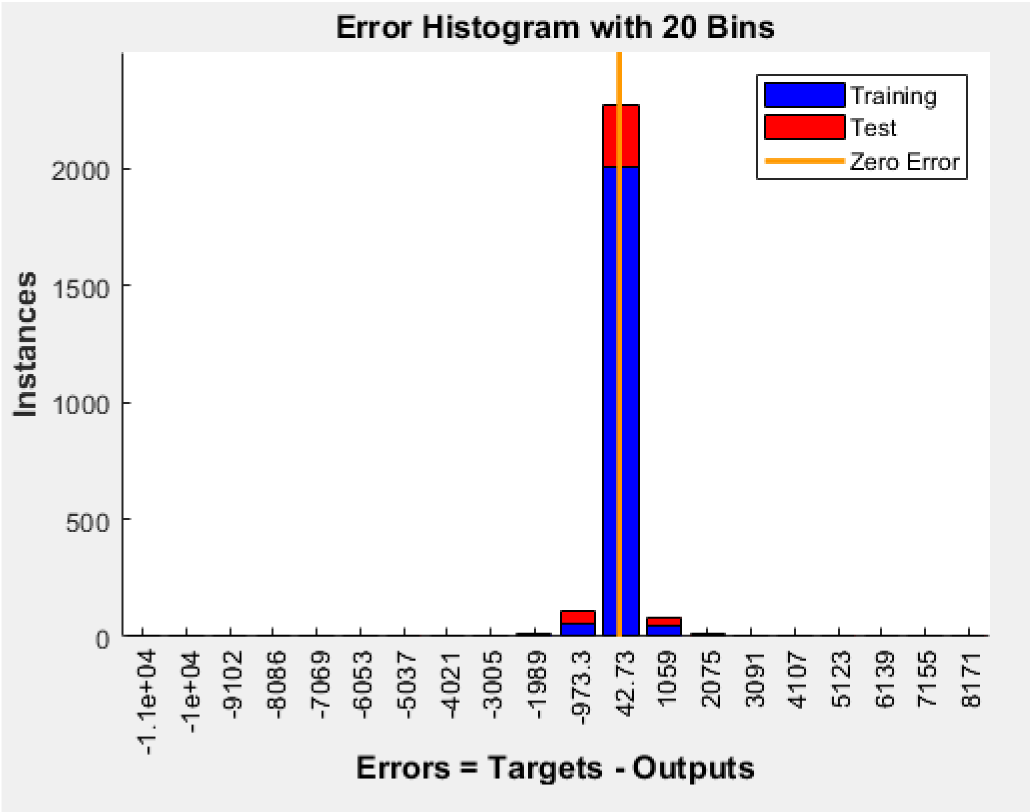


Figure 9.7: Error Histogram

The histogram above shows the error between the values for training set, validation set and the test set. The number of instances shows the frequency of event, while x axis shows the error between target and output values. As we can see that the error is normally distributed. The test data is has a very low error, and the mean lies at the zero line. Hence the model is effective.

9.6 Comparison of Forecasting Techniques

In order to analyze the different models we have applied, we will be taking the mean absolute values and the standard deviation for all models and compare it with each other. The smallest Absolute error and the least deviation would be the best choice.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$
$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$$

Methods	**Mean Absolute Error**	**Standard deviation**
Artificial Neural Networks	330.3057929	475.1963217
Exponential Smoothing	793.11	797.99
Naïve	888.318681	846.709661
Moving Average	622.7978	511.5064

As seen from above the Mean Absolute error (in MW) of Artificial Neural Network is the smallest. Since the electric grid requires very precise values, we can select artificial neural network. As discussed, most energy comes from natural gas and the demand for natural gas directly depends on generation of electricity. Hence in order to integrate the supply chain and reduce the chance of bullwhip effect. We can use artificial neural networks to train past year data and forecast data for the next time period.

Results and Conclusion

The objective of this paper was to study the bullwhip effect, underlying causes and possible remedies of the bullwhip effect in supply chains, and show the effectiveness of demand forecasting models using quantitative and graphical approach. One of the major aim is to become fully integrated. However, this may not be possible due to difference of strategies and goals. Hence, new advanced techniques like artificial neural network can be employed to accurately forecast demand and order batching. The increase in accuracy of demand information will help to reduce the bullwhip effect. Hence, demand forecasting using artificial neural network instead of traditional techniques is valid and practical approach to reduce the inefficiencies due to the amplification in rate of change of demands. The results of this paper shows that the artificial neural network forecasts accuracy is better than the traditional approaches. With smart grid system being introduced, this new approach will become more efficient as we would have more data to train, as well as more inputs that can be a deciding factor on the change of electric demand at a particular time. Hence reducing power outages due to high demand.

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