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Optimizing Demand and Forecasting in Supply Chain Management Using AI

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***Abstract*: This study demonstrates forecasting practices in supply chain management (SCM) at various areas, particularly Life science, Retail Chain, and FMCG. The authors depicts the scenario of forecasting practices based on secondary data and represents SCM role, demand management, collaborative coordination, etc. In addition, the study reveals the limitation and few practical solutions on forecasting to be useful in the business organization. Consequently the authors describe recommendation and proposes a model on forecasting management model. Though this paper highlights in intensive analysis, however, it unlocks further frontiers for the prospective researchers as well as practitioners in order to apply forecasting techniques.**

I.INTRODUCTION

Modern companies need to deal with different issues in challenging environment. The successful companies are more adaptive and promptly follow the updated or revised concepts of business management. Gradually they apply these techniques into functions. Supply Chain Management (SCM) is one of the new concepts in the corporate sector of Bangladesh which was practiced from late 90s. Initially the Multinational Companies (MNC) incorporated Supply Chain Management in their structures and later on other privates and local conglomerates embraced the concepts. Since beginning purchase and materials management were the main functions of SCM, but later on SCM took the integrated shape i.e. consists of sourcing, materials management, manufacturing support, and distribution management. Considering the competitive market scenario, SCM becomes the prime functioning area among the companies. SCM deals with direct, indirect, and services from the origin (as input materials) to end customers as final products.

Forecasting Management

Forecasting plays an important role in business process of a company. This is considered as far most beginning input in SCM dept. and within the organization. Forecasting as part of SCM functions attracts the attention of the companies gradually which time line evolution is close to that of SCM evolution in Bangladesh. Within the organization, marketing dept. submits the forecast in rolling fashion that may be aggregate form, SKU basis, and in SKU basis with place and date of delivery. Usually forecast is submitted at end or at beginning of the month with a consideration of freezing month.

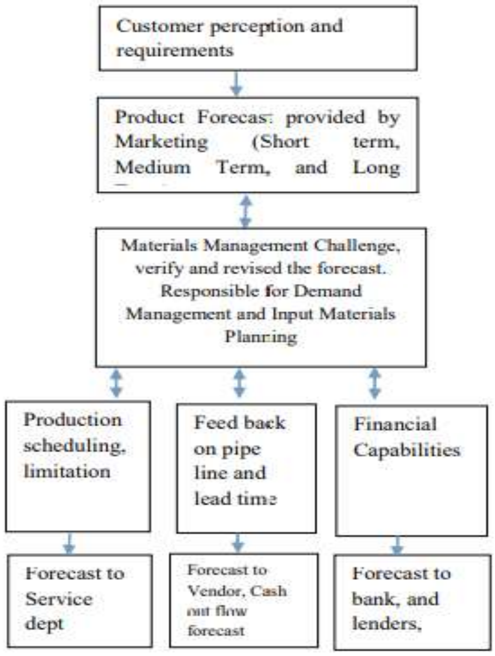

Figure 1 General flow of forecast

Spare Parts Forecasting

the maintenance or production department control the inventory of spare parts. Thus they prepare requisition for spare parts. Though recently limited number of forecasting method on spare parts have been developed, there is no use of these techniques in spare parts forecasting. The issue of spare parts hardly discussed in monthly coordination meeting. Products' character classification and demand pattern are the deciding factors for forecasting of spare parts. The life cycle of spare parts is a deciding factors as final product life cycle is related to it [35]. Most spare parts shows the intermittent demand that is happened at any moment and then remain long time without any demand.

Figure 2 Proposed forecasting management model

Demand planning

It becomes easier to plan for changes in demand if companies understand the demand and the expectations of the customer. Kotler (2003) defines demand management as the responsibility of the marketing organization which means demand forecast is the result of a planned marketing effort. Planning should not only simulate demand but also influence demand in order for companies to achieve their objectives. When evaluating demand planning, two main aspects need to be considered: materials and resources. The relation between these two sets the limit of how to priorities and influence demand.

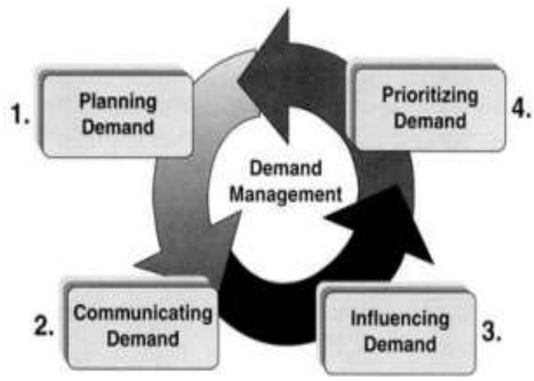

Figure 3 Broad view of demand management

II.LITERATURE REVIEW

S gilaninia et al. [6] in this study, researchers tried to identify of economic factors in the supply of Iranian tourists. In this regard 20 tourist destinations in the time period 2007 to 2011 were reviewed. with linear logarithm function and panel data estimation method was determined that there is significant relationship between per capita income of urban households and the number of tourism supply from Iran and also there is significant relationship between exchange rate and the number of tourism supply from Iran and income has been most important factor.

Y. Barlas et al. [7] Supply chain inventories are prone to fluctuations and instability. Known as the bullwhip effect, small variations in the end item demand create oscillations that amplify throughout the chain. By using system dynamics simulation, we investigate some of the structural sources of the bullwhip effect, and explore the effectiveness of information sharing to eliminate the undesirable fluctuations. Extensive simulation analysis is carried out on parameters of some standard ordering policies, as well as external demand and lead-time parameters. Simulation results show that (i) a major structural cause of the bullwhip effect is isolated demand forecasting performed at each echelon of the supply chain, and (ii) demand and forecast sharing strategies can significantly reduce the bullwhip effect, even though they cannot completely eliminate it. We specifically show how each policy is improved by demand and forecast sharing. Future research involves more advanced ordering and forecasting methods, modelling of other well-known sources of bullwhip, and more complex supply network structures.

HaixiaSang's et al. [8] this paper presents a simulation approach to analyze the rental housing supply chain's inventory problem. Unlike most products, the rental housing unit is a "circulation type" product, and the inventory problem is complicated. In this paper, a systematic and flexible process is proposed that efficiently provides critical decision-making support to managers to help them understand and validate the inventory problem in the rental housing supply chain. The proposed procedure considered inventory impact factors, such as the forecasting method, the lead time, the initial inventory level, and the inventory filling indicator. In addition, the procedure is applied to an actual rental housing supply chain to confirm its effectiveness. Furthermore, the proposed method was found to be both practical and powerful in assisting managers with their continuous decision-making efforts.

Bhardwaj et al. [9] the fashion apparel industry has significantly evolved, particularly over the last 20 years. The changing dynamics of the fashion industry have forced retailers to desire low cost and flexibility in design, quality, and speed to market, key strategies to maintain a profitable position in the increasingly demanding market. This article reviews the literature on changes that have happened in the fashion apparel industry since the 1990s, highlighting the emergence of a concept of 'throwaway' or fast fashion. It describes fast fashion from a supplier as well as a consumer's perspective, and draws attention to several potential research issues.

III OBJECTIVE

The objective of the paper is to propose a forecasting technique which ismodelled by artificial intelligence approaches using artificial neural networks.

To demonstrate effectiveness of the proposed approach using real-world data from a company which is active in the field of footwear distribution in Bhopal.

To get input data from a store of Khadim located at New market, Bhopal and produce the demand for the next year using data for financial year march 2017 to march 2018.

To get output results more effective in deciding the future demands of the store studying the demands of last year sale.

IV.METHODOLOGY

Methodology

Supply chain is a network which includes some companies and sectors. In this network, the material is acquired and processed into intermediate or finished products, and finished products then are sent to the users. Therefore, it can be seen as a multi-level system, including production, distribution, retail and other sectors. Supply chain management means that through designing, planning and controlling the supply chain, logistics, information flow and capital flow, a balance between supply and demand is achieved, customer satisfaction is improved, and overall operating costs of the supply chain is reduced. Based on the foregoing characteristics, neural networks currently applied in the supply chain management are mainly in the following three areas: optimization, forecasting and decision support.

1 Optimization

Neural network is the most popular computing technology to solve the optimization problems. It has an important significance for supply chain management. Currently, it has been studied how to apply neural networks to solve the supply chain management optimization problem, such as shop scheduling, warehouse management, selection of transportation route and so on. Some of these problems are the core problems to build the logistics information system of the enterprise. In addition, compared with other technologies, neural network has a strong adaption ability, and it can promptly consider and accommodate emerging constraints with real-time processing capabilities.

2 Forecasting

For a long time, uncertainty is the biggest obstacle for company decision-makers. The uncertainty in supply chain comes mainly from changes in product demand, delivery delays and mechanical failures Because of the inaccurate forecasting for the local aspects of the supply chain, the overall supply chain will have a big fluctuation and this volatility will progressively enlarge. Thus, how to improve the forecasting accuracy and minimize the uncertainty of supply chain management has become the core issue. As we all know, the information supporting our decision-making generally is not sufficient, which has become the insurmountable obstacles of other forecasting techniques such as expert systems, statistical methods, and time series. But the black box function in neural network can avoid this obstacle, and obtain a more satisfactory forecasting result. Furthermore, the neural network is essentially a nonlinear system. Many of the supply chain forecasting problems are more complex, non-linear prqoblems, which the linear forecasting tools are powerless, while the neural network is even easier.

3 Decision support

When managers are making decisions, there are two problems they are facing. One is that the decision-making information is too large, and the other is that the decision-making information is incomplete. As mentioned earlier, they are serious impediment to the application of expert systems, statistical methods. In contrast, the neural network simulates the human brain thinking. To some extent, it has a "creativity ", so that it can make more rational and informed decisions only with the incomplete information. Now, most of the research for decision support system focused on the management and analysis of the decision-making data.

Due to the neural network's unique identification ability, data classification capabilities and self-organizing capabilities, it becomes the ideal data search technology in supply chain management. A neural network system for determining the potential customer in the sales process has been developed. Another important issue the decision support system faced is how to find the intrinsic relationship between the data from the huge data. Self- organization and generalization capabilities of the neural networks become a powerful tool for solving this problem.

4 ANN

ANNs are information processing systems that simulate the behavior of the human. ANNs obtain the inherent information from the considered features and learn from the input data, even when our model has noise. ANN structure is composed of essential information processing units, which are neurons. They are defined into several layers and interconnected with each other by defining weights. Synaptic weights show the interaction between every pair of neurons. These structures distribute information through the neurons. The mappings of inputs and estimated output responses are calculated through combinations of different transfer functions. We can use the self-adaptive information pattern recognition methodology to analyze the training algorithms of the artificial neural networks. The most commonly used computation algorithm is the error back propagation algorithm.

Neural networks can be divided into single-layer perception and multilayer perception (MLP) networks. The multilayer perception network includes multiple layers of simple, two state, sigmoid transfer functions having processing neurons that interact by applying weighted connections. A typical feed-forward multilayer perception neural network consists of the input layer, the output layer, and the hidden layer. The multilayer perception (MLP) with the back propagation learning algorithm is used in this study because numerous previous researchers used this type of ANN, and it is also a general function approximator.

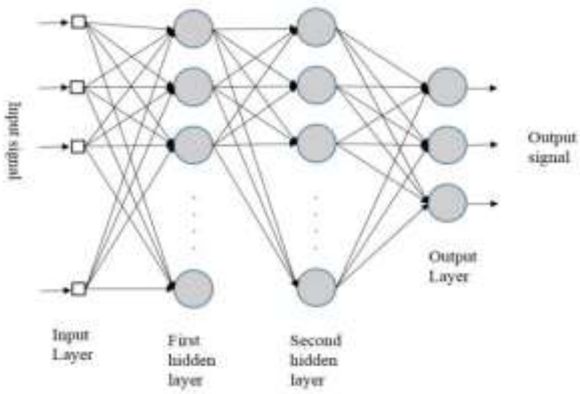

Figure 4.1 Architectural Graph of an MLP Network with Two Hidden Layers.

The development of ANN models was based on studying the relationship of input variables and output variables. Basically, the neural architecture consisted of three or more layers, i.e. input layer, output layer and hidden layer as shown in Fig. 1. The function of this network was described as follows:

$$Y_j = f\left(\sum_i w_{ij} X_{ij}\right)$$

where Yj is the output of node j, f (.) is the transfer function. wij the connection weight between node j and node i in the lower layer and Xij is the input signal from the node i in the lower layer to node j.

MATLAB tool box is used for neural network implementation for functional approximation for demand forecasting. Different back propagation algorithms in use in MATLAB ANN tool box are:

a) Batch Gradient Descent (traingd)
b) Variable Learning Rate (traingda, traingdx)
c) Conjugate Gradient Algorithms (traincgf, traincgp,traincgb, trainscg)
d) Levenberg-Marquardt (trainlm)

1) Batch Gradient Descent (Traingd) : The batch steepest descent training function is traingd. The weights and biases are updated in the direction of the negative gradient of the performance function. There are seven training parameters associated with traingd: epochs, show, goal, time, min_grad, max_fail, and lr. The learning rate lr is multiplied times the negative of the gradient to determine the changes to the weights and biases.

2) Variable Learning Rate (Traingda): With standard steepest descent, the learning rate is held constant throughout training. The performance of the algorithm

is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm may oscillate and become unstable. If the learning rate is too small, the algorithm will take too long to converge. It is not practical to determine the optimal setting for the learning rate before training, and, in fact, the optimal learning rate changes during the training process, as the algorithm moves across the performance surface

The performance of the steepest descent algorithm can be improved if the learning rate is adjusted during the training process. An adaptive learning rate will attempt to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface. (Math works, 2000)

3). Conjugate Gradient Algorithms (Traincgf) : The basic back propagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing more rapidly. It turns out that, although the function decreases more rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In the conjugate gradient algorithms a search is performed along conjugate

directions, which produces generally faster convergence than steepest descent directions. Depending on the search functions we have different training algorithms like traincgf, tracing, traincgb, trainscg. (Mathworks, 2000)

4). Levenberg-Marquardt Algorithm (trainlm): Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed forward networks), then the Hessian matrix can be approximated as

$$H = J^T J$$

and the gradient can be computed as

$$\dot{G} = J^T e$$

where is J the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and **e** is a vector of network errors. The Jacobian matrix can be computed through a standard back propagation technique that is much less complex than computing the Hessian matrix.

This algorithm appears to be the fastest method for training moderate-sized Feed forward neural networks (up to several hundred weights). It also has a very efficient MATLAB implementation, since the solution of the matrix equation is a built-in function, so its attributes become even more

pronounced in a MATLAB setting. (Mathworks, 2000)

Bagging

When small changes in learning data occur, the decision trees become unstable. If the first cutting variables are different because of a minor change in the learning data, the entire structure of the tree may be modified. Bagging, as well as a tree-based ensemble methods, employs the fact that singular trees may produce unstable results but the correct prediction on average. Bagging trains a number of trees on a boot and applies all the constructed trees on the test set. The final prediction is the average value of the predictions resulting from each tree. The superiority of bagging over singular classification or regression trees was introduced by Bühlmann and Yu (2002).

Data Collection

To empirically evaluate the performance of the Neural network method a daily data set collected at Khadim stores from financial year march 2017 to March 2018 is used. In this paper, We want their retail locations. We used the information from New Market station, Bhopal Madhya Pradeh. In applying the ANNs already emphasized in pervious section, the data set was divided into a training and a test set. the training data included the history of unit sales. Because the amount of unit sales for all 111 different products is wide ranging and highly fluctuating, the best method to evaluate our prediction models will be the Root Mean Squared Logarithmic Error (RMSLE), Equation (3) is shown below:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\log(p_i+1)-\log(a_i+1))^2}$$

The Data depicting quantity, rate and gross amount for a particular product with a specific size for certain date of sale has been described below. The mentioned data is a sample of the data for entire financial year from March 2017 to March 2018.

V.RESULTS AND DISCUSSION

MATLAB ANN tool box is used for neural network implementation for functional approximation of demand forecasting. Input for the neural network demand forecasting model:

1. Previous weekly sale

2. Moving average of last 2 weekly sales

3. Moving average of last 3 weekly sale

Output of neural network is the forecasted demand for the next weekly sale. M file programmers are written for demand forecasting using ANN MLP model and RBF network.

Figure 5.1 1ST WEEK FORECASTING

Figure 5.2 2ND WEEK FORECASTING

Figure 5.3 3RD WEEK FORECASTING

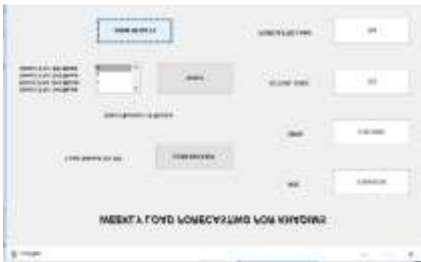

Figure 5.4 4TH WEEK FORECASTING

PERFORMANCE EVALUATION

I. Result analysis with different training function of neural network

Table 1 Levenberg-Marquardt Training Function

	Actual Demand	Forecasted Demand	MSE	RMSE
1ST WEEK	250	252	1.50943	1.22859
2ND WEEK	191	184	4.01887	2.00471
3RD WEEK	217	157	1.68182	1.29685
4TH WEEK	333	359	1.94958	1.39627
Bayesian Backpropagation Training Function				
	Actual Demand	**Forecasted Demand**	**MSE**	**RMSE**
1ST WEEK	250	250	**0.0377358**	**0.194257**
2ND WEEK	191	190	**0.0188679**	**0.137361**
3RD WEEK	217	217	**0**	**0**
4TH WEEK	333	334	**0.0084034**	**0.0916698**

Bayesian Backpropagation Training Function outperforms with minimum error.

II. Result analysis with different transfer function of neural network

Table 2 Bayesian Backpropagation Training Function

Linear Transfer Function				
	Actual Demand	Forecasted Demand	MSE	RMSE
1ST WEEK	250	1648	699.774	26.4532
2ND WEEK	191	352	14.8491	3.85345
3RD WEEK	217	407	7.97727	2.82441
4TH WEEK	333	1546	110.899	10.5309
Transig Transfer Function				
	Actual Demand	Forecasted Demand	MSE	RMSE
1ST WEEK	250	252	**0.0377358**	**0.194257**
2ND WEEK	191	190	**0.0188679**	**0.137361**
3RD WEEK	217	215	**0.0454545**	**0.213201**
4TH WEEK	333	334	**0.00840336**	**0.0916698**

Table 5.3 Levenberg-Marquardt Training Function				
Linear Transfer Function				
	Actual Demand	Forecasted Demand	MSE	RMSE
1ST WEEK	250	390	10.566	3.2505 4
2ND WEEK	191	324	12.622 6	3.5528 4
3RD WEEK	217	437	10.363 6	3.2192 6
4TH WEEK	333	575	9.0084	3.0014

Transig Transfer Function				
	Actual Demand	Forecasted Demand	MSE	RMSE
1ST WEEK	250	192	**5.9245 3**	**2.4340 4**
2ND WEEK	191	53	**15.018 9**	**3.8754 2**
3RD WEEK	217	113	**3.6363 6**	**1.9069 3**
4TH WEEK	333	124	**8.8487 4**	**2.9746 8**

Transig Transfer Function with Bayesian Backpropagation Training Function outperforms better with minimum error.

III. Month wise result analysis

Table 5.4 Bayesian Backpropagation Training Function with Linear Transfer Function				
Month	**Actual Deman d**	**Foreca sted Deman d**	**MSE**	**RMSE**
Jun-17	397	7095	1630.79518 1	40.3831051 4
Jul-17	1152	8640	375.012853 5	19.3652486
Aug-17	2375	13448	2341.09953 7	48.3849102 2
Sep-17	632	11064	1412.27338 1	37.5802259 3
Oct-17	2199	1968	1818.29040 4	42.6414165 3
Nov-17	2826	5909	2815.53273 1	53.0615937 5
Dec-17	1630	13517	2140.86915 9	46.2695273 2
Jan-18	2171	18298	1658.16056 9	40.7205177 9
Feb-18	1726	18400	1952.32287	44.1850978 3
Mar-18	2092	1896	1298.65591 4	36.0368688 1
Apr-18	1195	1333	162.600682 6	12.7514972 7
May-18	574	1083	14.5652173 9	3.81644040 8
Jun-18	553	7017	978.434782 6	31.2799421 8

Table 5 Bayesian Backpropagation Training Function with Tansig Transfer Function				
Mont h	**Actual Deman d**	**Forecasted Demand**	**MSE**	**RMSE**
Jun-17	397	392	0.03012048 2	0.173552 534
Jul-17	1152	1157	0.02313624 7	0.152106 038
Aug-17	2375	2372	0.10416666 7	0.322748 612
Sep-17	632	620	0.17985611 5	0.424094 465
Oct-17	2199	2200	0.02777777 8	0.166666 667
Nov-17	2826	2819	0.20090293 5	0.448221 97
Dec-17	1630	1635	0.06542056 1	0.255774 433
Jan-18	2171	2174	0.15243902 4	0.390434 405
Feb-18	1726	1690	0.44394618 8	0.666292 87
Mar-18	2092	2091	0.00268817 2	0.051847 585
Apr-18	1195	1196	0.52901023 9	0.727330 901
May-18	574	573	0.00621118	0.078811 041
Jun-18	553	552	0.00483091 8	0.069504 805

Mean absolute error is calculated between the actual sales and forecast sales using the output obtained by running M-file programme. The results of forcast are presented in the form of tables for different monts using different methodologies.

The Mean Square Error for different methodologies have been analyzed and it is identified that the MSE is minimum for Bayesian Backpropagation Training Function with Tansig Transfer Function.

VI.CONCLUSION

To demonstrate the effectiveness of the proposed methodology, demand forecasting issue was investigated on a footwear distribution company as a real-world case study. The prediction performance of recurrent neural networks a simulated time series data and a practical sales data have been used. This is because of influence of several factors on demand function in retail trading system. It was also observed that as forecasting period becomes smaller, the ANN approach provides more accuracy in forecast.

Evaluation results indicate that ANN method performs more effectively than traditional forecasting methods in estimation of the more reliable predictions for our case. It is observed that Radial Basis Function Neural Network gives the best forecasting accuracy due to the network architecture. The ability to increase forecasting accuracy will result in lower costs and higher customer satisfaction because of more on-time deliveries. The proposed methodology can be considered as a successful decision support tool in forecasting customer demands.

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