# Inventory Classification using Fuzzy Approach and Performance Validaiton using Learning based Methods

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***Abstract*—** Inventory Analysis and Control has become inevitable for a manufacturing industry. Among the various items of inventory not all are of equal importance and therefore decisions as to when and how many to buy or make can be taken by classifying the inventory items based on values. For this evaluation, ABC inventory classification which is one of the most commonly used approaches is considered. The data is taken from the manufacturing sector of Usha Martin Ltd, a leading manufacturer of wire strands located in Jharkhand. Through this paper an attempt is made to use fuzzy membership degrees in segregating the inventory into various classes based on the valuation of the items. Further, an adaptive neuro fuzzy inference system (ANFIS) based approach is adopted to automate the process of inventory classification. The results are compared with that obtained from Multi Layer Perceptron (MLP) and Time Delay Neural Network (TDNN) which are standard leaning based methods. The ANFIS based approach is found to be reliable over data set considered for the work. This would therefore provide useful insights to the company for proper maintenance of their inventory stock based on the importance of the items.

***Keywords:*** inventory, ABC classification, fuzzy membership

## I. INTRODUCTION

Inventory management constitutes one of the important branches of management science. Inventory is the list of goods in stock i.e. total amount of materials contained in a unit or store. In the manufacturing facilities, inventory management is one of the major planning and control challenges facing the managers. Efficient inventory management is indispensable for the success of any business. All the elements of inventory like raw materials, semi-finished and finished goods are key determinants of the firm’s profitability as they block capital. Thus the categories and the amount of the products in the inventory is the key problem. Also it constitutes the core problem of inventory management. Therefore, inventory management has the primary function in dealing with the uncertainties of enterprises and maintaining the stability of production. Thus it is very essential to classify the inventory items which can help managers employ a proper strategy for managing the categories and the amount of products in their inventory. This way, through a proper classification approach, the cost of maintaining the inventory can be reduced considerably.

A study of literature reveals that quite a large number of classification approaches has been used by researchers. To name a few includes ABC classification approach, the CVA classification method, the AHP classification method etc. Inventory in group A accounts for about 20% of the items in the warehouse and 80% of the dollar usage. Inventory in group B accounts for about 30% of the items and 15% of the dollar usage. Inventory in group C accounts for about 50 % of the items and 5 % of the dollar usage. In 1988 Cohen and Ernst [**1**] reported a work in which the results of the use of multiple criteria ABC analysis have been provided to classify the storage inventory. The studies showed that the managers can use both “cost criteria” and “non-cost criteria” in the classification of warehouse inventory and formulate specific policies by using different annual consumption costs, maximizing the rate of inventory criteria to manage warehouse inventory. In 2008, Liang and Liao [**2**] proposed an optimization approach regarding the inventory classification problems at the conditions when inventory items should be classified based on a target or multiple targets, such as minimizing turnover. Mitra et. al [**3**] in their study found that the priorities of the items changes according to different inventory analysis techniques. The management of the company decides which process to follow taking into account their budget, supply, demand, inventory carrying capacity etc. Yun and Yang in 2010 [**4**] presented a study wherein the authors attempted to compare the classification techniques based on artificial intelligence and traditional classification techniques (MDA). In 2010 [**5**], an article was presented entitled “Fuzzy AHP-DEA approach for inventory classification based on multiple criteria ABC approach”. In this article, two approaches of Data envelopment Analysis and fuzzy analytic hierarchy process were combined for multiple criteria ABC classification of inventory

This paper is an attempt to introduce fuzzy membership degrees of evaluation index in inventory classification. The proposed approach includes six steps: the selection of the evaluation indexes, the formulation of the fuzzy membership functions of evaluation indexes, the calculation of the fuzzy membership degrees of evaluation indexes, the sequencing of the fuzzy membership degrees of evaluation indexes, the selection of the inventory types and the inventory classification results. Further, an adaptive neuro fuzzy inference system (ANFIS) based approach is adopted to automate the process of inventory classification. The results are compared with that obtained from Multi Layer Perceptron (MLP) and Time Delay Neural Network (TDNN) which are standard leaning based methods. The ANFIS based approach is found to be reliable over data set considered for the work. The MLP and TDNN methods are taken as benchmark techniques for comparing the results obtained from ANFIS. This approach is quite effective with regard to the management of enterprises.

## II. INVENTORY CLASSIFICATION APPROACH BASED ON FUZZY MEMBERSHIP DEGREES AND ANFIS

The complete work is described using a block diagram as shown in Figure 1. There are two aspects of the work. First, the fuzzy based classification results are generated. The classification results are next applied to ANFIS, MLP and TDNN. The ANFIS is used as the primary classification technique which learns the approach to automate the complete method. The MLP and the TDNN are used as benchmark methods to check the reliability of the ANFIS based method.

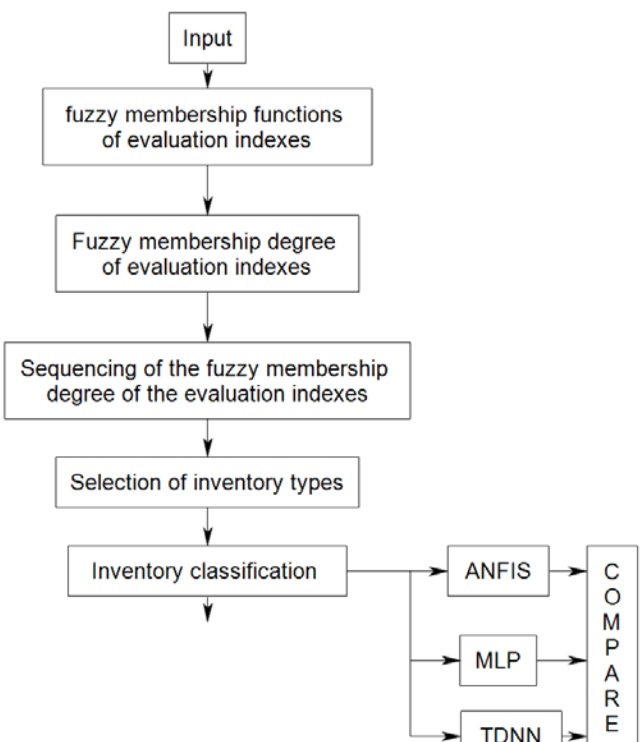


Figure 1: Process logic of the work

The first step is to generate the classification outcome of the inventory items. The steps are discussed below.

A number of fuzzy concepts revolve around the human thinking processes which are not precise and ambiguous in nature. The inventory classification based on fuzzy evaluation indexes includes six steps:

1. Formulation of the fuzzy membership functions of evaluation indexes
2. Calculation of the fuzzy membership degree of evaluation indexes
3. Sequencing of the fuzzy membership degree of the evaluation indexes
4. Selection of inventory types
5. Inventory classification result

With regards to the evaluation indexes for inventory classification, there are several factors which can be considered as per the operation and management of the manufacturing unit. In this paper, the economic values of different products in a year or month are selected as the evaluation indexes.

Once the evaluation indexes are selected, the fuzzy membership functions of indexes of different products need to be formulated. Here, the fuzzy membership functions of the economic value of a specific product with regard to the total economic value of all the products need to be formulated. It is formulated as the ratio between the value of the specific product and the total value of all products and it can be described as the following:

$$m_i = \mu(V_i) = \frac{V_i}{V_{total}} \quad , i \in N$$

where i denotes the categories of products, $V_i$ is the economic value of $i^{th}$ product in a specific time period, its unit is rupees; $V_{total}$ is the total economic value of all the products in a specific time period which is expressed in rupees. Also, $\mu(V_i)$ represents the fuzzy membership function of the value of $i^{th}$ product and the total value of all products, $m_i$ represents the fuzzy membership degree of the value of $i^{th}$ product with regards to the total value of all products and can be any positive real number between 0 and 1.

### *A. Working Procedure [6]*

Step 1. Calculation of fuzzy membership functions represented as $m_i = \mu(V_i) = \frac{V_i}{V_{total}} \quad , i \in N$ (1)

Step 2 .Sequencing of the membership functions which denotes the impact degrees of the products on the total economic values of all products and it is represented as

$$S_i = Seq(m_i) \quad , i \in N \qquad (2)$$

Step 3: The next step is to categorize the various items on the basis of their valuation. In this paper, the various items in the manufacturing unit are classified on the basis of their importance viz. A (important type), B (ordinary type) and C (unimportant type).

The inventory items are formulated as

$$C_{INV} = \{A, B, C\} \qquad (3)$$

With the fuzzy membership degrees of the evaluation indexes of different products and the selection of the inventory types, the inventory classification results can be achieved accordingly.

*B .Numerical Example*

The feasibility of the proposed approach can be achieved by taking the real time data of a manufacturing unit based in Jharkhand viz Usha Martin Ltd (UML). The economic value of some products used by UML are given in Table 1.

Table 1: Economic value of some products used by UML

| Month | Items | Units | Total Rs |
|---|---|---|---|
| Jan | Borax Penta | mt | 345600 |
| Jan | Servo system-60 | ltr | 185500 |
| Jan | Plastic Bobbin DIN | Nos | 73060 |
| Jan | enamel paint | ltr | 1087.66 |
| Feb | HDPE sheet Plain | mt | 340400 |
| Feb | Soap 7080 | kg | 53187.5 |
| Feb | enamel paint | ltr | 1133.56 |
| Feb | Plastic Bobbin DIN | Nos | 57460 |
| Mar | Servo system-60 | ltr | 101500 |
| Mar | Plastic Bobbin DIN | Nos | 57460 |
| Mar | Rustop Paper | Roll | 69600 |
| Mar | HDPE sheet Plain | Kmt | 368150 |
| Aprl | Marker tape | kg | 151125 |
| Aprl | Plastic Bobbin DIN | Nos | 51125 |
| Aprl | road marker | ltr | 84240 |
| Aprl | Rustop Paper | Roll | 62400 |
| May | Marker tape | kg | 281775 |
| May | Servo system-60 | ltr | 108500 |
| May | Plastic Bobbin DIN | Nos | 202995 |
| May | Plastic Bobbin DIN | Nos | 37895 |
| May | Rustop Paper | Roll | 62400 |
| May | sheet Plain | Kmt | 286750 |
| May | Thermic fluid | ltr | 234850 |
| Jun | Marker tape | kg | 548275 |
| Jun | Plastic Bobbin DIN | Nos | 160855 |
| Jun | wrapping film 4" | kg | 180180 |
| Jun | plastic sheet | Nos | 126250 |
| Jun | Thermic fluid | ltr | 165550 |
| Jun | Soap 7080 | kg | 31050 |
| July | Marker tape | kg | 583050 |
| July | Plastic Bobbin DIN | Nos | 219960 |
| July | Plastic Bobbin DIN | Nos | 120705 |
| July | HDPE roll mtrs | Roll | 86955 |
| July | Thermic fluid | ltr | 281050 |
| Aug | Marker tape | kg | 609700 |
| Aug | Plastic Bobbin DIN | Nos | 478020 |
| Aug | Plastic Bobbin DIN | Nos | 114205 |
| Aug | HDPE roll | Roll | 334955 |
| Aug | Thermic fluid | ltr | 350350 |
| Sept | 3mm Marker tape | kg | 451100 |
| Sept | Plastic Bobbin DIN | Nos | 59605 |
| Sept | HDPE roll | Roll | 412455 |
| Sept | Thermic fluid | ltr | 192610 |
| Oct | Marker Tape | kg | 105000 |
| Oct | Marker tape | kg | 356200 |
| Oct | Servo system-60 | ltr | 87500 |
| Oct | Plastic Bobbin DIN | Nos | 346115 |
| Oct | Plastic Bobbin DIN | Nos | 90675 |
| Oct | Plastic Bobbin DIN | Nos | 59605 |
| Oct | HDPE Roll | Roll | 257455 |
| Nov | Marker tape | kg | 267150 |
| Nov | Servo system-60 | ltr | 87500 |
| Nov | Plastic Bobbin DIN | Nos | 429815 |
| Nov | HDPE roll | Roll | 257455 |
| Dec | Cutting oil | ltr | 105455 |
| Dec | plastic Bobbin DIN | Nos | 28795 |
| Dec | Rustop Paper | Roll | 206880 |
| Dec | Thermic fluid | kg | 142450 |
| Dec | HDPE roll | Roll | 109120 |

The fuzzy membership degrees of the fifty nine products can be calculated according to their annual value and the fuzzy membership function as given by eq. (1). The calculation results of the fuzzy membership degrees of the products are listed below in Table 2.

*Table 2: Fuzzy membership degrees of products*

| Product No | Total Value | Membership Values($m_i$) | Product No | Total Value | Membership Values ($m_i$) |
|---|---|---|---|---|---|
| 1 | 345600 | 0.06894 | 31 | 219960 | 0.0439 |
| 2 | 185500 | 0.03700 | 32 | 120705 | 0.0241 |
| 3 | 73060 | 0.01457 | 33 | 86955 | 0.0173 |
| 4 | 1087.66 | 0.00022 | 34 | 281050 | 0.0561 |
| 5 | 340400 | 0.06790 | 35 | 609700 | 0.1216 |
| 6 | 53187.5 | 0.01061 | 36 | 478020 | 0.0953 |
| 7 | 1133.56 | 0.00023 | 37 | 114205 | 0.0228 |

| | | | | | |
|---|---|---|---|---|---|
| 8 | 57460 | 0.01146 | 38 | 334955 | 0.0668 |
| 9 | 101500 | 0.02025 | 39 | 350350 | 0.0699 |
| 10 | 57460 | 0.01146 | 40 | 451100 | 0.0900 |
| 11 | 69600 | 0.01388 | 41 | 59605 | 0.0119 |
| 12 | 368150 | 0.07343 | 42 | 412455 | 0.0823 |
| 13 | 151125 | 0.03014 | 43 | 192610 | 0.0384 |
| 14 | 51125 | 0.01020 | 44 | 105000 | 0.0209 |
| 15 | 84240 | 0.01680 | 45 | 356200 | 0.0710 |
| 16 | 62400 | 0.01245 | 46 | 87500 | 0.0175 |
| 17 | 281775 | 0.05620 | 47 | 346115 | 0.0690 |
| 18 | 108500 | 0.02164 | 48 | 90675 | 0.0181 |
| 19 | 202995 | 0.04049 | 49 | 59605 | 0.0119 |
| 20 | 37895 | 0.00756 | 50 | 257455 | 0.0514 |
| 21 | 62400 | 0.01245 | 51 | 267150 | 0.0533 |
| 22 | 286750 | 0.05720 | 52 | 87500 | 0.0175 |
| 23 | 234850 | 0.04684 | 53 | 429815 | 0.0857 |
| 24 | 548275 | 0.10936 | 54 | 257455 | 0.0514 |
| 25 | 160855 | 0.03208 | 55 | 105455 | 0.0210 |
| 26 | 180180 | 0.03594 | 56 | 28795 | 0.0057 |
| 27 | 126250 | 0.02518 | 57 | 206880 | 0.0413 |
| 28 | 165550 | 0.03302 | 58 | 142450 | 0.0284 |
| 29 | 31050 | 0.00619 | 59 | 109120 | 0.0218 |
| 30 | 583050 | 0.11630 | | | |

After the inventory classification results are obtained, these are used with an ANFIS block which is used to automate the approach and compared with MLP and TDNN.

### *C. ANFIS BASICS*

The ANFIS is based on the Sugeno-type fuzzy systems and can be implemented using a multilayered feed forward structure [7] as shown in Figure 2.

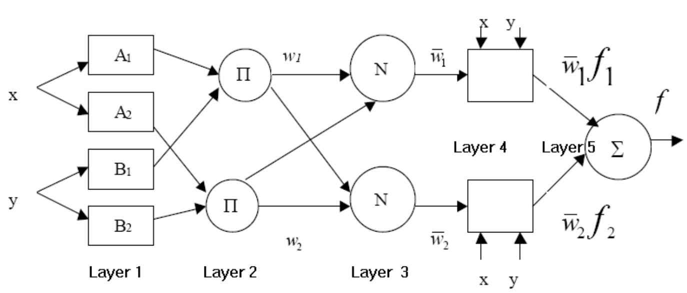


Figure 2: ANFIS structure

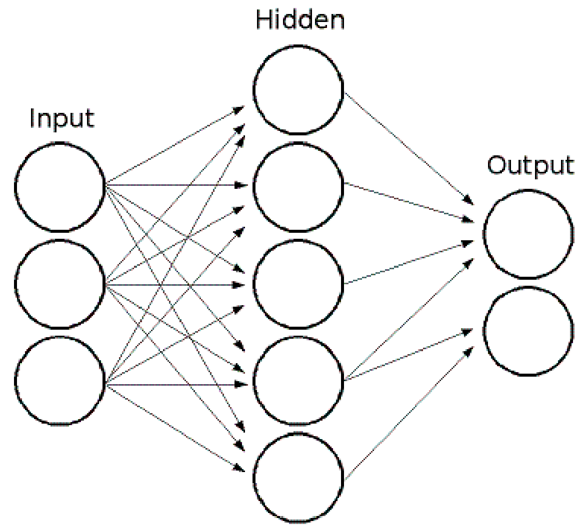


Figure 3: MLP layout

In Layer 1 (fuzzification), each node generates the membership grades of a linguistic label. Here a membership function of the type generalized bell function maybe used. In Layer 2 (antecedent), using any other fuzzy AND operation, the nodes calculate the firing strength of each rule. Next, in Layer 3 (normalization), the nodes find out the normalized firing strength. It calculates ratios of the rule's firing strength to the sum of all the rules firing strength. The nodes of Layer 4 (consequent) compute consequent parameters which are dependent on Layer 3. In the Layer 5 (aggregation), the overall output is calculated where each node aggregates the final output as the sum of all incoming signals. The layers are linked by connectionist links which are adaptive and update during each cycle of learning. The output is compared with the desired goal and the updating of the weights which multiply the inputs to each layer is continued till the objective is attained.

### *D. MLP*

The MLP is a multi-layered feed forward Artificial Neural Network (MLP) which is made up of one input and one output layer and one or several hidden layers with log-sigmoid, tan-sigmoid or purely linear activation functions. A generic MLP architecture is shown in Figure 3 [7]. The MLP is rained with back propagation algorithm till it learns the patterns completely. The choice of number of hidden layers and the activation functions depend upon the requirements. In our case we have used a one hidden layer MLP with 45 numbers of artificial neurons of log-sigmoid type to learn the inventory classification patterns.

### *E. TDNN*

The TDNN is another multi layered feedforward ANN like MLP but has delayed feed in the input. With this feeding method, the TDNN is able to track variations in data due to time. Like MLP, it also has multiple layers with input, output and hidden types and is trained with back propagation algorithm. In our case with have used 1 to 2 numbers of positive delay to develop time tracking ability of the ANN. Figure 4 shows a layout of the TDNN [7].

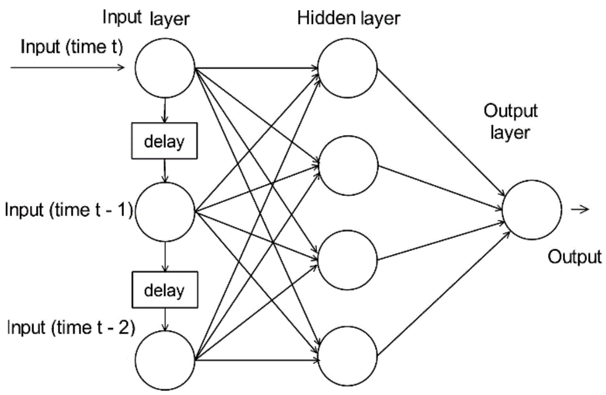


Figure 4: TDNN layout

## III. EXPERIMENTAL RESULTS AND DISCUSSION

The data set considered for the work consists of readings of 59 products recorded over a three year period considering two-week intervals. Out of the total data set, 50% are reserved for testing, 35% are used for training and 15% are applied for validation of the training. The first part of the work involves generation of the fuzzy membership classification outcomes. The approach has already been discussed in Section II. The results are discussed below.

The fifty nine products are now sequenced as per the sequencing eq. (2). The sequencing results of the fuzzy membership degrees of products are listed in Table 3

Table 3: Sequencing results by the fuzzy membership degrees of products

| Product No | Sequencing no | Membership values | Product No | Sequencing no | Membership values |
|---|---|---|---|---|---|
| 35 | 1 | 0.05228 | 58 | 31 | 0.012215 |
| 30 | 2 | 0.049995 | 27 | 32 | 0.010826 |
| 24 | 3 | 0.047013 | 32 | 33 | 0.01035 |
| 36 | 4 | 0.040989 | 37 | 34 | 0.009793 |
| 40 | 5 | 0.03868 | 59 | 35 | 0.009357 |
| 53 | 6 | 0.036855 | 18 | 36 | 0.009304 |
| 42 | 7 | 0.035367 | 55 | 37 | 0.009042 |
| 12 | 8 | 0.031568 | 44 | 38 | 0.009003 |
| 45 | 9 | 0.030543 | 9 | 39 | 0.008703 |
| 39 | 10 | 0.030041 | 48 | 40 | 0.007775 |
| 47 | 11 | 0.029678 | 46 | 41 | 0.007503 |
| 1 | 12 | 0.029634 | 52 | 42 | 0.007503 |
| 5 | 13 | 0.029188 | 33 | 43 | 0.007456 |
| 38 | 14 | 0.028721 | 15 | 44 | 0.007223 |
| 22 | 15 | 0.024588 | 3 | 45 | 0.006265 |
| 17 | 16 | 0.024161 | 11 | 46 | 0.005968 |
| 34 | 17 | 0.024099 | 16 | 47 | 0.005351 |
| 51 | 18 | 0.022907 | 21 | 48 | 0.005351 |
| 50 | 19 | 0.022076 | 41 | 49 | 0.005111 |
| 54 | 20 | 0.022076 | 49 | 50 | 0.005111 |
| 23 | 21 | 0.020138 | 8 | 51 | 0.004927 |
| 31 | 22 | 0.018861 | 10 | 52 | 0.004927 |
| 57 | 23 | 0.017739 | 6 | 53 | 0.004561 |
| 19 | 24 | 0.017406 | 14 | 54 | 0.004384 |
| 43 | 25 | 0.016516 | 20 | 55 | 0.003249 |
| 2 | 26 | 0.015906 | 29 | 56 | 0.002662 |
| 26 | 27 | 0.01545 | 56 | 57 | 0.002469 |
| 28 | 28 | 0.014195 | 7 | 58 | 0.000097 |
| 25 | 29 | 0.013793 | 4 | 59 | 0.000093 |
| 13 | 30 | 0.012958 | | | |

The inventory types of this example are selected as three types according to eq. (3). With the sequencing results in Table 3 and the fuzzy membership degrees of products, the inventory types of the fifty nine products can be classified. The product No 35, 30, 24 and 36 with few categories but greater values are the important inventory type A. The products No 40, 53, 42, 12, 45, 39, 47, 1 and 5 are the ordinary inventory type (B). The rest of the products with many categories but small values are the least important type C. The inventory classification results are listed in Table 4.

Table 4: Inventory Classification result

| Product No | Product Type | Product No | Product Type |
|---|---|---|---|
| 35 | A | 59 | C |
| 30 | A | 18 | C |
| 24 | A | 55 | C |
| 36 | A | 44 | C |
| 40 | B | 9 | C |
| 53 | B | 48 | C |
| 42 | B | 46 | C |
| 12 | B | 52 | C |
| 45 | B | 33 | C |
| 39 | B | 15 | C |
| 47 | B | 3 | C |
| 1 | B | 11 | C |
| 5 | B | 16 | C |
| 38 | C | 21 | C |
| 22 | C | 41 | C |
| 17 | C | 49 | C |

| | | | |
|---|---|---|---|
| 34 | C | 8 | C |
| 51 | C | 10 | C |
| 50 | C | 6 | C |
| 54 | C | 14 | C |
| 23 | C | 20 | C |
| 58 | C | 29 | C |
| 27 | C | 56 | C |
| 32 | C | 7 | C |
| 37 | C | 4 | C |

As already discussed, the ANFIS based approach is taken to automate the method. As part of this process, an ANFIS formed by bell membership functions with 25 nodes and two numbers of fuzzy rules have been implemented. The ANFIS is provided 59 pairs of input output data and 200 epoch cycles are set. With means square error (MSE) set at $10^{-6}$ the ANFIS learns the patterns. To add diversity to the training, the ANFIS is provided with 100 sets of data and the average reading taken.

Similarly, for the MLP, the training is carried out with back propagation algorithm for 59 sets of data with 200 epoch cycles targeting $10^{-6}$ MSE goal. The training cycles are stopped during validations to ascertain the level of learning taking place. A similar approach is adopted for training the TDNN. The MSE convergence of the ANFIS, MLP and the TDNN are shown in Figure 5. The MSE of the ANFIS shows atleast 12-15% improvement throughout the cycle. It indicates that the ANFIS is able to track minute variations in the inventory classification outcomes better. With better MSE convergence, the learning turns out to be robust and is found to be suitable for validating the accuracy for the proposed approach. The ANFIS with its multiple layers captures the finer details better than the MLP and the TDNN. The MLP is best at tracking static patterns while TDNN is known for its ability to capture time dependent variations. After the training part is over for the entire data set, testing is carried out. The outcomes of the ANFIS, ML and the TDNN for 30 sample counts are shown in Figure 6. The advantage of the ANFIS based approach is obvious.

With the inventory classification results of different products, the manufacturing unit can pay more attention and more money on the products of the important inventory type, maintain the inventory level of the products of the ordinary inventory type and reduce the inventory level of the products of the unimportant inventory type. The proposed classification approach can improve the economic profit and reduce the cost of companies.

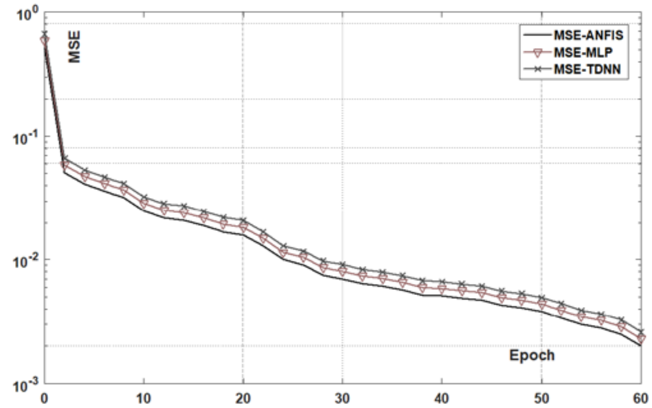


Figure 5: MSE convergence of ANFIS, MLP and TDNN upto 60 epochs for inventory classification

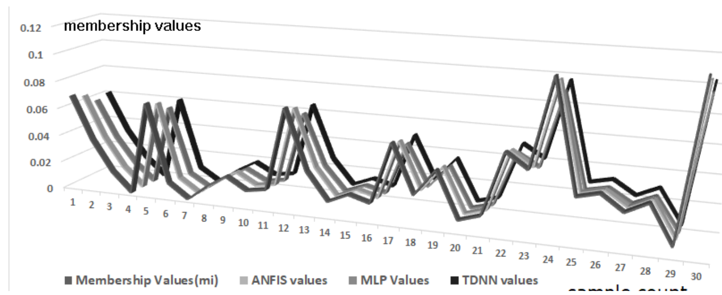


Figure 6: Membership values generated using ANFIS, MLP and TDNN based techniques compared to the actual value

## IV. CONCLUSION

In this paper, the various inventory items of a manufacturing unit is classified based on fuzzy membership degrees wherein the detailed classification approach is explained in detail. The approach is explained with a numerical example. According to the application results and the analysis, the presented approach can help the enterprises improve their inventory management level and reduce their costs. However with different inventory analysis technique classification of the items may change. We verified the outcome of the classification using ANFIS, MLP and TDNN based approaches. We found that these help in improving the reliability of the system. The ultimate choice rests on the management which decides on the process to follow depending on their budget, supply, demand, and inventory carrying capacity etc.

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