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AN EVALUATION OF THE PERFORMANCE OF ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS) AND PROBABILISTIC NEURAL NETWORK (PNN) FOR PREDICTING COMMUTER TRAIN SERVICE QUALITY: A CASE STUDY IN BANGLADESH

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ABSTRACT

Traffic congestions is a common problem in urban transportation system of major cities in Bangladesh. In recent time, the possibility of introducing commuter train services in urban cities are explored. It has been assess that the service of commuter trains can be a vital solution of traffic congestion. This paper deals with the assessment of service quality of commuter train based on users perception data collected from different cities of Bangladesh. For this purpose, a questionnaire survey have been carried out among 802 respondents who traveled in commuter train as their daily mode of transport. In order to evaluate the performance of existing commuter train service in the transportation system, two models have been used. These are (i) Adaptive Neuro Fuzzy Inference System (ANFIS) (ii) Probabilistic Neural Network (PNN). Accuracy of ANFIS and PNN have been evaluated using confusion matrix and root mean square error (RMSE). The efficacy of ANFIS and PNN found to be 61.50% and 67.40% respectively in training period. Moreover, in testing the models, the accuracy have been found as 47.80% and 44.10% respectively. Comparison shows that ANFIS is most suitable for commuter train service quality prediction than that of PNN. Finally, a stepwise approach was followed for ranking the commuter train service quality attributes and the results were compared with that of the public opinions. From the results, it is found that 'Bogie condition', 'Cleanliness', 'Behavior of staff', 'Toilet facility' are

the most significant attributes. It is hoped that the paper will be helpful for the decision makers for improving the service quality of urban transportation system.

KEYWORDS: Service Quality(SQ), ANFIS, PNN, Root Mean Square Error, Correlation.

1. INTRODUCTION

Traffic congestion is a common occurrence almost in all the cities in a developing country like Bangladesh. A large number of non-motorized vehicles (scooters, bikes, rickshaws, human haulers) and motorized vehicles (vans, push carts, microbuses, cars, jeeps, trucks) occupy the road, reducing road capacity and creating congestion, thus making the roads unsafe for not only the pedestrians but the motorists as well. In addition, rapid increase of the urban population are creating pressure on the existing transportation system.

Railway is very popular sector of transportation practice in Bangladesh because of low costing and enjoyable journey. It made a great contribution to solve the communication demand as well as the employment problems which have a significant effect in the national economy of Bangladesh. A large group of peoples are engaged with this subsector from staff to executive level to operate the whole system. However as it is serving a great amount of passengers, the quality of service is the main concerning issue in that way. So ensuring desire quality of service for the passenger of all groups is the main challenge for this sector. Targeting this challenge to identify satisfaction situation regarding the present service quality is the main aim of this study. Railway sector shares around 20% passengers among all transport sectors in Bangladesh, it is just after roadway which covers around 65% and waterway have a contribution of about 16% of total passengers. For freight transportation it covers around 16% on the other hand roadway cover 48% and waterway cover about 35%.[1]

In consideration to this situation, the Government of Bangladesh formulated a “Strategic Transportation Plan (STP)” with the cooperation of World Bank in 2015. The STP compiles a policy as “Urban Transport Policy”, identified priority issues and recommended implementation of mass transit system and urban expressway in the city. The plan has received official node of the government of Bangladesh. Therefore it is expected that donors will come forward to assist improvement of the traffic situation and urban environment on the basis of STP. In this context a JICA study team is now conducting a study with the aim of formulating basic concept of urban development and formulating development projects for Japan International Cooperation Agencies (JICA) assistance. Bangladesh Railway (BR) concentrate its services aiming long haul passenger and goods but not responding to the transport services required for the densely populated country, particularly nearby areas of cities like Dhaka. However, BR has now started appreciate the requirement and started operation of commuter services on a limited scale with their available rolling stocks not suitable for commuter services.[2]

Compared with other modes, such as bus or subway, commuter rail service typically has low operating costs per passenger mile. Safety and equipment standards are largely regulated separately from those of passenger service convenience and necessity.[3] The evaluation of public transport service quality provides a valuable feedback to commuter operators to ensure continuous improvement of level of service (LOS). Recently, the government of Bangladesh has taken an initiative to reduce the traffic congestion in Dhaka by introducing elevated expressways, Mass Rapid Transit (MRT) and Bus Rapid Transit (BRT) systems and for the districts adjacent to Dhaka the commuter railway services.[4] In Bangladesh commuter train service has been introduced in some routes by Bangladesh Railway. These routes include Kamalapur to Tongi, Dhaka-Joydebpur-Dhaka route, Kamalapur-Narayanganj, Chittagong-Najirjhat route, Chandpur-Laksham-Comilla etc. Encouraging the use of commuter train and improving its service quality can meet the increasing demand of mobility in an environment friendly and energy efficient way. Statistical and empirical models are most commonly used for evaluating service quality of existing transportation system. Evaluation of service quality of Railways may give the true picture about the short comings in Railway passenger service.[5]

Bangladesh Railway presently operating nineteen pair of Commuter Trains mainly on the following three routs: (a) Dhaka (Kamlapur) - Narayanganj, (b) Dhaka (Kamlapur) - Tongi-Joydevpur, (c) Chittagong - Chittagong University route. Except on these routs, it also operates sevenmore trains in the name ‘Commuter Train’ but these are virtually medium distance local trains. About four pair of DEMU (Diesel Electric Multiple Unit) train provided by Bangladesh Railway for regular commuters of Kamalapur Joydebpur route along with privately owned Turag Express. Passengers from Tongi, Jodebpur, Dhirsom, Cantonment, Banani, Airport are currently availing this service. On the other hand around fifty up down trips run daily through Dhaka-Rajshahi, Dhaka-Mymensingh railway route via Joydebpur junction, where standing tickets are sold for commuters.In addition for the passengers of Gandaria, Pagla, Fotullah, Chashara and Narayangonj there are six DEMU trains along with thirty two up down trips from Kamalapur to Narayangonj every day. Approximately 40,000 passengers are carried to and from Dhaka by commuter rail service on daily basis. In this context commuter train service is a viable alternative to road transport and it requires more attention for further development.

This study is concerned with the commuter train service quality (SQ) analysis which is depending on a number of attributes in different routes in Bangladesh. The objectives of the study can be as follows:

i. To develop ANN and ANFIS-based empirical models for the estimation or prediction of service quality(SQ) of commuter trains in Dhaka city.

ii. To identify and rank the significant attributes influencing SQ of commuter trains depending on neuron's connection weights as well as the results obtained from step-wise approach.

The expected outcome of the proposed study will help in understanding the existing problems for the users in using or traveling in commuter trains and also will help to improve the service quality of the commuter trains in Bangladesh. The policy makers may also get an idea for improving the most important attribute from the model developed.[6]

2. LITERATUE REVIEW

Conventional models have underlying assumptions and predetermined fundamental relationships. Modeling non-linear relationship between users' satisfaction and attributes were widely adopted over last few decades. In these methods, SQ attributes were considered as independent variables and users' satisfaction was taken as dependent variables. Then coefficients were estimated by relating SQ attributes with users' satisfaction. Chou et al. (2014) proposed SEM model to test relationship among service quality, customer satisfaction and customer loyalty on high speed rail service in Taiwan. The study showed that most significant attributes were—cleanness of train, attitude and appearance of employee, comfort of air condition, on time performance of the train.[7] De Oña et al. (2014) focused on the factors affecting the SQ of railway in Northern Italy using the decision tree approach. The research found that courtesy and competence in station, workability of windows and doors, regularity of train frequency were the major factors for SQ of railway.[8] Aydin et al. (2015) proposed a combined fuzzy hierarchy process to assess customer satisfaction levels of rail transit. The study provided operational deficiencies related to rail transit through customer satisfaction surveys.[9]

Non-parametric models of Artificial Intelligence (AI) such as ANFIS can provide advantages over other statistical regression models like linear regression, logistic regression, ridge regression, lasso regression etc, in analyzing large datasets. They can model non-linear relationships with progressive capability and have scope for model validation as well. Recently, these models are applied widely in the field of science, engineering and market researches. Non-linear relationships in many transportation problems can be solved accurately by using Fuzzy logic based approach (Teodorovic and Vukadinovic, 1998). Yen and Langari (1999), Passino and Yurkovich (1998), and Lewis (1997) have performed extensive study on fuzzy logic and Fuzzy Inference System (FIS).[10-11] Later, Neural Network (NN) based learning was incorporated into FIS to solve many transportation problems. Teodorovic and Vukadinovic (1998) presented potential applications of fuzzy logic and NNs in solving transportation problems.[12]

Islam et al. (2016) adopted PNN, Generalized Regression Neural Network (GRNN) and Pattern Recognition Neural Network (PRNN) to assess the significant attributes which influence the SQ for Dhaka city bus transit.[13] In another study, Islam et al. (2016) used PNN and ANFIS to construct and compare the prediction models for bus SQ of Dhaka city. They ranked the SQ attributes according to their effect and identify the significant attributes. The study revealed that ANFIS performed better than PNN for the evaluation of bus transit SQ.[14]

Inspired by the most recent studies, this thesis paper depicts the application of the ANFIS and PNN in the development of a new fuzzy logic-based and neural network based approach for exploring the relationship among attributes of intercity train’s SQ with passengers’ satisfaction level. Particularly, previous studies showed that the ANFIS based SQ assessment seems to be a feasible approach for any mode of public transport. Dataset were trained and tested using ANN to check the fitness of the calibrated FIS for estimating the parameters of observed attributes or variables of railway SQ under normal days and special day scenarios. Despite uncertainties and nonlinearities, ANFIS represents a mathematical framework that can model the relationship among observed variables, hidden layers and output variables quite remarkably.

3. FRAMEWORK OF ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

A neuro-fuzzy approach which can learn from the training data was used accordingly. Artificial Neural Network (ANN) creates a computational structure which functionally can perform like human brain. It interconnects neurons or nodes those use input data and

Membership Functions (MFs) to process and transmit outputs. Jang et al. (1993) adopted the network learning algorithm to Fuzzy-Logic Inference System (FIS) and named the structure as ANFIS.[15] It combines the FIS and ANN. ANFIS can process train data to grain experience and create a fuzzy-logic based network with complex algorithm. The algorithm works stepwise. The FIS was used to model non-linear relationship and the NN was used to calibrate the parameters of input and output MFs. The ANFIS tool in MATLAB 12 was used in this research to predict train's overall SQ.

The calibration of MF was performed by using input data (i.e. observed attributes) and output data (i.e. overall passenger's satisfaction) through the learning process. The process consists of two main steps, the collection of learning data and FIS generation. Data collection consisted of gathering sufficient relevant training data describing the relationship between observed variables or attributes and the corresponding overall passengers' satisfaction level by using numerical ranking. For every individual test, a training database with 802 respondents was collected from Stated Preferences (SP) survey. The structure of the FIS was constrained to allow 181 MFs for input attributes and the shapes of the input MFs were selected.

The structure of ANFIS comprises of five-layers, those are—(i) fuzzification; (ii) fuzzy and; (iii) normalization; (iv) defuzzification; and (v) output layer as shown in Figure 2 (a). Each of these layers is connected through direct links and nodes. Nodes are process units which consist of adaptive and fixed parameters. By setting learning rules, adaptive parameters can be altered and the membership functions are reformed. In the structure of ANFIS, the first layer consists of attributes or observed variables of train SQ. Second layer comprises of MF of each input. Different rules are organized in the third layer. Each rule represents output MF in the fourth layer. Final output or overall SQ satisfaction is calculated by the weighted average method in the fifth layer.

The first step of ANFIS is identification of the input and output variables. It uses first-order Sugeno fuzzy model and two typical if-then fuzzy rules with a set of two input variables (x, y) and one output (f) is considered. a and b are the coefficient of the input variables and c is the constant term.[15]

Rule 1: If x is P1 and y is Q1, then f1 = a1x+b1y+c1 (1)

Rule 2: If x is P2 and y is Q2, then f2 = a2x+b2y+c2 (2)

All nodes in first layer i.e. fuzzy layer are adaptive. It is also known as input layer. The relationship between the output and input MFs of this layer is as follows:

$O_m^1 = \mu_{P_m}$ (i); m= 1, 2 (3)

$O_n^1 = \mu_{Q_n}$ (j); n= 1, 2 (4)

Here, x and y are the input of nodes Pm and Qn respectively. Pm and Qn are the linguistic labels used in the fuzzy theory for dividing the MFs. The second layer is labeled as M. The layer is also known as input MF. All nodes are fixed in this layer and perform as simple multiplier. The outputs of this layer are firing strengths represented as:

O_m^2 =w_i = $\mu_{P_m}\mu_{Q_n}$ (j); m, n = 1, 2 (5)

The third layer is labeled as N. The layer is known as rule. Nodes are also fixed nodes and perform as a normalizer to the firing strengths from the previous layer. The outputs of this layer are normalized firing strengths and given by:

O_m^3 = w_{avg} = $\frac{w_m}{\Sigma w_m}$; m = 1, 2 (6)

All nodes are adaptive in the fourth layer. The layer is also known as output MF. The output of each node in this layer is the product of the normalized firing strength and a first order polynomial. The outputs of the layer are as follows:

O_m^4= $w_{avg}f_m$= w_{avg} $(a_1x+b_1y+c_1)$; m= 1,2 (7)

Only one single fixed node performs the summation of all incoming signals in the fifth layer and it is labeled as Σ. Therefore, the overall output of the model in the fifth layer represented as: $O_m^5 = \sum_{i=1}^{2} w_{,avg} f_m = \frac{\sum_{m=1}^{2} w_m f_m}{\Sigma w_m}$; m = 1, 2 (8)

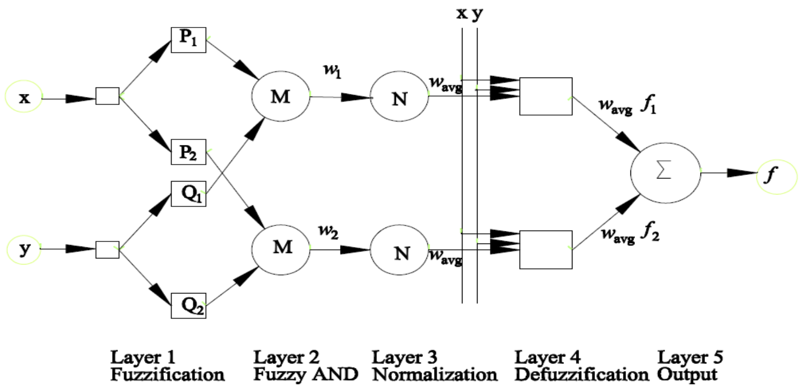

Figure 1: Structure of ANFIS.

4. Framework of probabilistic neural network (PNN): Probabilistic Neural Network (PNN) can map any input pattern to any number of classifications. It is a four-layered neural network which operates by minimizing the ‘expected risk’ function. It is based on well-established statistical principles derived from Bayes’ decision strategy and non-parametric kernel based estimators of Probability Density Functions (PDFs). The four layers of PNN architecture are: input layer, pattern layer, summation layer and output layer. Figure 3 shows a PNN architecture.[16]

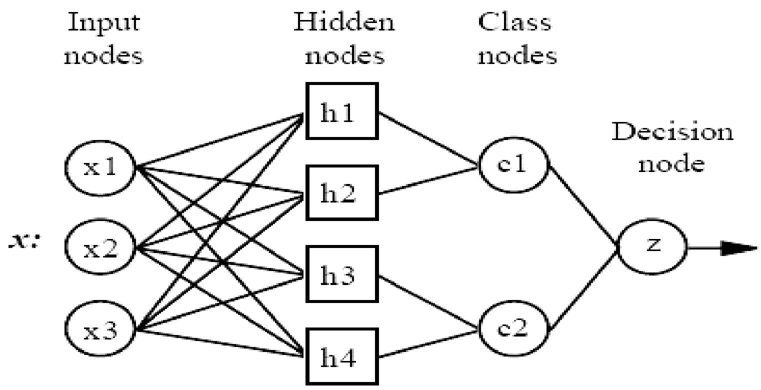

Figure 2: Architecture of PNN.

The number of nodes in the pattern layer is equal to the number of training instances. The number of nodes in the summation layer is equal to the number of classes in the training instances. The input layer is fully connected to the pattern layer. The input layer does not perform any computation and simply distributes the values of user attributes to the neurons in the pattern layer. The pattern layer is semi-connected to the summation layer. Each group of training instances corresponding to each class is just connected to one node in the summation layer. In other words, the summation units simply sum the inputs from the pattern units that correspond to the category from which the training pattern was selected. Finally, output layer shows the estimated class extracted from summation layer. PNNs are found to be the best neural classifiers among all other ANNs due to their design architecture (Jang et al. 1993). Training in PNN is relatively fast as each input is shown to the network only once. Unlike the traditional neural networks, no learning rule is required to train a PNN and no predefined criterions are needed.

To build the network, at first, the products of the example vector and the input vector are summed. For each class node, these activations are summed. The pattern node activation (h) shown in the following equation, is simply the product of the two vectors (E is the example vector, and F is the input feature vector).

$$h_i = E_i F \quad (9)$$

The class output activations (SQ) are then defined as:

$$C_j = \frac{\sum_{i=1}^{N} e^{\frac{(h_i - 1)}{\gamma^2}}}{N} \quad (10)$$

Where, C_j = output class; N = sample size; h_i = hidden-node activation; γ =smoothing factor.

5. METHODOLOGY

A questionnaire survey was conducted among around 802 users of commuter train of different age, gender, occupation type and different purpose of using commuter train. The questionnaire survey was constructed into two sections (a) to collect information about the socioeconomic characteristics of the users (gender, age, occupation, purpose of travelling) and (b) to collect service quality attributes about the commuter train (e.g. fitness of train, seat comfort, service availability, movement flexibility, safety, journey end connectivity and security). The survey was carried out in both weekdays and weekends and also in different hours (peak and off-peak hours) in a days.[17] From the survey data 12 attributes are selected. The attributes were selected based on—(i) Literature review of prior SQ analysis of train, (ii) Interview of train passengers and (iii) Collecting opinion from the expert transportation planners and engineers. These were the input data for developing two models (i) ANFIS and (ii) PNN. To evaluate model performance (i) Confusion Matrix and (ii) Root Mean Square Error (RMSE) was followed. A stepwise approach was also adopted to rank the output and to compare with the public opinion.

6. Model Development

Table 1 presents the users perception about the current service of commuter train. From this table about 12 attributes have been selected for model input. These attributes were selected based on passengers opinion. The rating has been used as input data for the development of PNN and ANFIS. From this input data, forecasting technique was applied to examine the predictive capacity of the models. Data samples were divided into two sub-samples: a training sample (80% of the total data sample set) and forecasting sample (20% of the total data sample set). MATLAB 12 was used for development of the models. The accuracy of the prediction have been tested by comparing the outputs with corresponding observed targets. Table 1 shows the model parameters related to Probabilistic Neural Network (PNN) and Adaptive Neuro-Fuzzy Interface System (ANFIS). These parameters were used for the development of two models.

Table 1: Parameters Related to Probabilistic Neural Network (PNN) and Adaptive Neuro-Fuzzy Interface System (ANFIS) for Commuter Train SQ Prediction Models.

PNN		**ANFIS**	
Number of input variables	12	Number of input variables	12
Number of layers	4	Number of layers	5
Initial function	Initlay	Number of membership function	181
Performance function	Mse	MF type	Gaussian
Performance parameter	regularization	Trasnsfer function of hidden layer	Tansigmoid
Scaling method	normalization	Scaling method	Normalization
Training algorithm	Radial basis	Transfer function of output layer	Linear
		Training algorithm	Back-propagation
		Training cycles, epochs	10
		Training goal	0.01

7. Evaluation of model performance and comparison of ANFIS and PNN

Performance analysis of models have been carried out by two methods i.e (i) Confusion Matrix (ii) Root Mean Square Error (RMSE). Confusion matrix is used to verify the one-to-one matching between output classes (1 to 5) and target classes (1 to 5). The diagonal green boxes in Figure 5 illustrate the amounts and percentages that are identical in both output and corresponding target classes. The red boxes illustrate the amounts of misclassifications. The right-bottom blue box represents the total correct classifications (green) and misclassifications (red) in percent (%). The correlation and error between actual SQ and predicted SQ of commuter train was also verified by computing the RMSE value. Then the ranking of attributes have been prepared for both ANFIS and PNN.

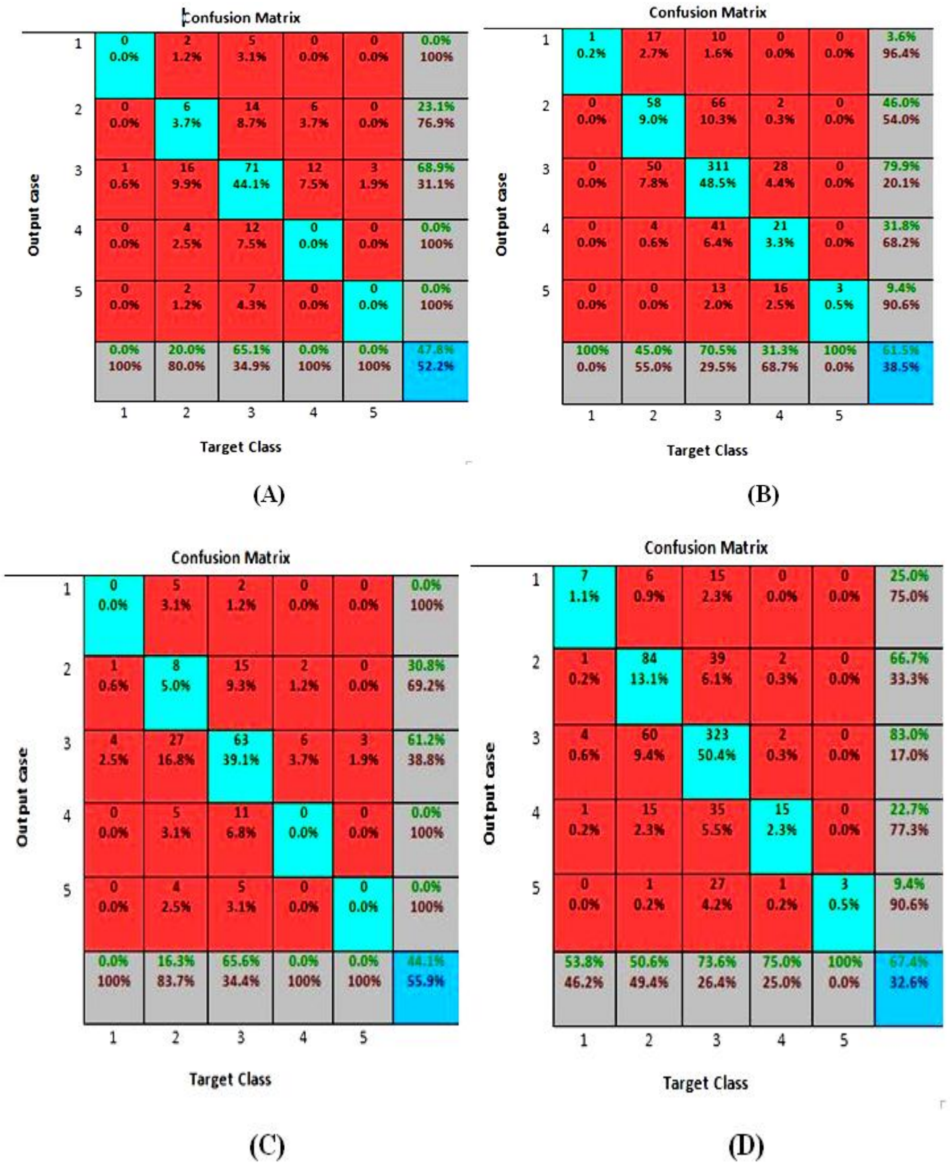

Figure 3: Confusion matrixes for ANFIS of, (a) tested model (b) trained model and, confusion matrixes for PNN of, (c) tested model (d) trained model.

Comparison between the accuracy of ANFIS and PNN model in predicting the Service Quality (SQ) of commuter train is given below by Table 2. In prediction of Service Quality (SQ), ANFIS was 61.50% accurate in training period which is about 395 of total 641 predictions and in testing period the accuracy is 47.80% which is about 77 out of 161 predictions which matches with the actual value. In PNN the accuracy is 67.40% in training period which is 433 out of 641 predictions and 44.10% in testing period which is 72 out of 161 predictions which matches with actual Service Quality (SQ).

Table 2: ANFIS and PNN model accuracy in predicting Service Quality (SQ).

Models	Training Period	Testing Period
ANFIS	61.50% (395 out of 641)	47.80% (77 out of 161)
PNN	67.40% (433 out of 641)	44.10% (72 out of 161)

8. Comparetive analysis of model results

Stepwise approach was utilized to rank the commuter train service quality attributes. Table 3 shows the results of attributes ranking comparison between ANFIS, PNN and Public Opinion. In stepwise approach a single attribute is considered to develop models both in ANFIS and PNN to find out the significant attribute and the output of every developed network by a single attribute was then compared with the actual SQ of the test sample. This comparison has been done by evaluating RMSE and public opinion.

Table 3: Attributes ranking comparison among ANFIS, PNN and Public Opinion.

Attributes	ANFIS model		PNN model		Public opinions
	RMSE	RANK	RMSE	RANK	
Bogie Condition	0.807079	1	0.811409	1	1
Cleanliness	0.807573	2	0.815228	2	2
Female Harassment	0.811409	3	0.939142	4	3
Behavior of Staff	0.837773	4	0.863332	3	4
Noise Level	0.838738	5	1.150209	12	8
Toilet Facility	0.949011	6	1.000000	5	7
Ventilation System	1.009274	7	1.074839	11	5
Waiting Room Facility	1.036597	8	1.045547	6	6
Ease of Entry-Exit	1.042572	9	1.071846	7	9
Comfort Level	1.045547	10	1.072146	10	12
Overall Security	1.048513	11	1.072046	9	10
Ticket Cost	1.05147	12	1.071946	8	11

The ranking of attributes based on RMSE value indicates the significance of the individual attribute under different case. From table it is found that 'Bogie Condition' has got the lowest RMSE value i.e 0.807079 using ANFIS model and ranked as first significant attribute to be treated. Whereas by using PNN model, also 'Bogie condition' became the first attribute that should be considered for improving SQ of commuter train because of the lowest RMSE value i.e 0.811409. Practically it is seen that bogies of the train are not very clean and also the seat arrangement and other service for the passengers are not properly provided in the study area. Comparing the practical scenario and model analysis the results are quite similar. Considering the second ranking 'Cleanliness' has got second lowest RMSE value using both ANFIS (0.807573) and PNN (0.815228). Bogie cleanliness is one of the major factors that may arise some effect on the overall quality. Sometimes passengers face some behavioral problems by the staffs of commuter train which affects the overall SQ provided by the BR. From table it is found that 'Ease of entry-exit', 'Ticket cost', 'Air ventilation' etc has got highest RMSE value which indicates the better quality of service provided for passengers. So these are not very significant attributes for taking immediate action.

In the questionnaire survey respondents were asked to give their opinion about 12 most significant attribute that should immediately be treated for better SQ of commuter train. From their perception a ranking of the attributes have been made in ascending order to understand the performance of the model and respondents response. It should be noted that respondents were independent to give their valuable opinion in this section. From Table 3, it is seen that about top 4th attributes matches to the public opinion. From 5th to 8th attribute there is dissimilarity in the sequence. Last four attributes were randomly matched to the public opinion.

9. DISCUSSION

Results from this study reveals that the performance of both ANFIS and PNN model were found satisfactory. The accuracy rate of the training period for ANFIS was 61.5% and for testing period was 47.8%. Whereas for PNN the training period accuracy found from confusion matrix was 67.4% and for testing period it was 44.10%. This shows the model performance using the practical data set was quite satisfactory.

Respondents rated the exiting service quality of commuter train in 1 to 5. By this rating the ranking of the attributes have been made by which the most significant attribute was identified. From RMSE value analysis inside "Bogie condition" of the train got the lowest value both in ANFIS (0.807079) and PNN (0.811409). Passengers also rated inside "Bogie condition" as most significant problem. Passengers found that the inside space of the train is not properly arranged and cleaned frequently. This often discourages them to avoid commuter train to use daily basis. Public opinion and the model results both gives the same output about the existing condition of bogies. So the first initiative of the authority can be providing a proper arranged and cleaned bogie of the train. In second case, from this research, it is found that cleanliness is not very satisfactory into the train which also affects the public opinion about to ride in commuter train. The prediction capabilities of ANFIS and PNN models found in this research work are expected to encourage practitioners around the world to apply these tools for SQ studies of other transport systems (intercity bus, train, ferries etc). Hence, ANFIS is greatly influenced by the parameters such as membership function, learning algorithm etc. This study reveals that the accuracy is not up to the standard level. For getting more accurate result the some other membership functions like triangular, trapezoidal or other shapes may be used. An investigation of additional learning algorithm (resilient propagation, nonnegative least square) may be used for improving the performance of ANFIS.

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REFERENCES

1. Rahman K.R., Rahman M. A Service Quality Attributes Affecting the Satisfaction of Railway Passengers of Selective Route in South wastern Part of Bangladesh. The oretical and Empirical Researches in Urban Management, (August 2019).
2. Zullig, JR. E. W, David Phraner S**.** North American Commuter Rail. A1E07: Committee on Commuter Rail Transportation, (2000).
3. Study on expansion of commuter services of Bangladesh Railway, Dhaka Urban Transport Network Development Study Final Report 6-1 Appendix, March 2010; 6.
4. Prasad D., Shekhar R. B. Impact of Service Quality Management (SQM) Practices on Indian Railways - A Study of South Central Railways. International Journal of Business and Management, September 2010; 5(9).
5. Study on Expansion of Commuter Services of Bangladesh Railway, Appendix 6. Dhaka Urban Transport Network Development Study, (March 2010).
6. Mowrin A.N., Commuter Train service Quality Prediction and User Attribute Ranking using Neural Network and Fuzzy Approach. (2018); M. Sc Engg Thesis, Department of Civil Engineering, Bangladesh University of Engineering and technology (BUET).
7. Chou, P.F., Lu, C.S., Chang, Y.H. 2014. Effects of service quality and customer satisfaction on customer loyalty in high-speed rail services in Taiwan. Transportmetrica A: Transport Science, 10(10): 917-945.
8. De Oña R., Eboli. L., Mazzula, G. 2014. Key factors affecting rail service quality in the Northern Italy: a decision tree approach. Transport, 29(1): 75-83.

9. Isikli E., Aydin N., Celik E. and Gumus A. T. 2017. Identifying Key Factors of Rail Transit Service Quality: An Empirical Analysis for Istanbul. Journal of Public Transportation, 2017; 20(2).
10. Yen, J., Langari, R. 1999. Fuzzy Logic, Intelligence, Control, and Information. Prentice Hall, 68.
11. Lewis, H.W. 1997. The foundations of fuzzy control. Plenum Press, New York.
12. Teodorovic, D., Vukadinovic, K. 1998. Traffic control and transport planning: A fuzzy sets and neural networks approach. Springer Science & Business Media, 13.
13. Islam, M.R., Hadiuzzaman, M., Banik, R., Hasnat, M.M., Musabbir, S.R., and Hossain, S. 2016. Bus service quality prediction and attribute ranking: a neural network approach. Public Transport, 8(2): 295-313.
14. Islam, M.R., Musabbir, S. R., Ahmed, I., Hadiuzzaman, M., Hasnat, M. M., and Hossain, S. 2016. Bus service quality prediction and attribute ranking using probabilistic neural network and adaptive neuro fuzzy inference system. Canadian Journal of Civil Engineering, 43(9): 822-829.
15. Jang, J. S. R. 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE Transactions on Man and Cybernetics, 23(3): 665–685.
16. Zhao, D., Shao, C., Li. Jaun, C., and Liu, Y. Travel Mode Choice Modeling Based on Improved Probabilistic Neural Network. In Traffic and Transportation Studies, ASCE, 2010; 685-695.
17. Mowrin A.N., Hadiuzzaman M., Barua S., Rahman M.M. Identifying Key Factors of Commuter Train Service Quality: An Emperical Analysis for Dhaka City. Malaysian Journal of Civil Engineering. (July 2019); DOI:10.11113/mjce.v31n2.568.