EFFICIENT DISTRIBUTION OF FLY ASH BASED ON ARTIFICIAL INTELLIGENCE MODEL: A CASE OF NTPC, FARAKKA

Rohit R P, KalyaniMenon and P K Sarkar
SPA Delhi
sshpstar@gmail.com; kalyani.v.menon@gmail.com&sarkarpradip52@gmail.com

ABSTRACT

Supply chain is a complex and dynamic system encompassing the behaviour of different participants. The paper attempts to develop a neuro-fuzzy model to capture the behaviour of supply chain, demand modelling and selection of best mode for disposal of fly ash from case study location, NTPC Farakka. Traditional models suffer from limitations which affect the accuracy of their forecasting. In this study, neuro-fuzzy model has been designed to predict the distribution pattern and mode selection. Primary objective of the study is to capture the firm’s behaviour, which influences mode choice and distribution. Four parameters namely, production capacity, travel cost, travel time and mode preference were considered to capture the behaviour of users. Three modes have been considered in this study namely road, rail and iwt. Output from the model predicts the flow of fly ash to different clusters through different modes. In case of cement industries, the base year demand was 68783MT/month while model prediction was 65568MT/month, having an error of only 4%, while in case of brick industries 10% variation was observed. Overall mode share obtained from the model based on individual cluster behaviour: 36% by road, 45% by rail and remaining 19% by IWT. Thus, an attempt was further made to explore the potential opportunities of transport system that best suits each cluster. Best mode selection was carried out by incorporating both, the obtained mode choice behaviour of firms as well the economical and sustainable aspects.

KEYWORDS: Neuro-fuzzy model, Mode Choice, Demand Allocation,Fly ash

1. INTRODUCTION

Traditional methods used for the travel demand models are mainly linear and multiple regression model, logit models etc. The limitation of the conventional modelling techniques is that it does not have the capability to capture the ambiguity, vagueness and uncertainty involved in the human made decisions. Neuro-fuzzy logic is found to be the primary technique to deal with these uncertainties because of its linguistic variables and rules. This study attempts to develop a neuro-fuzzy model based travel demand model for efficient distribution of fly ash to all the potential demand clusters. The neuro-fuzzy based travel demand model has been developed in MATLAB platform. This study also details out the application of soft computing in transport planning.

The case study, NTPC Farakka power plant is a Super Thermal Power Plant of 2100MW capacity located in North of Kolkata at a distance of 294 km, within the District of Murshidabad, West Bengal. It is well connected by Road, Rail and Water, NH 12 and NH 33 passing through Farakka and National Waterways 1: Allahabad to Haldia also passes by Farakka, providing Farakka a strategic locational advantage.As Fly ash is a by-product of coal based power generation, ash utilization in a sustainable manner is one of the key concerns of NTPC. 12000MT/day of fly ash is produced from Farakka NTPC, of which 20% is Bottom Ash which is directly transferred to Ash Ponds. The remaining generated fly ash is ideal foruse in manufacturing of cement, concrete, concrete products, cellular concrete products, bricks/blocks/ tiles etc.By considering the extent of potential markets as well as neighbouring states around Farakka, 13 potential demand clusters for the fly ash have been identified. These clusters are located in Nepal, Bhutan, Bangladesh, Assam,Siliguri, Kolkata and in other areas of West Bengal.

Distribution of resources to these destined clusters is based on in-built fuzzy rules which depict the behaviour of the clusters and firms. Neuro fuzzy that comes under artificial intelligence have the capability to mimic the nature of these individual firms leading to accurate predictions. The study aims to develop a neuro-fuzzy model to capture the behaviour of supply chain, demand modelling and selection of best mode for the disposal of fly ash from NTPC Farakka. Since, forecasting is an integral part of supply chain management, study helps to provide an accurate direction for the resource allocation and distribution pattern. This also helps to overcome the limitations of traditional forecasting models, which suffer from serious limitations affecting their accuracy. Based on the precise prediction, NTPC will thus be able to optimize and integrate the limited resources to organize the freight transport to make itin an efficient, economical and sustainable manner.

2. LITERATURE REVIEW

2.1 Fuzzy logic

LotfiZadeh introduced fuzzy logic in 1965. Psychology of commuters is difficult to be captured by using discrete models like Multinomial logit, Binary logit etc. Fuzzy logic mechanism deals with rules as it captures the psychology of travellers on different variables. Many researchers claims that fuzzy logic mechanism are more efficient to deal with uncertain conditions. Several researchers worked on fuzzy approach to model user's mode choice and they were successful in getting precise results(Pradip.Sarkar 2013).

LoftiZadeh proposed the *set membership function* to deal with the uncertainties for making suitable decisions. Membership value function ranges between values 0 and 1. With the help of these membership functions approximation can be made easily with defined ranges which is not possible in conventional methods. Fuzzy logic comprises of key elements namely *Input variables*, *Output variables*, *Linguistic variables*, *membership functions* and *rules*. Creating fuzzy rules from the numeric data was proposed further by researchers are used for mode choice modelling and trip distribution(Vythoulkas 2003). Choice behaviour model using fuzzy logic proved to be a reliable soft computing technique which can deal with the uncertainty, ambiguity, subjectivity and imprecision(Pradip.Sarkar 2013).(Sarkar 2012)showed the procedures for creating fuzzy rules using linguistic variables to develop the fuzzy logic based four stage model. There are other ways to generate fuzzy rules are through ANFIS (Adaptive Neuro Fuzzy Inference System) method through clustering technique (Tharwat O. S 2014).

In an easy way, linguistic variables are those variables which represent the status of input parameters. If travel time is one of the parameter then its linguistic variables are Less, Medium and High, which explains the range for respective variables. Input parameters are called as fuzzy sets and have linguistic variables with corresponding ranges. In simple language IF X AND Y THEN Z rules are used to describe the set of conditions in terms of linguistic variables rather than using mathematical formulas. Figure 1 demonstrates the basic concepts of fuzzy logic mechanism.In fuzzy inference system, input variables are given in the form of crisp values which gone through a process of fuzzufication, where every input variables are analysed and ranges are made considering appropriate membership functions.Later set of combinations of rules are made and are loaded in the fuzzy inference engine where all the membership functions will be analysed with respective conditions where output will be estimated.

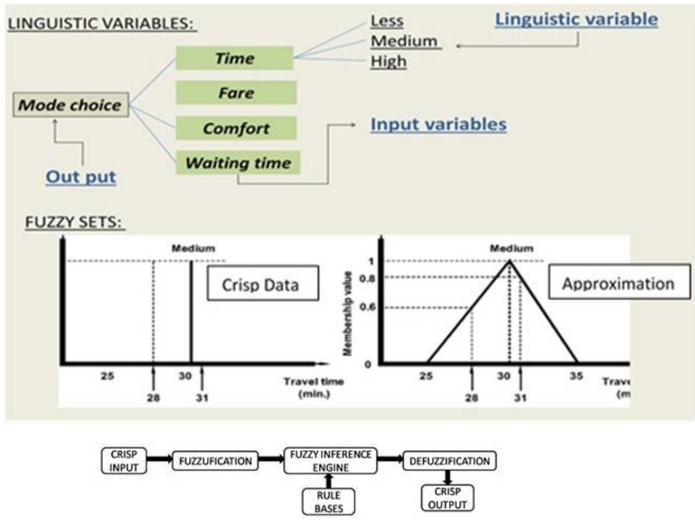

FIGURE 1Basic components of fuzzy logic

(*Source: Pradeep Sarkar,2013)*

2.2 Artificial neural network:

Neural networks have different layers made up of number of 'nodes' interconnected with 'activation functions'. ANN comprises of three main layers namely; input layer, hidden layer and output layer where the actual process are carried out through system of 'weighted connections'. ANN works on the basis of learning rules where weights are assigned on each connection according to the input patterns. Learning capability of ANN works with the principle called 'Back Propagation'. Through back propagation process errors are minimised through number of epochs (iterations) and there by assign weights to each connections. Figure 2 represents the architecture of neural networks with input layers, hidden layers and output layers.

For ANN model, data sets need to be divided into three categories namely – training, validating and testing. Training of the data set thereby generates the ANN with assigned weights, links and nodes. One of the limitations of the model is that it cannot predict something which is outside the range of data base (Nicanor R. ROXAS 2016). Yaldi sates that ANN is a powerful model which captures the fundamental relationships among the data which is hard to describe.

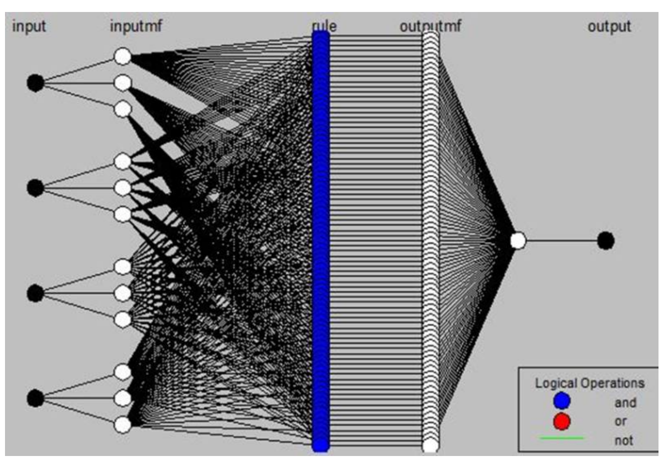

FIGURE *2*Basic Architecture of Neuro Fuzzy model

2.3 Neuro fuzzy model:

Neuro fuzzy model is a hybrid model of both fuzzy logic and neural networks. The hybrid model seems to be more accurate than conventional neural network model. Past studies showed that NF and adaptive network based fuzzy inference system (ANFIS) forecasting models perform successfully in dynamic systems with uncertainties in and uncontrollable parameters (i.e., human behaviour). Fuzzy systems have the ability to represent comprehensive linguistic knowledge given for example by a human expert and perform reasoning by means of rules(Akhil V. Gite 2013). On the other hand neural-networks are adaptive systems that can be trained and tuned from a set of samples. Once they are trained, neural-networks can deal with new input data by generalizing the acquired knowledge. Researchers like (Celik 2004), (Darshana 2011) , (Salini & Katti 2016), (Minal & Sekhar 2014), (Holland 2000). (Pulugurta & Arun 2013)also examined the application of soft computing techniques in transportation planning exercise.

Through Adaptive neuro fuzzy inference system trains the base data by minimizing error based on number of iterations or epochs. ANN works on the basis of back propagation process thereby learn and adapt the existing situation and variations. Neuro-fuzzy systems are fuzzy systems which use artificial neural networks (ANNs) theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way human's process information.

3. METHODOLOGY

In this study, neuro-fuzzy model has been designed to predict the distribution pattern and mode selection.Neural network based algorithm is used along with fuzzy logic to exploit the advantage of the self-adaptability and learning the existing behaviour of areas through training. This hybrid system called "Adaptive network based fuzzy inference system". Matlab 2014 software was used to formulate demand forecasting model. The study methodology consists of broadly 4 stages which include:

Stage 1: Literature Review, wherein relevant literature addressing the applicability of fuzzy logic and ANN in transportation demand forecasting and analysis and supply chain management where reviewed. The structuring of the study and identification of relevant parameters were carried out based on the reviewed literatures.

Stage 2: This stage includes the data collection stage. Primary objective of the study is to capture firm's behaviour which influences mode choice and distribution. Data has been collected through primary and secondary sources. Parameters that influence the mode choice namely, location of potential market destinations, typology of firm, production capacity, fly ash requirement and desire to shift to alternate modeshasbeen collected through telephonic survey and focus group discussions using stated preference technique. 212 samples were collected for various categories like cement industries, brick manufacturers and bulk suppliers. Separate models were created for these categories for accurate prediction.

Stage 3: Identification of parameters and model development: Developing neuro-fuzzy model involves five stages. Firstly, input-output database for base year was developed. Four parameters namely, production capacity, travel cost, travel time and mode preference were considered to capture the behaviour of users, and was considered as input parameters. Commodity flow was taken as output variable. Three modes have been considered in this study (road, rail and IWT) as mode choice preferences. Each of the parameter has an influence on the demand of fly ash willing to be taken from Farakka. For example, if the production capacity of firm is higher and requires bulk quantity of fly ash, then transportation by road increases cost as compared to IWT or Rail, as the number of trucks required would be high. Similarly, travel time and travel cost also influences the user's mode choice decision.

In the second stage, initial membership function for input and output variables were created. For each input output variables, triangular shaped membership functions were created by making appropriate ranges through training process. Next stage deals with the formulation of rule base for the model. By considering the possible relationship between the input-output parameters 972 rules were generated in neuro-fuzzy platform. In the last stage, the data was trained to reduce errors.

Stage 4: Model validation wherein the created model was validated.Using ANFIS tool, the base year data are trained and model captures the variations and tries to minimise the error based on backpropagation process.Validation of the model has been carried out by plotting the predicted result from the model and base year data sample

Stage 5: Analysis of modal split in terms of sustainability.Once the modal split was obatained as per the base scenario, it was analysed and altered to reduce the dependence on road by considering the preferences, to bring about a better sustainable freight model; and this forms the final modal that can be adopted.

4. DEMAND MODELLING

Supply chain is the complex and dynamic system comprising the behaviour of different participants. Thus the model should be able to capture each individual participants/industries behaviour which influences the mode choice to a particular cluster in which the industry is located. Thisenables calculation of the total commodity flow between each origin-destination pair through different modes.Basically, model should decide and capture the different tiers of demand assessment, which are:

1. Commodity flow to different clusters
2. Commodity flow based on topology wise (Cement, Brick, Agro-based, etc.).
3. Commodity flow through different modes.

Therefore, model should have the capability to capture the three tier level of output mentioned above.

4.1.Identification of Demand Clusters

For the purpose of identifying distinct demand clusters, the potential demand points with respect to each category of industry likecement, brick etc were mapped. Since Cement industries are major consumers of Fly ash, cement industries within 500 km radius from Farakka have been included. Similarly Brick industries and Agro industries surrounding Farakka have been considered. Small suppliers were also considered.

Based on the identification of above mentioned industries, clusters have been delineated. A cluster is an area where there is agglomeration of different type of industries or where similar type of industries is present in large number. Some of the industries which are far away from clusters have been neglected in cluster delineation.

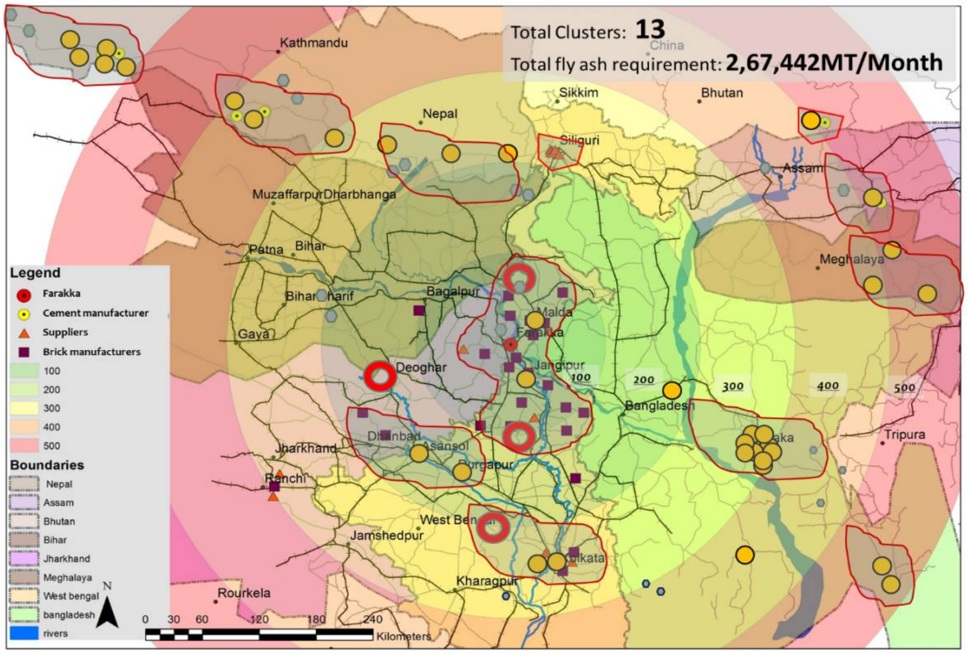

FIGURE 3 Identified Potential Demand Clusters

Thus a total of 13 clusters have been delineated, which is shown in the above figure. These clusters are Biratnagar,Kapilavastu, Birgung, Bhutan, Siliguri, Malda, Asansol, Guwahati, Shillong, Kolkata, Dhaka, Barisal, and Chittangong. While delineating, connectivity of clusters with different modes has also been given importance.

4.2.Development of demand model

Neural network based algorithm is used along with fuzzy logic to exploit the advantage of the self-adaptability and learning the existing behaviour of areas through training. This hybrid system is called “Adaptive network based fuzzy inference system”. Matlab software is used to formulate demand forecasting model. This model development can be classified into five distinct stages, which are shown in the figure4.

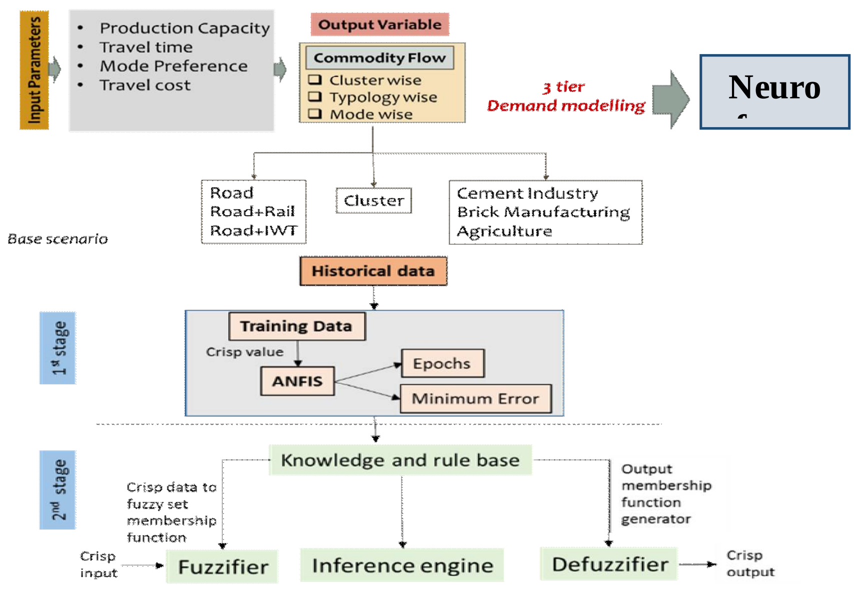

FIGURE 4Methodology adopted for modelling

Stage 1: Generation of Input Output Data for the Base Year

Input parameters selected for model prediction includes:

- Cluster code: It is considered as a dummy variable to increase the accuracy of the model at the cluster level. This enables the model to predict outputs at cluster level and well as individual firm level.
- Production capacity: It is considered in order to capture the demand prediction for different types of firms with different production capacity. For example, a firm having high production capacity tend to have more amount of fly ash for the cement production or brick manufacturing etc.
- Travel time: This captures the variation of demand with respect to delivery time, which in turn reflects in mode preference for the transportation of fly ash.
- Travel cost: This is included to capture the variation of demand with respect to cost as parameter. And hence the transport mode preferred to be also economical and sustainable.
- Mode preferred: This captures the preference of the industries/users, in order to predict the amount of flow of fly ash carried through different modes such as Rail + Road, Road, IWT + Road respectively to respective clusters. This in turn helps in assessment of handling capacity requirement for the various transport systems.

Output parameter will be in terms of flow of commodity from Farakka to respective cluster. Thus base year data for each OD pair data has been collected from the primary survey.

Stage 2: Setting Initial Membership Function for Input and Output Variables

For every input output variables membership triangular shaped membership functions are created by making appropriate ranges for each variable. In case of cluster code, each cluster is represented by appropriate membership function there by increases the accuracy and makes a realistic prediction taken in to consideration the firms present in the specific locations. Figure 5 shows the membership function created for the input parameter cluster code under cement industry category where 12 different membership functions are created to capture the variations and character of all these 12 clusters which helps the model to make predictions at cluster level.

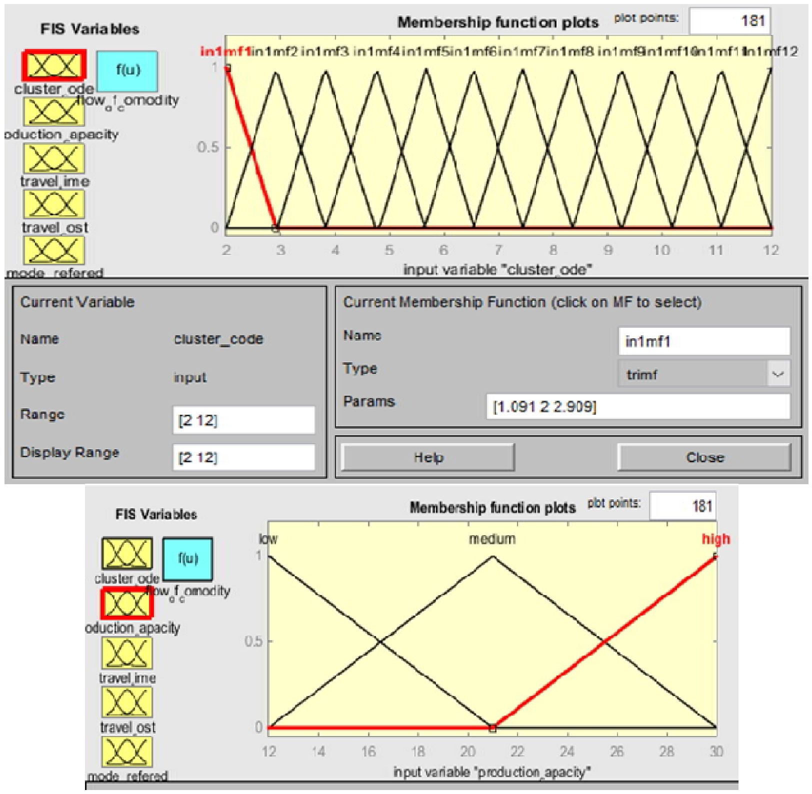

FIGURE 5 Membership function used in the Fuzzy Inference System

In case of production capacity, 3 triangular shaped membership functions are created with appropriate ranges indicating low, medium and high as shown in the figure above. So that predictions are made on basis of different capacity wise industries. Similarly, for other parameters 3 triangular membership functions are created accordingly. Table 1 shows the fuzzy sets created for all variables for brick manufacturing industry

TABLE1Fuzzy sets for each membership functions of different variables (brick manufacture)

Input Variable	Fuzzy Sets			Range of dataset
Cluster Code	14 different membership functions, ranging from 1 -14			[1 14]
Production Capacity	low [3 12 21]	Medium [12 21 30]	High [21 30 39]	[12 30]
Travel Time	Less [0 60.69 187.1]	Medium [60.69 187.1 313.5]	More [187.1 313.5 439.9]	[60.69 313.5]
Travel Cost	Less [0.5 1.4 2.1]	Medium [1.52 2.2 3.0]	More [2.23 3.07 3.90]	[1.4 3.07]
Mode Preferred	Road [0 1 1.995]	Rail + Road [1.002 2 2.995]	IWT+Road [2.003 3 4]	[1 3]

Stage 3: Rule Base Generation for the Model

There are some ways for rule generation in ANFIS. The common way is grid partitioning which partitions the input space and sets membership functions. Another way is deriving rules by experts and inserting rules to the system, if possible. This way can increase the speed of training and can train the FIS with fewer numbers of observations. With the help of rule base model able to answer to questions like:

IF TRAVEL TIME IS "LOW" and TRAVEL COST is "LOW" THEN COMMODITY FLOW is " ? "

IF TRAVEL TIME IS "HIGH" and TRAVEL COST is "LOW" then COMMODITY FLOW is " ? "

IF TRAVEL TIME IS "HIGH" and TRAVEL COST is "HIGH" then COMMODITY FLOW is " ? "

These kinds of rules are made to capture the behaviour of each firm. Thus considering all permutation and combinations 972 rules are generated in neuro-fuzzy platform. The above figure shows the combination of rules for one linguistic variable of input parameter. Similarly, all combination of rules are made for each linguistic variables under each input variables

Stage 4: Training the Data Set

Using ANFIS tool, the base year data are trained and model captures the variations and tries to minimise the error based on back propagation process. Data has been trained for fifty iterations (Epochs) in order to get better results.

Stage 5: Validation of the Model

Validation of the model has been carried out by plotting the predicted result from the model and base year data sample.Gap between predicted and observed values are reduced by increasing the number of iterations and by changing rules and membership functions. Thus the model becomes more accurate in terms of prediction. In case of brick manufacturing industries, the model shows a variation owing to low sample size. While for suppliers and cement industries, having adequate sample size, model shows only slight variations.

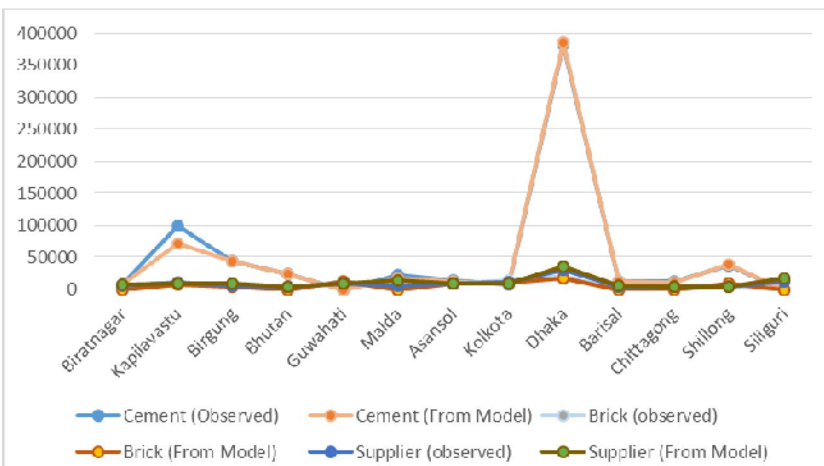

FIGURE 6 Model validation for all clusters of different topology

4.3.Output from the neuro fuzzy model

Output from the model predicts the flow of fly ash to different clusters through different mode share. In case of cement industries, the base year demand comes out to be 68783MT/month and model prediction comes out to be 65568MT/month thus error comes out to be only 4%.

TABLE 2 Total fly ash requirement and mode share for cement industries

Name	*Average Production	*Commodity Flow			*Avg. Flyash flow to cluster	No.of sampled industries	Remaining industries	*Total Fly ash Required (MT/annum)
		Rail	Road	IWT				
Biratnagar	75	3.4	0	0	3.4	2	1	10.2
Kapilavastu	140	1.6	0	10.1	11.7	7	3	107
Birgung	223.333	0	14.3	0	14.3	3	5	114.4
Bhutan	800	0	24	0	24	1	1	48
Guwahati	150	0	34.9	3.6	38.5	4	1	192.5
Malda	50	9	0	0	9	2	1	27
Asansol	50	0	6.5	0	6.5	2	2	26
Kolkota	10	.165	0	4.12	4.285	2	5	2.995
Dhaka	10	.572	0	3.8	38.572	10	6	617.152
Barisal	150	0	0	6.4	6.4	2	1	19.2
Chittagong	258.5	0	0	5.321	5.321	2	4	31.926
Shillong	431	.528	0	12.3	12.828	3	1	51.312
Total								1247.685
Monthly Demand.								106.224

**Figures are expressed in thousands*

Total number of sampled industries is 40. Whereas, remaining industries 31. Assuming the same character of sampled industries to the left over industries the total demand from cement industry sector estimated to be 106224MT/month. Thus daily demand comes out to be 3541MT/day. Similarly, analysis was carried out for both brick manufacturing industries and Suppliers. Overall demand prediction from the model considering the other potential markets for brick manufacturing industries come out to be 78950, while from base year survey it was found to be 70700MT/month. Thus the error comes out to be nearly 10% which may be due to the low sample size. For suppliers base year demand was predicted as 112728/month (3757MT/day), while that from survey was 4520 MT/day. Considering all, the total demand to each cluster was identified, which is shown in the table below.

From the above it can be seen that total estimated demand from Farakka is nearly 16000MT/day, while the current production of Fly ash under ideal plant working condition is only 12,000MT/day. Excluding the bottom ash and the requirement for the adjacent cement factory, the remaining fly ash to be disposed off comes out to be only 9000MT/day. Since demand exceeds the supply, 100% of fly ash can be distributed to the respective destinations. Overall mode share predicted from the model based on cluster behaviour is: 36% by road, 45% by Rail and remaining 19% by IWT. This considers only the behaviour of firms. This is further revised so that the final mode share tries to explore the potential opportunities of transport system that best suits particular cluster, making it economical and sustainable.

TABLE 3 Total Cluster wise Demand

Name	Modal Share			Total Demand (MT/month)	Commodity Flow		
	Rail	Road	IWT		Rail	Road	IWT
Biratnagar	36	64	0	7065	2543	4522	0
Kapilavastu	37	63	0	54707	20242	34465	0
Birgung	8	92	0	57693	4615	53078	0
Bhutan	46	54	0	7437	3421	4016	0
Guwahati	17	52	31	50722	8623	26375	15724
Malda	86	14	0	7742	6658	1084	0
Asansol	26	74	0	23573	6129	17444	0
Kolkota	9	35	56	80230	7221	28081	44929
Dhaka	53	15	32	161689	85695	24253	51740
Barisal	63	0	37	6114	3852	0	2262
Chittagong	31	0	69	6069	1881	0	4188
Shillong	19	60	21	19685	3740	11811	4134
Siliguri	42	58	0	11596	4870	6726	0

5. BEST MODE SELECTION SCENARIO

Best mode selection has been carried out by considering both mode choice behavior of firms as well as considering the economical and sustainable point of view. This was carried out in two stages, wherein in the first stage the quantity from the model was alloted without any changes as per the first mode preference, and allotting the second preferred mode when capcity of that system is reached, and so on to 3rd preferred mode also. After step 1, 44% of the total demand is to be carried by road which is equivalent to 3798 trucks/month. More preference on road is costly and not sustainable, thus this allottment was modified in step 2.Thus 2nd step has been carried out to reduce the road users: If road has lower prefernce then it was shifted to the better preferred mode ie; If 3rd preferred mode is road then, shifting from road to 1st preferred mode, followed by doing the same if the 2nd prefernec is also road.To make optimal utilization of IWT and Rail which are more economical and sustainable, all combinations are carried out. Hence, 55% of the commodity flow through rail whereas, 42 % through IWT, which reduces the dependency on road transportation, making it a more sustainable transport model.

6. CONCLUSION

In this study, a Neuro-fuzzy model was developed to capture the behaviour of supply chain, demand modelling and selection of best mode for disposal of fly ash from case study location, NTPC Farakka. The model was designed to predict the distribution pattern and mode selection, by capturing the firms behaviour by taking into consideration production capacity, travel cost, travel time and mode preference. This allowed the estimation of the potential demand from Farakka, which was found to exceed the current production, enabling complete utilization. The model also predicted the model share by considering the firms behaviour (36% by road, 45% by rail and remaining 19% by IWT). This was further refined by considering the economical and sustainable aspects, wherein the dependency on road was reduced following the preferences captured in the model; thereby resulting in an economical and sustainable transport model.

REFERENCES

1. Akhil V. Gite, RMBBMR 2013, 'ANFIS Controller and Its Application', *International Journal of Engineering Research & Technology*, pp. Vol.2 - Issue 2.
2. Celik, M 2004, 'Modeling freight distribution using artificial neural networks', *Journal of Transport Geography*, pp. 141-148.
3. Darshana, O 2011, 'Application of Fuzzy Logic and Genetic Algorithm in Trip Distribution', *INTERNATIONAL JOURNAL OF ENGINEERING DEVELOPMENT AND RESEARCH (IJEDR)*, pp. 52-54.
4. Holland, R 2000, 'Fuzzy Logic Model of Mode Choice', *PROCEEDINGS OF SEMINAR K OF THE EUROPEAN TRANSPORT CONFERENCE* , Cambridge.
5. Minal & Sekhar, CR 2014, 'Mode choice Analysis: the data, the models and future ahead', *IJTTE*, pp. 269-285.
6. Nicanor R. ROXAS, AMF 2016, 'Application of Artificial Neural Network to Trip Attraction of Condominiums in Metro Manila', *Proceedings of the 23rd Annual Conference of the Transportation Science Society of the Philippines* , TSSP, Quezon City, Philippines.
7. Pradip.Sarkar 2013, 'Development of fuzzy logic based mode choice model considering various public transport policy', *IJTTE*, pp. 408-425.
8. Pulugurta, S & Arun, A 2013, 'Use of Artificial Intelligence for Mode Choice Analysis and Comparison with Traditional Multinomial Logit Model', *Conference of Transportation Research Group of India (2nd CTRG)*, Elsevier Ltd.
9. Salini, PS & Katti, BK 2016, 'Developing A Fuzzy Rule Based Urban Trip Distribution Model On Income Criteria Basis At Zonal Level: A Case Study ', *IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)* , pp. 39-47.
10. Sarkar, A 2012, 'Application of fuzzy logic in transport planning', *International Journal on Soft Computing (IJSC)*, pp. Vol.3,No.2.
11. Tharwat O. S, H 2014, 'Identification of Uncertain Nonlinear MIMO Spacecraft Systems Using Coactive Neuro Fuzzy Inference System (CANFIS) ', *INTERNATIONAL JOURNAL OF CONTROL, AUTOMATION AND SYSTEMS* , p. VOL.3 NO.2.
12. Vythoulkas 2003, 'Modeling discrete choice behavior using concepts from fuzzy set theory, approximate reasoning and neural networks. ', *Transportation Research Part C: Emerging Technologies*, pp. 51-73.
13. YALDI, G, 'Developing a fuzzy-neuro model for travel demand modelling '.