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RESEARCH ARTICLE

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DEMAND FORECASTING MODELING SUPPLY CHAIN USING A NEURAL NETWORK

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ABSTRACT

Demand forecasting is an important issue for manufacturing companies . It can affect several areas of the company. Indeed, such forecasting is decisive in the management of the production systems as inventory management and production planning .It is possible to use soft computing applied to demand forecasting, for both long-term and short-term forecasting. Among several techniques, Artificial Neural Networks (ANN) has been widespread to solve prediction and forecasting problems. This work aims at applying Elman ANN (ENN) to forecast the sales demand in Wasit company for textile industries in Iraq.

The performance is compared to the real sales data and the forecast data to calculate forecast error using mean square error (MSE).

Demand forecasting will assist the company on understand customers' demands, then put the plans for customers satisfaction and achievement of maximum profits.

1. INTRODUCTION

Textile industry in Iraq is characterized by its historical authenticity as being one of the meaningful economic activities Mesopotamia is well-known for since past ages, it is still an object of society interest and need.

Textile industry is one branch of great and widely spread manufacturing industries which means any activity that change fibers and threads to another type of textile, which is a final suitable product for human use.

Demand forecasting has attracted the attention of many research works. Many prior studies have been based on the prediction of customer demand based on time series models such as moving-average, exponential smoothing, and the Jenkins method, and casual models, such as regression and econometric models [1] .

Artificial intelligence forecasting techniques have been receiving much attention lately in order to solve problems that are hardly solved by the use of traditional methods. ANNs have the ability to learn like humans, by accumulating knowledge through repetitive learning activities. Animal brain's cognitive learning process is simulated in ANNs [2] .

Aburto and Weber (2007) [3]presented a hybrid intelligent system combining Autoregressive Integrated Moving Average models(ARIMA) and NN for demand forecasting in SCM and developed an inventory management system for a Chilean supermarket.

Rahman (2008)[4]study a classical ARIMA model is developed for a single dataset, and the Bayesian method is applied to the selected ARIMA model with the purpose of forecasting demand from the dataset that contains missing values. In the proposed model, the Bayesian ARIMA is studied to forecast seasonal demand when there are missing values in the data series.

Wang etal. (2011) [5] used an artificial neural network and time series analysis for short-term solar irradiation forecasting. Diffused radiation, temperature, relative humidity and time were used as inputs in the neural network model, and double hidden layers were applied with two transfer functions, tang-sigmoid and log-sigmoid.

Kumar et al.(2014)[6]studies developed a comparative forecasting mechanism based on ANN and different training methods. To demonstratethe effectiveness of the proposed methodology, demand forecasting issue was investigated on a valve manufacturing company as a real-world case study.

Kochak and Sharma (2015)[7] studies developed a cooperative forecasting mechanism based on ANN and training methods. The effectiveness of forecasting the demand signals in the supply chain with ANN method and identify the best training method. Demand forecasting issue was investigated on a manufacturing company as a real-world case study.

2. Demand Forecasting in a Supply Chain

Demand forecasting is the activity of estimating the quantity of a product or service that consumers will purchase in future. Forecasting of future demand is essential for taking decisions related to supply chain [8]. Forecasting is being used for a company to plan its resources and its capacity to be able to meet the customer demand in the best possible way. Forecasting have also daily impacts on different levels within a company, levels such as strategic, operational and tactical. The most important demand is the primary demand. The primary demand is affecting the rest of the supply chain since they are anticipating its production towards it .Demand forecasting is the activity of estimating the quantity of a product or service that consumers will purchase in future. It involves techniques including both quantitative and quantitative methods. Quantitative methods include educated guess, prediction, intuition , etc whereas quantitative methods are based on the use of past sales data or current data from test markets. It may be used in making pricing decisions, in assessing future capacity requirements , or in making decisions on whether to enter a new market not[9].

3.Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) have been used to solve different kinds of problems such as classification, regression, optimization, clustering, and forecasting. Based on its capacities, neural networks have been used to solve problems in different areas, e.g. time series prediction [10].A neural network is a set of interconnected neural processing units that imitate the activity of the brain. These elementary processing units are called neurons. Figure (1) illustrates a single neuron in a neural network.

In the Figure, each of the inputs x_i has a weight w_i that represents the strength of that particular connection. The sum of the weighted inputs and the bias b is input to the activation function f to generate the output y. This process can be summarized in the following formula [11]:

$$y = f\left(\sum_{i=1}^{n} X_i w_i + b\right) \qquad (1)$$

A activation function controls the amplitude of the output of the neuron[9].

Multilayer neural networks contain one or more hidden layers of neurons between the input and output layers.

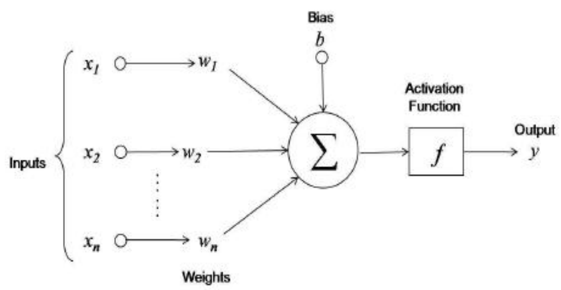

Figure (1) Artificial Neuron Model[11]

4. Elman Neural Network (ENN)

Elman Neural Network (ENN) is a type of partial recurrent neural network, which consists of two-layer back propagation networks with an additional feedback connection from the output of the hidden layer to its input layer. The advantage of this feedback path is that it allows ENN to recognize and generate temporal patterns and spatial patterns. This means that after training, interrelations between the current input and internal states are processed to produce the output and to represent the relevant past information in the internal states[12].

However, since ENN often uses back propagation (BP) to deal with the various signals, it has proved to be suffering from a sub-optimal solution problem. At the same time, for the ENN, it is less able to find the most appropriate weights for hidden neurons and often get into the sub-optimal areas because the error gradient is approximated [13].Furthermore, The efficiency of the ENN is limited to low order system due to the insufficient memory capacity. Therefore, several approaches have been suggested in the literature to increase the performance of the ENN with simple modifications. Also these improved modifications attempt to add other feedback connections factors to the model that will increase the capacity of the memory in order to overcome the tendency to sink into local minima. However, gradient descent (back propagation) used by ENN has the disadvantages of being trapped in local minima resulting in sub optimal solutions and calculations are not as straightforward since it requires functional derivatives. So the gradient descent method for ENN still holds various disadvantages which is difficult to overcome[14].

Elman network necessary using a feedback connection form the layer output to the layer input as Figure (2) . This recurrent connection allows the Elman network to both detect and generate time-varying patterns.

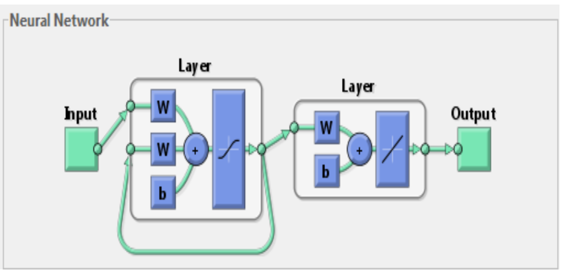

Figure (2) Elman network in Matlab program

5.Proposed Model for Sales Demand Forecasting in a Textile Factory

Demand forecasting is an important issue for manufacturing companies . It can affect several areas of the company. Indeed, such forecasting is decisive in the management of the production systems as inventory management and production planning .

The monthly sales data used from the years (2012 to 2015), andthe years (2012 to 2014) in ***train stage*** and using the networks as inputs and outputs, whereyear 2013 consider output to year 2012 and input to year 2014 .

We will consider the base year data of year 2014 in 12^{th} month to calculate next year data of 2015 but 2015 data are available nonetheless cannot consider as a forecasting data only consider as atarget data.To calculate the forecasting error between actual data of 2015 and forecasting data 2015in ***test stage*** to calculateMSE to network and measure forecasting accuracy , then the demand pattern forecasts for 12 months of 2016 are made in ***forecast stage*** as Figure (3).

6.Sales Demand Forecasting for Products Textile Factory

There are three products for products textile factory will forecasting for years 2016 after applied Elman network ,where use real data for sales demands for products
printed striped weave, poplin weave and plain weave.

6.1. Sales demand forecasting forPrinted Striped Weave

Table (1) represent real data for sales from year (2012 to 2015) and forecasting for years 2016,the result explain is mean square error (MSE=93214000) and Figure (4) represent test stage and figure(5) forecast stage for this product .

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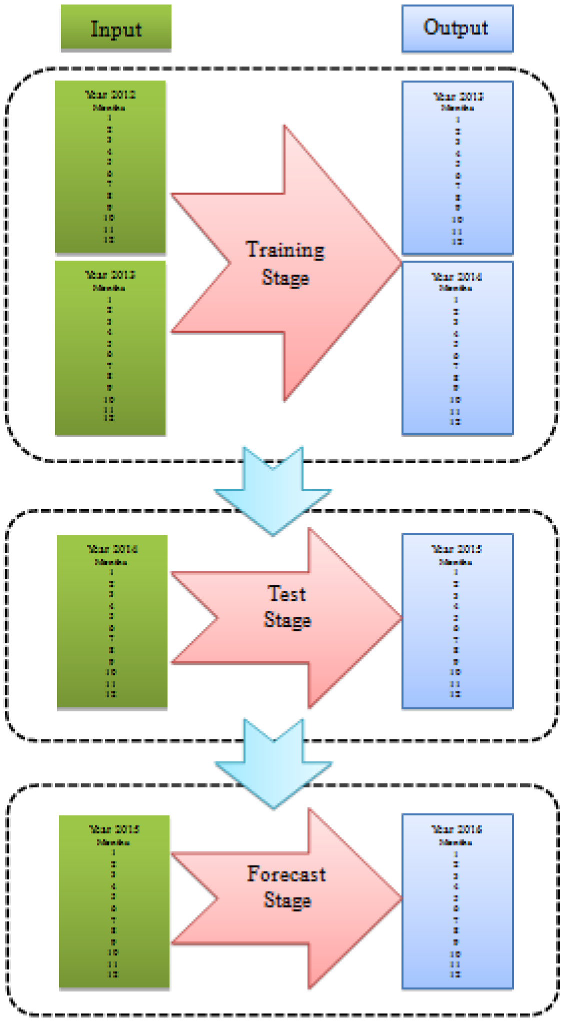

Figure (3) Forecast process in this proposed model using Elman Network

Table (1) Data of Printed Striped Weave

Month	Actual values				Forecast values	
	2012	2013	2014	2015	2015	2016
January	**33690**	**89360**	**100010**	**87480**	**98560**	**94990**
February	**52560**	**75620**	**94940**	**69720**	**70840**	**88440**
March	**50190**	**51990**	**44180**	**42010**	**48240**	**49440**
April	**55870**	**99690**	**111780**	**93690**	**109840**	**109580**
May	**47270**	**57870**	**65560**	**63245**	**68160**	**61130**
June	**54250**	**60000**	**52920**	**52686**	**54690**	**49160**
July	**53140**	**41430**	**53980**	**31450**	**51440**	**54650**
August	**10330**	**15660**	**73960**	**62540**	**62880**	**10210**
September	**52450**	**62880**	**68020**	**58240**	**69870**	**65540**
October	**41680**	**69700**	**76700**	**86500**	**80940**	**78590**
November	**34580**	**71040**	**88020**	**82540**	**85090**	**82720**
December	**40000**	**36660**	**37850**	**47500**	**37790**	**37300**

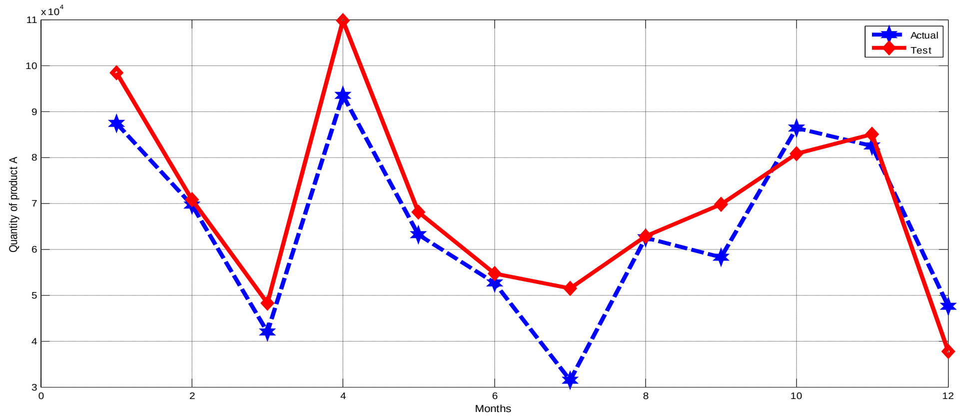

Figure (4) Test Stage for Printed Striped Weave

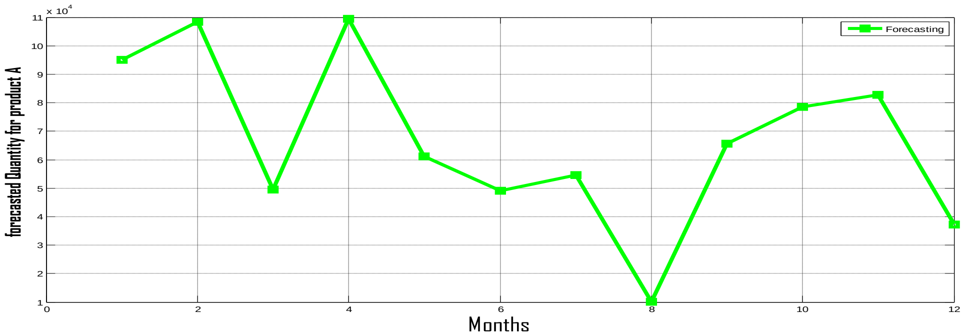

Figure (5) Forecast Stage for Printed Striped Weave

6.2.Sales demand forecasting for Poplin Weave

Table (2) represent real data for sales Poplin Weave from year (2012 to 2015) and forecasting for years 2016,the result explain is mean square error (MSE=630260000) and figure (6) represent test stage and figure(7) forecast stage for this product.

Table (2) Data of Product Poplin Weave

Month	Actual values				Forecast values	
	2012	2013	2014	2015	2015	2016
January	**22500**	**25920**	**57190**	**39570**	**34570**	**75890**
February	**45200**	**50280**	**65745**	**23490**	**69210**	**62980**
March	**40400**	**46440**	**81540**	**30835**	**44980**	**103970**
April	**44400**	**46200**	**55080**	**48555**	**59150**	**51300**
May	**40500**	**37500**	**86680**	**94840**	**81660**	**86730**
June	**39500**	**32490**	**57510**	**83850**	**54730**	**51930**
July	**31150**	**32400**	**41880**	**52570**	**41920**	**42800**
August	**24700**	**37410**	**52225**	**69420**	**59650**	**46170**
September	**42000**	**52010**	**52890**	**57635**	**52330**	**52880**
October	**43320**	**43320**	**97330**	**94840**	**123070**	**70510**
November	**32100**	**33480**	**64798**	**36975**	**91180**	**43790**
December	**31000**	**33060**	**60630**	**32520**	**44430**	**67060**

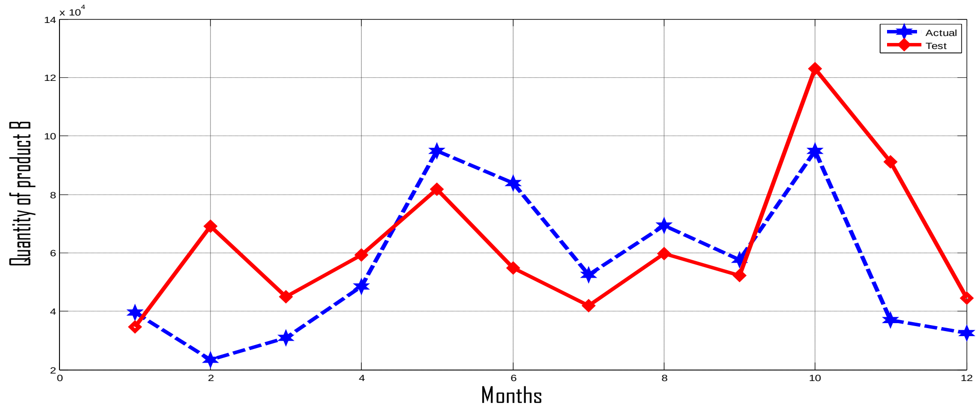

Figure (6) Test Stage for Poplin Weave

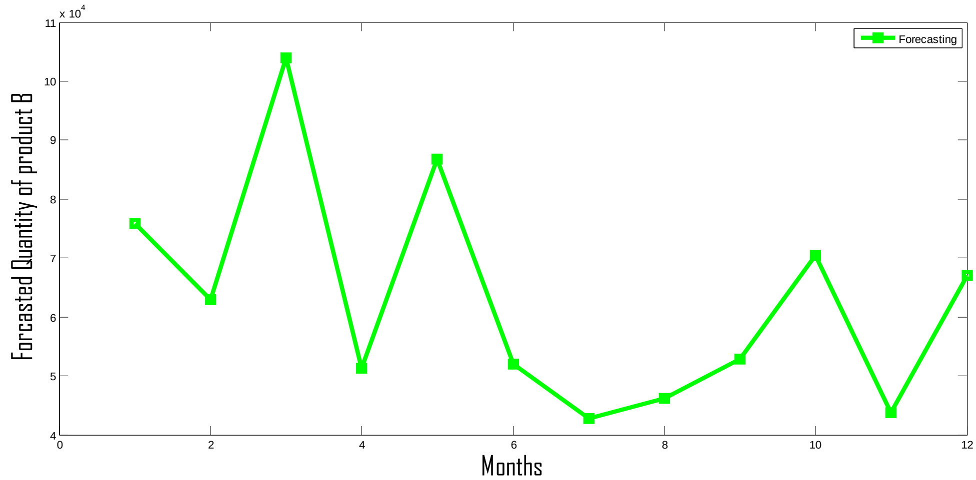

Figure (7) Forecast Stage for Poplin Weave

6.3. Sales demand forecasting for Plain Weave: Table (3) represent real data for sales Plain Weave from year (2012 to 2015) and forecasting for years 2016,the result is mean square error (MSE=1718800000) and Figure (8) represent test stage and Figure(9) forecast stage for this product.

Table (3) Data of product plain fabric

Month	Actual values				Forecast values	
	2012	2013	2014	2015	2015	2016
January	**111500**	**189340**	**255600**	**209640**	**207510**	**208610**
February	**188000**	**202500**	**346170**	**336363**	**343440**	**311670**
March	**165700**	**278920**	**364510**	**335800**	**312340**	**290050**
April	**190400**	**182900**	**162440**	**110505**	**180040**	**173460**
May	**160500**	**186720**	**232200**	**241265**	**224160**	**207110**
June	**144440**	**156420**	**206820**	**221030**	**139220**	**141570**
July	**663500**	**78810**	**81560**	**99145**	**80570**	**80080**
August	**895400**	**102149**	**186946**	**221775**	**137990**	**106140**
September	**46312**	**72312**	**93380**	**103480**	**83480**	**77060**
October	**150400**	**160470**	**182080**	**187820**	**178140**	**187120**
November	**195680**	**180180**	**165560**	**156955**	**175420**	**181900**
December	**180030**	**190530**	**158550**	**160500**	**160340**	**155530**

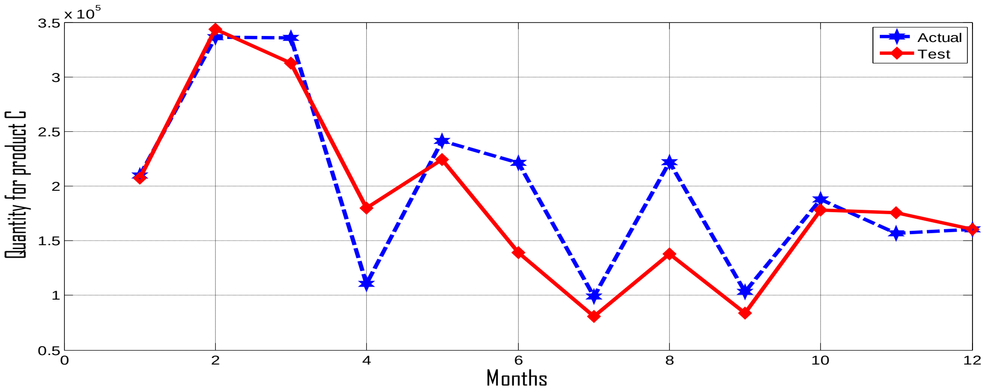

Figure (8) Test Stage for Plain Weave

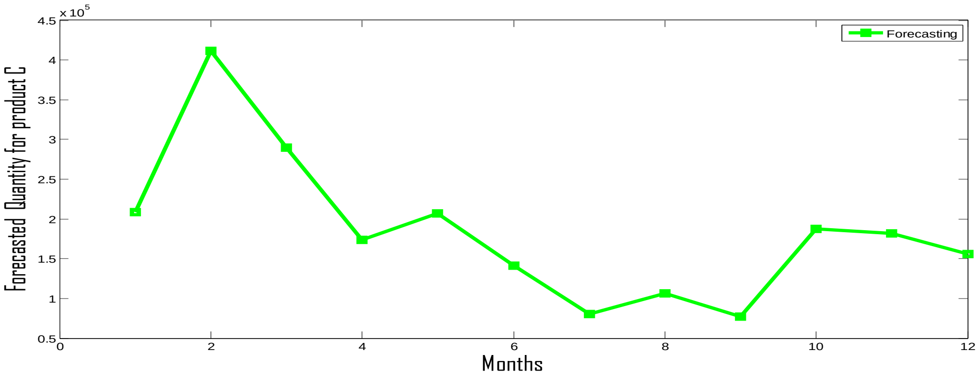

Figure (9) Forecast Stage for Plain Weave

7. Conclusion

The objective of this paper was to study the forecasting for the products of was it textile factory with ANN method and used a Elman network.

This model used the monthly sales data from the years (2012 to 2015), and the years (2012 to 2014) used in train stage, where considered year 2013 as output to year 2012 and input to year 2014.

We will consider the base year data of year 2014 in 12th month to calculate next year data of 2015 but 2015 data are available nonetheless cannot consider as a forecasting data only consider as a target data .To calculate the forecasting error between actual data of 2015 and forecasting data 2015 in test stage to calculate mean square error, then the demand pattern forecasts for 12 months of 2016 are made in forecast stage .

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