Effective supply chain coordination with hybrid demand forecasting techniques

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ABSTRACT- Effective supply chain is the main priority of every organization which is the outcome of strategic corporate investments with deliberate management action. Value-driven supply chain is defined through development, procurement and by configuring the appropriate resources, metrics and processes. However, responsiveness of the supply chain can be improved by proper coordination. So the Bullwhip effect (BWE) and Net stock amplification (NSAmp) values were anticipated and used for the control of inventory in organizations by both discrete wavelet transform-Artificial neural network (DWT-ANN) and Adaptive Network-based fuzzy inference system (ANFIS). This work presents a comparative methodology of forecasting for the customers demand which is non linear in nature for a multilevel supply chain structure using hybrid techniques such as Artificial intelligence techniques including Artificial neural networks (ANN) and Adaptive Network-based fuzzy inference system (ANFIS) and Discrete wavelet theory (DWT). The productiveness of these forecasting models are shown by computing the data from real world problems for Bullwhip effect and Net stock amplification. The results showed that these parameters were comparatively less in case of discrete wavelet transform-Artificial neural network (DWT-ANN) model and using Adaptive network-based fuzzy inference system (ANFIS).

KEYWORDS: Bullwhip effect, Hybrid techniques, Net stock amplification, and Supply chain flexibility.

1 INTRODUCTION

Value-driven supply chain is defined through improvement and procurement of the suitable resources, metrics and processes, however uncertainties exist due the phenomenon known as bullwhip effect which is noticed in forecast- driven distribution channels due to which sometimes bigger swings occur in inventory to response of customer demand as companies look back at supply chain (SC) while producing products. As the demand of a customer is not always stable so organizations must forecast demand accurately for betterment of inventory control and other costs related to demand. This can be reduced by better supply chain coordination, as coordination between all agents is improved then flow of information will be effective for management decisions (Luis Aburto 2005). Uncertainties which exist due to uneven demand, lead time and manufacturing processes can have major effect on the effectiveness of supply chain management as shown by various studies. (Sodhi &Tang 2011) proposed that one of the chief manifestation of improbability is Bullwhip effect. Lee (1997) identified that major factors for bullwhip effect were variation in prices, shortages of supplies and non-zero lead time. The performance of supply chain management can be enhanced by measuring Bullwhipffect (BWE), average inventory level and cost of supply chain as these are other most influencing factors.

Effective forecasting is challenging area for research as time series pattern is followed in demand. According to Boute and Lambrecht (2009) decreasing Bullwhip effect (BWE) does affect the inventory variations which again influence other costs associated with a business like storage costs and can be minimized to some extent by using time series models such as Autoregressive (AR), it can also be done to anticipate the range of customer demand as some error is always present in prediction. This error is major concern for analysts as this error exist between predicted and actual demand. To improve this area of concern there are hybrid forecasting techniques in which present demand of customer is considered by taking past factors into account. In this work various values from past data were considered to anticipate in coming demand which can be done by assuming the behaviour of past demand data including information of other outside factors which is also called single parameter time series analysis (Makridakis et al.1998; Mukhopadhay 2011). As demand is not linear in this dynamic world so flexibility of supply chain is very important that can adopt various changes so traditional models like Auto regressive, Moving average, Exponential moving average, Autoregressive moving average, Moving average, Exponential moving average, Autoregressive moving average and Autoregressive integrated moving average has been purposed for improvement forecasting accuracy, hence reducing the Bullwhip effect (BWE), but the problems with these models is they are not beneficial for nonlinear patterns. As in case of commercial markets the data exhibits various patterns like fluctuations, instable clustering etc. Therefore, these type of static assumptions are not stable for time series models so researchers are using models such ANN and ANFIS for non linear patterns. Therefore, ANN and ANFIS are adopted as better models for forecasting as these models work in areas where efficiency of time series models is limited. (Hwarng, 2001; Wei, Song, & Khan, 2012). Moreover, stationary or statistical data is not required by these techniques. Wavelet theory is also important as it can be used to investigate problems related to forecasting.

To reduce the uncertainties different hybrid techniques are combined such as Autoregressive Integrated Moving Average(ARIMA) models and Neural networks for the prediction of demand models like Discrete wavelet transforms and Artificial neural network(DWT-ANN model) can be used for improvement of forecasting as these models are used for both linear and non-linear data series another model ARIMA is also used widely for time series models for linear modeling as it rarely check the presence of non-linearity in time series data. In this work discrete wavelet transforms is applied to preprocess the data. In which by using this model, decomposition of a time series signal which is non linear is done into approximate and detail signals of patterns which are known. Artificial intelligence techniques are used for forecasting of real world data. The integrated approaches of DWT with ANN is called DWT-ANN technique and integrated approach of DWT-ANFIS is called as DWT-ANFIS technique. In this paper both techniques were first validated by using data from automobile component (input shaft) monthly sales and bike sales after which results for these techniques are compared with base forecasting techniques. For checking accuracy of these models Root Mean Square Error (RMSE) was calculated. BWE and NSA were also calculated for input shaft sales data for the justification to reduce Bullwhip effect and Net stock amplification with better forecasting technique.

2 RELATED WORK:

There are many forecasting techniques used for effective demand forecasting. In this work only hybrid techniques are considered used in forecasting. So literature for hybrid forecasting is reviewed, also performance measures for effective supply chain are taken into consideration. As information technology industry is growing and developing some new forecasting models such as ANN, combination of fuzzy and ANN (ANFIS) and even wavelet techniques, which can be used for improving forecasting and uncertainties such as Bullwhip effect which was observed by Forrester (1961). Further it was shown through beer distribution game by Sterman. In past evaluation of the Bullwhip effect (BWE) have been done and models were developed for effective coordination. Loung (2007) had examined the Autoregressive coefficients effect on the Bullwhip effect (BWE) for two stage supply chain. Chen et al (2000) had examined the Bullwhip effect (BWE) by forecasting retailer demand through Moving average (MA) time series model. Z. A. Bashir (2009) proposed a model for hourly load demand using adaptive artificial neural networks (ANNs) and used particle swarm optimization (PSO) to compensate networks weight in the introductory stage of ANN's PSO algorithm helped for better load characterization which created better forecasting model. Susmita Bandyopadhyay & Ranjan Bhattacharya (2013) have developed general expressions of Bullwhip effect (BWE) based on the generalized ARMA demand process under the various inventory policies.

Sanjita Jaipuria (2013) proposed DWT-ANN model for forecasting demand and also included the models of discrete wavelet transforms (DWT) analysis and artificial neural network (ANN) to reduce the bullwhip effect. Xiaolong Zhang (2004) worked with ARMA model and applied ARMA-in-ARMA out, model property to examine the demand signal in the supply chain. Its practical implications were discussed for reducing the bullwhip effect for better coordination of supply chain. N. Q. Hung (2009) proposed a new Artificial Neural Network technique for improved forecasting of rainfall performance that was a real case study for rainfall forecasts and results showed ANN forecasts had advantage on other model and Sensitivity analysis that was done for outcome indicated that the most important input variable besides rainfall itself is the wet bulb temperature in forecasting rainfall.

K. Devika (2014) intend to model and optimize the bullwhip effect (BWE) and net stock amplification (NSA) for the three stage supply chain in which retailer, wholesaler and a manufacturer were involved under various scenario to tackle the addressed problem, a proposed Novel multi-objective hybrid evolutionary methodology (MOHES) is a hybrid of two known multi-objective algorithms i.e. multi-objective electro magnetism mechanism algorithm (MOEMA) and population-based multi-objective simulated annealing (PBMOSA) results indicated that the hybrid approach gives superior outcomes as compared with the others and even for coordination for Bullwhip effect (BWE). Shariar Yousefi et al. (2004) introduced wavelet based model for market data on crude oil for forecasting over different horizons to compare results for future oil markets to check there efficiencies of prices. Tugba Efendigil ET a. (2009) proposed forecasting model for uncertainty in customer demands in multilevel supply chain through ANN model compared results with ANFIS. Turgay partal at el. (2009) proposed model for precipitation of meteorological data from Turkey in which wavelet-neural network method which combined two models discrete wavelet transform (DWT)-Artificial neural network (ANN) and results showed that that wavelet-ANN model provided good fit for data that was observed. Khan and Shadehpour (2009) proposed another technique known as wavelet coefficient predictor for analyzing speed of wind from data that was obtained from common places.

3. PROBLEM STATEMENT AND METHODLOGY:

In this highly competitive business world, flexibility plays very important role to achieve new heights by overcoming various fluctuations such as price, demand etc. So the performance of supply chain is improved by using the hybrid forecasting methods instead of conventional methods. In next section these techniques are discussed briefly. External factors are not considered which effect sales as only data for time series is analyzed and used for forecasting. In this work assumptions were done for time series pattern from all factors influencing the demand. This work is proposed to highlight effectiveness hybrid forecasting methods over conventional techniques. As it was observed in this study while using non linear data with models like ANN and ANFIS, it is tough and uncertain to know right data pattern. This uncertainty generated by nonlinear patterns causes the less accurate results. So to improve the forecasting effectiveness, this study uses wavelet theory to preprocess the data before forecasting. To implement the hybrid forecasting data in this study we collected the monthly sales data of input shaft from a supplier to Automobile Company. After proving that the hybrid techniques performs very well than pure forecasting techniques like ANN, ANFIS to justify good forecasting technique leads to reduce reducing BWE and NSA. Validation of hybrid methods to data of bike sales which was taken from a major dealer and data for both input shaft sales and monthly bike sales compared the results with conventional forecasting techniques.So, the outcome of this work was DWT-ANN integrated models gave better results than ARIMA. In methodology integrated models of DWT-ANN and DWT-ANFIS were used.

DESCRIPTION OF SELECTED INTELLIGENT TECHNIQUES

3.1.1 Artificial Neural Network (ANN):

These networks are trained by some kind of learning rule that adjusts the connections weights according to available data trying to minimize an appropriate error function (Wei, Zhang, & Li, 1997). The training can be done with records of past response. ANN structure consists of basically three layers one is input, hidden and output layer. In this work data is split into three parts such as seventy five percent is used for training fifteen percent is used for validation and ten percent for checking. Figure 5 respresents the performance of its data under neural network tool box and it shows MSE is minimum when no iteration reached 6

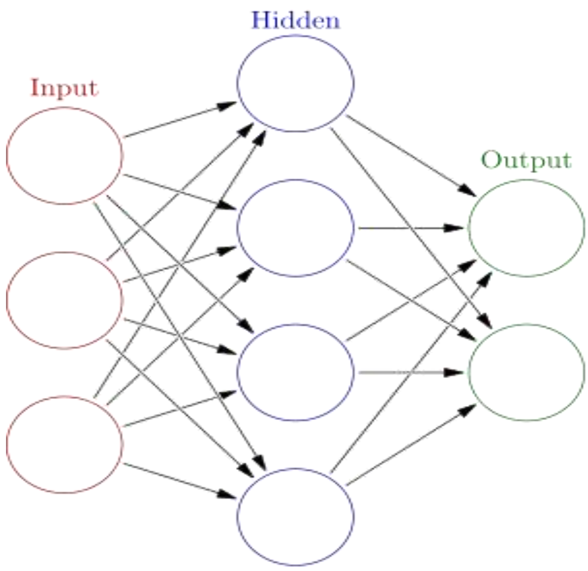

Figure .1 ANN Network diagram

Training of network is done in such a way that the training data set performs a function of mapping between incoming and outgoing values by regulating the connection weight values. Figure 2 represents tryst state of neural network tool box for the given data along with error value.

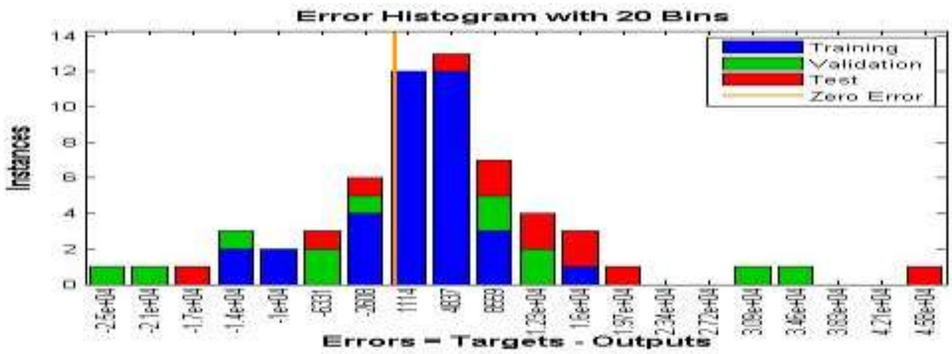

Figure.2-Error historam

3.1.2 Adaptive neuro fuzzy inference system (ANFIS):

In this method neural networks automatically finds the fuzzy rules to control the disadvantages of ANN and fuzzy techniques, as it can be trained as its membership functions are adaptive. It consist of fuzzification rules, normalization data, desfuzzification and signal restoration by the various layers, which are known as multi-layer feed-forward network but the major drawback of this ANN is that it cannot give unconventional relationship for system. Past data is used for demand as input and demand data which was observed is used as an output parameter. Figure 3 shows structure of ANFIS. Further in this work to tune the parameters of a sugeno-type fuzzy inference system ANFIS hybrid algorithm is used in this work. Figure 2 shows error histogram

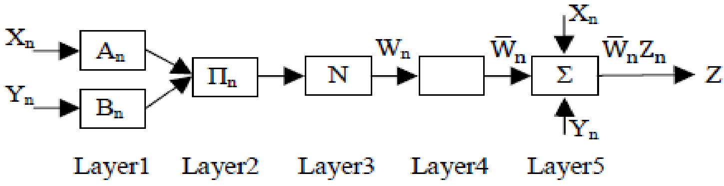

Figure. 3 Structure of ANFIS

3.1.3 Discrete wavelet theory:

For forecasting of future requirements values understanding of patterns of past data is important for the non linear requirement it is tough to find pattern so this nonlinear data was given to ANN directly. As there is a chance of uncertainty for Artificial neural network and it cannot predict accurately so to analyze data pattern WT theory plays important role .To check the pattern of data wavelet theory is important tool. It can be used for processing of data for forecasting algorithms.

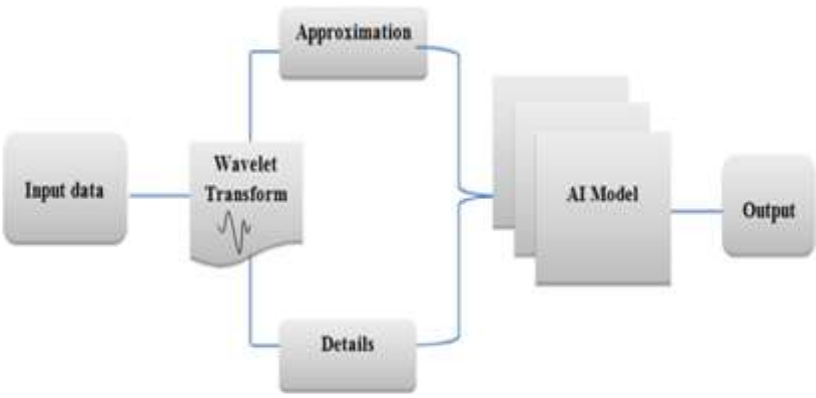

Figure 4. Diagram of hybrid wavelet–AI forecasting model.

3.2.1 DWT-ANN model:

Artificial neural networks are used for better prediction so here in this study discrete wavelet model is used for decomposition of signal to find various patterns of data...These patterns can be separated with decomposition for analyzing signal. Although variety of methods are used under discrete wavelet theory but in this study Daubechies wavelet family is used and it is written as dbN wavelet (Wei et al., 2012). For neural networks in forecasting db1 family and decompose signal in level 3 is used and explained under section 3.1.3. In this D_n (t) and A_n (t) are the details and the approximation signals The Details of D_1, D_2, D_3 are inputs which are given to Artificial neural network with approximation A_3 and calculation of future vales for every signal were done separately to get final results by combining those values and best results were considered for calculation of Bullwhip effect and Net stock amplification.

3.2.2 DWT-ANFIS model:

For ill effected time series data ANFIS is not effective alone so preprocessing of data is important before using with ANFIS model so DWT is used to enhance performance of model. The data is decomposed with using db1 at third level. The randomness of signals was checked. When more random points are present in signal the noise signal is considered unpredictable so this type of signal was not used for analysis as noise can effects the results of model. It was observed during experimentation that D_1 signal was having noise so it was removed from analysis. So inputs for signals A_3, D3, D2 were given for the ANFIS model

Model validation:

For validation of models results were compared with conventional models like ARIMA for which data was taken from dealer of bikes. The decomposition of this data was done by db5 at level 3 in which DWT model was used. Results of every signal were combined to give final results. On the basis of RSME from calculated values in table 1.It is understood that RSME value for hybrid model is less than base model which shows that accuracy can be improved by using DWT model. For comparison with ARIMA models for the calculation of Bullwhip effect and Net stock amplification best results were used. ANFIS gives better results when used with DWT. The forecasting values for ANFIS were calculated, table 2 presents training and testing errors of various combinations for ANFIS model. Secondly for DWT-ANFIS the decomposition of data db5 at level 3 was done. The forecasting operations based on various combinations of ANFIS for approximation and signal details of three signals to get final results by summing up these values. It shows that the signal which is having high frequency and low value, d_1 is erratic signal so it is difficult predict its pattern is precise while the comparing the values of ANN, ANFIS and ARIMA based models so it can be assumed that DWT-ANN is best model for the cases and is considered . So when calculated values are taken into account it can be considered that hybrid models are better than conventional models and also performance of integrated models for DWT with artificial intelligence techniques is better than integrated model of DWT-ARIMA models.

Table 1 Root mean square values for artificial neural networks

Delays	Hidden layer neurons	RMSE by pure ANN	RSME by DWT-ANN
4	7	5289.037681	17191.358
4	12	6909.949717	15066.75307
8	7	4121.518867	14733.1866
8	12	4542.416188	13573.76671
12	7	4770.968591	15400.86913
12	12	3003.513898	13028.11164

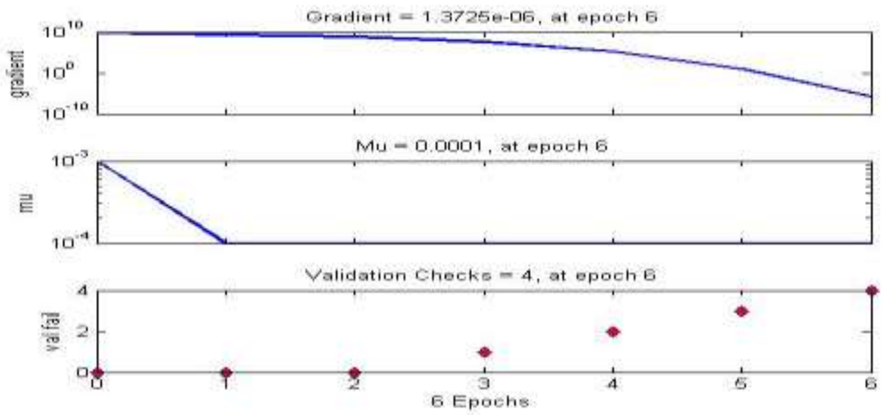

Figure .5

4. CASE STUDY:

In this study monthly sales data of Input shaft a main gear box component of a supplier for top automobile company was taken. As this component is integral part of gear box so its order depend on the no of automobile gear box made by automobile companies. For which we considered its schedule given for manufacturing from the supplier. To improve the forecasting of this firm by using hybrid models instead of conventional models as Company orders its steel requirement only after getting schedule or plan its steel inventories. DWT is used to decompose the original nonlinear data into some known patterns, now it is easy to predict the future values using these patterns by artificial intelligence techniques ANN and ANFIS.

Results and discussion:

The demand forecasting values were evaluated using ARIMA and DWT-ANN models from cases discussed and were used to find forecasting errors by training and testing of RMSE vales for different models as shown in table 2.

Table 2 Testing and training RMSE values of different models of ANFIS.

Membership function input	Input member ship functions	ANFIS model name	Training of rootmean square RMSE	Testing of root mean square
Tri member function	2	Tri member function	9856.34	15966.74
Tri member function	3	Tri member function	7645.83	42945.25
Trap member function	2	Trap member function	9865.56	17560.26
Trapmf	3	Trapmf	9355.34	43105.19
Gbell member function	2	Gbell member function	9283.25	17181.26
Gbell member function	3	Gbell member function	6841.64	406034.77
Gauss member function	2	Gauss member function	9785.7402	16314.367
Gauss member function	3	Gauss member function	6996.76	232067.42

While comparing ANN, ANFIS, DWT-ANN, DWT-ANFIS(with d_1), DWT-ANFIS (without d_1), ARIMA (0,1,1) the values for Root mean square error comes out to be 9709,16577, 2546, 15688,9942, 16,963, 12896 respectively. The Root mean square values for ANN, ANFIS, and DWT-ANFIS (with d_1) and for DWT-ANFIS (without d_1) comes out to be 119.868906, 170.6547, 20.60983177, 165.4498 and 119.5782 respectively. From the above values it can be assumed that effectiveness of ANN techniques can be enhanced with using integrated DWT. So noisy signal $d_1$is removed to improve the performance of ANFIS. In this work it is also observed that for DWT-ANFIS models the efficiency of ANFIS was decreased by signal d_1 for that d_1 was removed. Figure 6 shows regression analysis and past fit values.

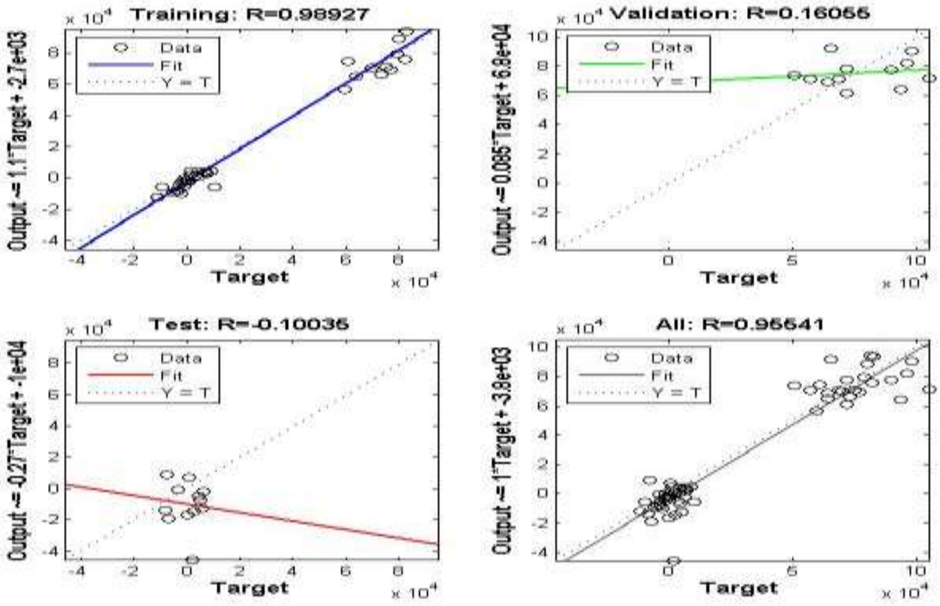

Figure .6 shows regression analysis and past fit values

The values which were estimated from ANN and ANFIS models from various cases and were used to find Bullwhip effect and Netstock amplification. The bullwhip effect was reduced by better forecasting model Lee (1997). For justification the effectiveness of Bullwhip whip effect and NSAmp were calculated. As per Boute and Lambrecht (2009), if Bullwhip effect is equal to unity that means variance is equal to demand. If BWE>1 that means bullwhip effect is present while BWE<1 means orders are less variable than demand as both these cases are not good for organizations as if BWE is greater than unity then there will be increase in order amplification that can lead to increase in manufacturing cost. If it is less than one than it becomes case of non – linear demand which can again lead to inventory cost. If BWE=1 that shows supply chain is working smoothly. For real life situations it's not feasible. As per (Sanjita Jaipuria and S.S Mahopatra 2014) reducing BWE does not always reduce inventory cost. There for NSamp is also important factor if NSAmp >1 it can again increase the costs of inventory. Therefore in this study The BWE and NSA were calculated for forecasting only:

t is calculated as $Q_t = F_t + (D_{t-1} - F_{t-1})$

BWE is calculated by:

$$BWE = \frac{variance\ of\ order}{variance\ of\ demand}$$

NSA is calculated by:

$$NSAmp = \frac{variance\ of\ netstock}{variance\ of\ demand}$$

When effectiveness of various supply chain models is considered for Bullwhip effect and Net stock amplification the values comes out to be as for ANN model BWE comes out to be 0.656836794 and NSAmp 0.355608, for DWT-ANN model BWE values are 0.981377382 and NSAmp 0.26207365, for ANFIS BWE values and NSAamp are 1.41258863 and 0.4569357 while for DWT-ANFIS 0.775896358 and 0.2695137 From these values it is concluded that hybrid models are very good to improve the performance of supply chain. As RMSE value of DWT-ANN is less than DWT-ANFIS model from the cases considered in this study which is cause of betterment of performance of Supply chain in case value of DWT-ANN is greater than DWT-ANFIS. From these values it can concluded that hybrid models can be used to improve the effectiveness of supply chain management. These values also shows that root mean square error values of DWT-ANN is less than DWT-ANFIS model and also performance of supply chain can be better by using DWT-ANN than DWT-ANFIS as shown by calculations.

CONCLUSIONS:

Models like ARIMA are better only when used in case where demand in linear pattern but in this competitive business environment it is not possible for this type of demand to exist. So models like artificial neural network and Adaptive neuro fuzzy inference system are preferred which are considered more effective. So in this work hybrid models were used in which forecasting data was prepressed by discrete wavelet theory model and prediction was done by artificial neural network and Adaptive neuro fuzzy. In this study it is shown that for calculation of BWE and Snap DWT is better. Also comparison of hybrid techniques was done in which it was observed that Hybrid models gave better results than ARIMA models. From literature review it is also concluded that for non linear time series data ANFIS model performance is not as good compared to other models for forecasting future values. As per the objective of this research it is proved that discrete wavelet transform-Adaptive neuro fuzzy interference give better results than Adaptive neuro fuzzy inference system .Considering drawback of work, in this study it is noticed that Artificial neural networks based models are better than Adaptive neuro fuzzy inference models. As in depth work was not done on ANFIS models so one cannot give much views about ANN for prediction. For cross sectional type of data ANFIS is better than ANN TugbaEfendigil et al. (2009). In this work external factors were not considered effecting the data. This can be also main cause for decrease in efficiency of Adaptive neuro fuzzy inference models. For ANN one type of transfer function Log sig (sigmoid) is used, it will be interested if it is used with other transfer function. In this work only Daubechies 5 (db5) is used for type of wavelets at level 3 decomposition so other wavelets can be also used for improving results. Instead of base stock policy this model can be also measured with some inventory controls.

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