APPLICATION OF NEURAL NETWORK AND FUZZY INFERENCE SYSTEM FOR BUS SERVICE QUALITY PREDICTION AND ATTRIBUTE RANKING IN DHAKA CITY

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November 2016

Application of Neural Network and Fuzzy Inference System for Bus Service Quality Prediction and Attribute Ranking in Dhaka City

by

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A thesis submitted for the partial fulfillment of the requirements for the degree of Master of Science in Civil & Transportation Engineering

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November 2016

Dedicated to my Family

The thesis titled "***Application of Neural Network and Fuzzy Inference System for Bus Service Quality Prediction and Attribute Ranking in Dhaka City***," submitted by Md. Rokibul Islam, Student No. 1014042410, has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Master of Science in Civil & Transportation Engineering on November 05, 2016.

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Declaration

It is thereby declared that except for the contents where specific references have been made to the work of others, the study contained in this thesis are the result of investigation carried out by the author under the supervision of Dr. Md. Hadiuzzman, Associate Professor, Department of Civil Engineering, Bangladesh University of Engineering and Technology. No part of this thesis has been submitted to any other university or other educational establishment for a degree, diploma or other qualification.

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November 05, 2016

Acknowledgements

I would like to take the opportunity to express profound gratitude to my supervisor Dr. Md. Hadiuzzaman for his invaluable guidance, encouragement, and continuous support throughout the whole journey of my Master's program. I have always found his support in any situation during the course of my study and research. I am grateful to have such a wonderful supervisor who helped me to grow confidence, think critically, and at the same time to achieve a profound academic background. I have really enjoyed working with him and I am hoping to work with him in future.

I would like to thank the members of the transport Faculty in the Department of Civil Engineering, especially Dr. Md. Mazharul Hoque, Dr. Moazzem Hossain, Dr. Md. Shamsul Hoque, Dr. Md. Mizanur Rahman for their insightful academic courses, which helped me to mature analytically and carry on with this research exertion.

I would like to give thanks to Rajib Banik and Irfan Uddin Ahmed from the traffic research group for providing me their valuable support to conduct this research.

I would like to acknowledge the research grant received for this study from the Committee for Advanced Studies and Research (CASR) of BUET, Dhaka.

I am indebted to my family and friends for their support and encouragements.

Above all, I am thankful to the Almighty Allah for His unbound blessings in my life.

Abstract

With a view to assessing the service quality (SQ) provided by the bus transit system, this study has conducted field survey through face-to-face interviews at main bus stops around Dhaka city throughout the month of December, 2014. The questionnaire was based on 22 attributes and some demographic variables. These attributes have been selected by analyzing users' demand and the transit experts' view towards service quality indicators. After conducting the on-board and off-board survey, a set of 655 samples has been selected for analyzing with Artificial Intelligence (AI) models.

AI is a strong method to simulate the human decisions to assess the quality of services depending on some attributes. However, to get the best tool for bus SQ analysis, this study compares prediction capabilities among AI models namely, Generalized Regression Neural Network (GRNN), Probabilistic Neural Network (PNN), Pattern Recognition Neural Network (PRNN) and Adaptive Neuro Fuzzy Inference System (ANFIS). The confusion matrices show that PNN performed better than other neural network models with 88.5% and 75.6% prediction accuracy in training and testing stages, respectively. Further comparison between PNN and ANFIS reveals that ANFIS outperforms PNN by prediction with 84.0% accuracy. Also, the R values of PNN and ANFIS prediction are 0.70788 and 0.79932, respectively. Whereas, the RMSE values for those models are 0.63607 and 0.50190, respectively. These also reveal the superiority of ANFIS than PNN model. Thus, ANFIS establishes itself as a best analytical tool for bus SQ estimation.

According to the relative importance, the selected attributes are ranked with the AI models and public opinion. Connection weight method and Stepwise approach are followed to determine the relative importance of the attributes. According to all of the techniques, 'Punctuality and Reliability', 'Seat Availability', 'Service Frequency' and 'Commuting Experience' are found to be the most important SQ attributes. These outcomes of this study will convey an efficient way to the service providers, operators, policy makers and transportation authorities to improve the bus SQ in view of attracting more passengers.

Keywords: Public Transport, Service Quality, Artificial Intelligence, Neural Network, Adaptive Neuro Fuzzy Inference System, Dhaka City.

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List of Abbreviations

Acronym	Definition
AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
FIS	Fuzzy Inference System
GRNN	Generalized Regression Neural Network
LOS	Level of Service
MLFN	Multi-layer Feed-forward Neural networks
NN	Neural Network
PNN	Probabilistic Neural Network
PRNN	Pattern Recognition Neural Network
PT	Public Transport
R	Coefficient of Correlation
RMSE	Root Mean Square Error
SQ	Service Quality
STP	Strategic Transportation Plan

Chapter 1

Introduction

1.1 General

With the rapid growth of population, Dhaka city has undergone developments that are unplanned and scattered. As a result, the city's urban transport system is facing difficulties in maintaining the required operational standard to meet the needs of ever-increasing population. However, Government of Bangladesh is now concerned to turn this susceptible city into a livable and developed place.

The roads of Dhaka city are clogged with vehicles all day long making travel unbearable. It has become a dream for city dwellers to travel on traffic jam free road. Unfortunately, Dhaka's struggles will prevail as it is growing at the second fastest rate of the twenty most populated metropolises in the world. The impact of such rapid growth has major consequences on the ability of the transport sector to provide mobility for all people, as they seek to take advantage of employment, education, health and social opportunities. As Dhaka is also the economic, cultural and administrative hub of Bangladesh, huge amount of people travels daily by foot, pedal rickshaws, auto-rickshaws, tempos, taxis, private cars, and a wide array of buses. Citizens, predominantly being upper middle-class, are heavily dependent on public transport system of the city (Hossain, 2006). Among these travel modes, buses are the only available conveyance medium for dedicated mass transport system in Dhaka city. Some of the reasons for this could be cheap fares, easy accessibility, extensive routing etc. Although most of the buses in the city do not provide the required level of satisfaction to the commuters, yet they tend to ride in buses, finding no other option. According to Strategic

Transportation Plan (STP) 2010, 31% of all transport trips comprise of bus trips. Government caters for some of the demand through Bangladesh Road Transport Corporation (BRTC) bus services in various routes, but majority is claimed by the private sector occupying more than 95% of the public transport (Rahman, 2011). With such high influence together with commuters' lack of option, private organizations tend to ignore the service quality and satisfaction level of users. As a result, there is no improvement in public transport service and general commuters have to bear the dissatisfaction. Deterioration of public transport service is also linked to the lack of adequate public transport vehicles in the roadway of Dhaka city. According to Bangladesh Road Transport Authority's (BRTA) statistical report in 2012, 73.33% of the total number of registered vehicle in Dhaka is small private vehicles. Arguably presence of uncontrolled amount of private vehicles in the traffic stream is one of the major reasons of traffic stop-and-go situations in Dhaka city (Khan and Hoque, 2013). Hence congestion together with ever degrading bus service qualities have been the reasons behind public transport facilities not gaining enough popularity. Service qualities mostly include delay in travel, seating/standing discomfort, crush load, distance from home or work place to bus stops, etc. With the travel demand ever-increasing the public transport facilities need to be improved and made more attractive to the users. The rise in popularity of the public transport would mean less private vehicle in the roadway and could serve as a way to reduce congestion. To make public transport more popular, bus service quality needs to be improved through identification and analysis of service and performance attributes.

In the arena of public transport (PT), Service quality (SQ) is a key factor in attracting and retaining new users. An increase in passenger satisfaction turns into retained markets, increased use of the system, newly attracted customers, and a more positive public image (Transportation Research Board, 1999). Therefore, the ability to identify those factors having the greatest impact on SQ has become a guiding principle for PT planners and managers, helping them to decide where to direct their service operations and enhancement efforts. Service quality of public bus must be considered from the commuter's point of view rather than the operators. Quality is such an important issue that it is considered a really significant concept in our real life. It is regarded as a strategic organizational weapon. And, the pressing need of developing service organizations and upgrading their services necessitates the measuring of service quality. These assets are checking the quality progress and providing bases for improving it. From users' low service quality means the public bus loses its competitive edge over private vehicles and the ever-lasting problem of congestion prevails. There are two types of approaches that can be used to determine bus level of service, one of which includes objective measurement which makes use of actual field parameters and established methodologies described in Highway Capacity Manual. The other approach is the subjective assessment which makes use of the perception and judgment of the commuters. The later approach includes assessment and determination of the level of service involving users' perception of how they feel and sense the various qualities or attributes of the service and make judgments about level of service, acquire and interpret information, and often make decisions in response to these inputs. The first approach is more suitable to developed countries where the traffic system is well-organized and there's proper enforcement to prevent erratic behavior. For relatively underdeveloped country like Bangladesh the objective assessment is not suitable due to the variation in parameters with the expectation and needs of users. As users constitute one of the three components of a transportation system; and in many respects the most important component, user perception is a critical element within the concept of transportation services. The concept of user perception already has been used in many areas of transportation engineering, in the evaluation of 'Level of Service (LOS)' or the analysis of users' satisfaction through survey results. However, many of these measures of user satisfaction are not sufficient for explaining how much the users are satisfied or how much inconvenience they have experienced (Lee, 2006). There has not been any method designed to explain the needs, wants and desires of the transportation system user (Pietrucha, 2001). Hence the need to develop a suitable methodology to determine the Service Quality of bus in Dhaka city is necessary in the present context with carefully chosen parameters using feedback of user satisfaction levels as input data.

This research has been carried out focusing on obtaining the information regarding users' assessment of bus service qualities in linguistic terms and use of neural network and fuzzy logic to develop methodology to predict SQ of a bus based on the user feedback and to help in improving the service qualities.

1.2 Objective of the study

The overall objective of the study is to present a methodology that combines artificial intelligence of neural networks and logical reasoning of fuzzy inference system to predict level of service of a bus based on commuters' subjective assessment using multi-criteria decision making tools. The specific objectives of the study are:

- To explore the existing bus service quality in various routes of Dhaka city.
- To determine the best Artificial Intelligence (AI) model for the estimation/prediction of bus service quality.
- To formulate a general methodology by employing AI to analyze users' perception in determining or predicting bus SQ.
- To identify the most significant service quality attributes that influence the quality of bus services in Dhaka city.
- To validate and evaluate the results of the methodology developed.

1.3 Scope of the study

The tool prepared through this research can be used by the operators and decision makers to evaluate SQ of a bus service based on users' perception. Most of the service providers tend to focus on profit maximization without any regard to user satisfaction, as a result of which popularity of the service declines. Hence, to attract users and maintain operational standards the operator can use this tool to monitor, evaluate and implement improvements in service.

Also, through attribute ranking, the transit agencies policy makers can identify those critical or important attributes that contribute more towards evaluation of SQ. Hence, by prioritizing those attributes and improving or developing those, may increase the overall SQ drastically. In this way, quick results can be achieved in attracting potential users of the service.

1.4 Organization of the Thesis

The study is organized into seven major chapters.

Chapter 1 includes introduction to the problem together with background, objective, and scope of the study and general direction of the research.

Chapter 2 comprises of the literature review of the studies carried out prior and during this research to undertake this thesis and fulfil the specific objectives. It includes overview of studies carried out on bus service quality determination, studies using neural networks and fuzzy logic and finally, use of those techniques to solve real life problems.

Chapter 3 discusses on Artificial Neural Networks and its similarities to biological neurons. Subsequently it illuminates on GRNN, PNN and PRNN.

Chapter 4 discusses on ANFIS which includes an introduction to fuzzy logic and neuro fuzzy inference systems. This chapter also includes the structure of ANFIS used to solve the problem and some discussion on learning algorithms.

Chapter 5 incorporates the methodology adopted to carry out the study, including selection of attributes, data collection, preparation and analysis, model development using training data set and attribute ranking procedure.

Chapter 6 presents evaluation of the model developed using test data set and makes use of some mathematical tools to analyse the results obtained from the model with that of users' provided data. Also in this chapter the ranking of attributes is presented and compared for both the model and public opinion.

Chapter 7 contains conclusions drawn from the study and analysis, recommendations to improve the prevailing service qualities in Dhaka city.

Chapter 2

Literature Review

2.1 Introduction

This chapter presents an extensive review of literatures that deal with different measurement methods and parameters used to measure the overall service quality of bus transit system. After a brief description of the importance of bus service quality measurement research in the next section, this chapter summarizes the available literature on bus service quality measurement in general along with the inherent limitations of these studies. Afterwards, it introduces the Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) which has been extensively used in business, social and medical science. Application of ANN and FIS in the study of bus service quality measurement is briefly summarized at the end which shows the prospective use of these techniques for this research.

2.2 Use of Bus as Public Transit

All shapes and sizes of vehicles are part of the traffic. The multiplicity of modes of transport, private cars, motor cycles, buses, taxis, cycle rickshaws, rickshaw vans, trucks, pushcarts and recently revived animal driven transports offers a rich range of choices to travellers and transporters of goods. But lack of relevant measures and firm decisions to cope with the complexity of traffic has created chaotic conditions. Different types of modes using the same road space characterize traffic environment. Current very diverse traffic mix is increasing the traffic delays constantly. Figure 2.1 is an illustration of the complex traffic composition in Dhaka.

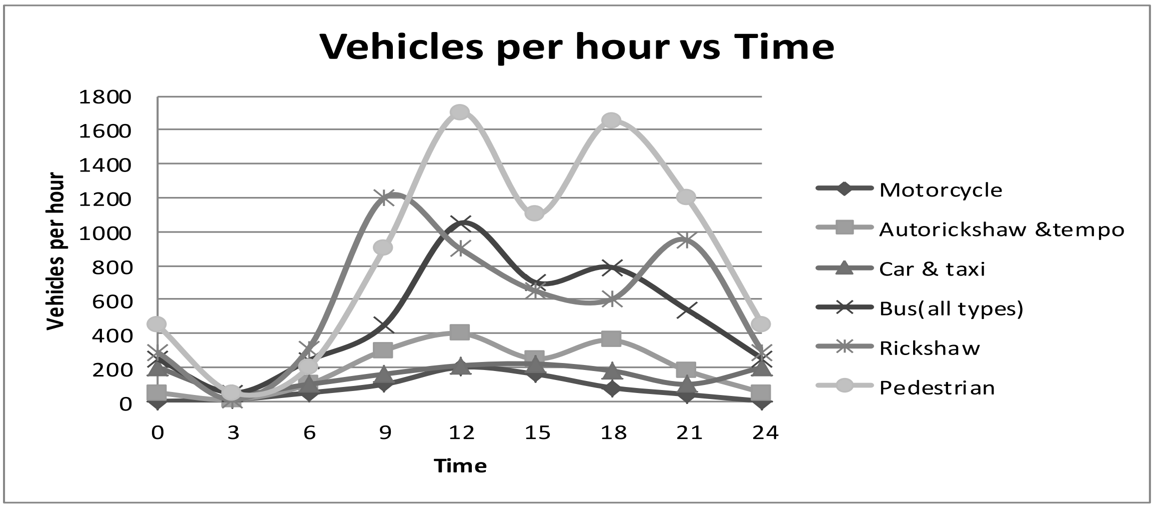


Figure 2.1: Illustration of traffic composition in Dhaka (Source: STP, 2004)

An attitudinal questionnaire survey was made by STP in 2004 on public transport. In reply to a question on 'reasons for using bus as usual travel mode' respondents said they preferred bus journey because of various reasons. Almost 73% said it is cheaper, 69% said they don't have any other alternatives, 31% said it is more or less reliable, 21% said it save time, 26% said it is convenient and comfortable too and 22% said it is comparatively safer. Only 10% said that they take bus because they cannot use their car to get to their work place due to the problem of parking.

In Dhaka, according to services, buses are classified into two types: (1) Counter bus service; and (2) Local bus service. Counter buses have specified stoppages for loading and unloading passengers. Passengers have to purchase ticket before boarding on counter buses. Few of the counter buses are air-conditioned. Whereas, local buses have no defined stoppages. They stop anywhere on the road for loading and unloading passengers. Passengers pay to conductor after boarding on the bus. Both counter and local buses remain over-crowded due to gap between demand and supply. However, there are a few seating service buses operating in certain limited routes which allow boarding passengers only if there is an empty seat available for the person.

Again according to size, Dhaka buses can be grouped in to 3 types: (1) Large bus; (2) Mini bus; and (3) Double decker. Large buses are those with at least 32 seats. However, more generally buses with length more than 10m are considered as large bus. The most significant recent change in the bus fleet composition is the increases in the number of large buses. This trend began with Sino Dipon in early 2003. They are now operating on four different routes with 105 buses. Minibuses have capacity of 15 to 30 seats excluding driver's seat and normally are around 8m long. According to the Bangladesh Road Transport Authority (BRTA), there are around 9311 numbers of registered large buses and 8459 numbers of registered mini buses in Dhaka city.

There are 39 different routes of bus service in Dhaka city approved by Dhaka Metropolitan Regional Transport Committee (DMRTC) in April, 2009. However, almost all of these routes have variations in routes for operation. No scientific methods or planning process are applied for identifying such bus routes for operating and bus stoppage (Rahman, 2011). Figure 2.2 demonstrates prevailing bus routes and number of buses operating at those routes.

STP conducted a survey on average trip length, travel time, speed and carrying capacity of existing mass transit system and got the following scenario as shown in Table 2.1.

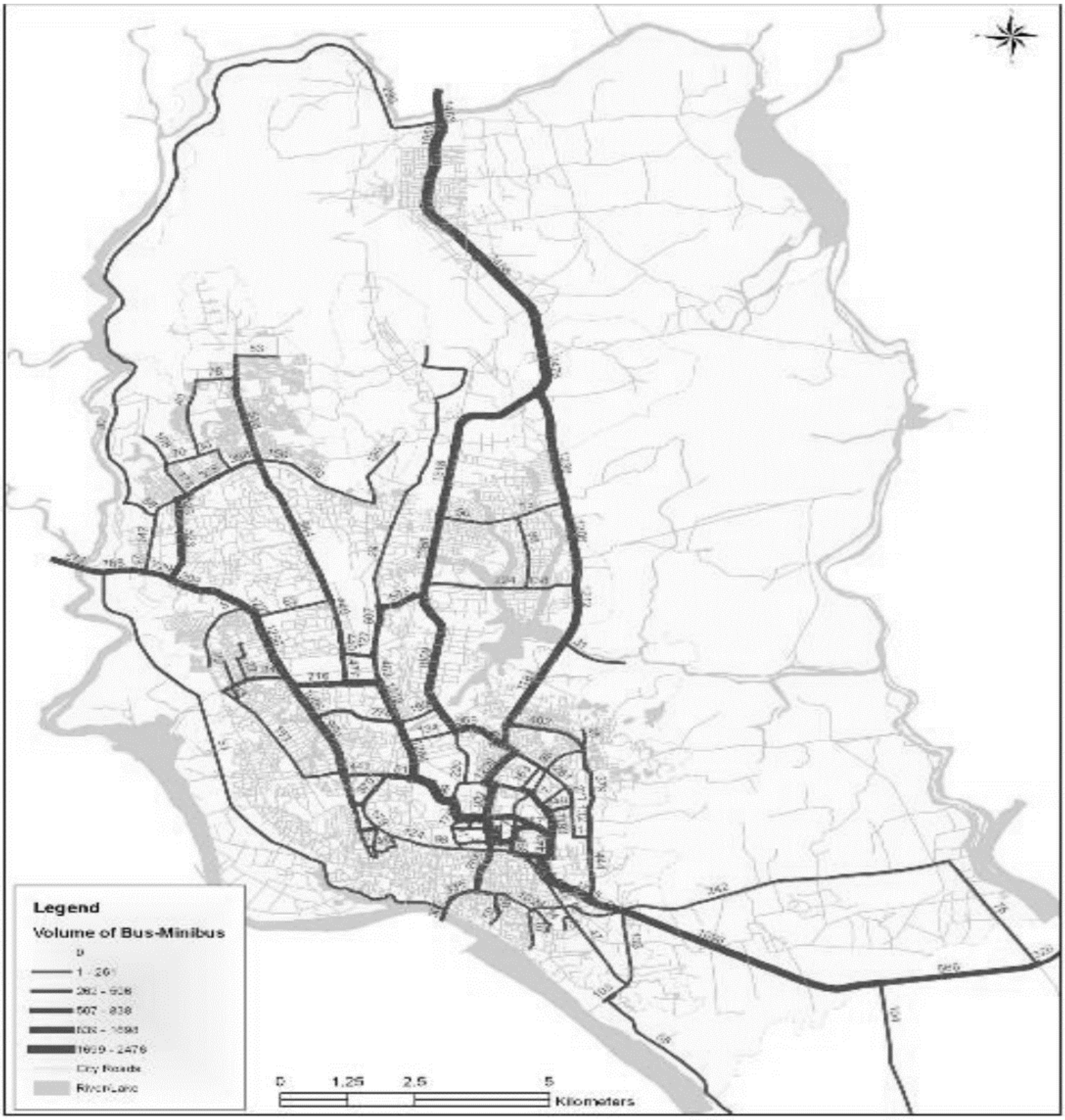


Figure 2.2: Prevailing bus routes and number of buses operating on those routes.

Table 2.1: Average trip length, travel time, speed and carrying capacity of existing mass transit system in Dhaka City.

Mode	Average Route length (km)	Average Journey time (min)	Average travel speed (km/hr)	Average running speed (km/hr)	Average boarding passenger	Pass-load at max. point	Average stops
Mini Bus	20.12	65.00	17.14	23.19	79.27	39.1	16.56
Large Bus	14.7	71.09	13.7	17.8	89.6	44.9	12.3
Double Decker	17.81	56.83	17.22	23.45	100.76	83.71	13.67
School/ Staff bus	13.5	37.25	20.9	23.0	44.4	43.4	7.8

2.3 Bus Service Quality measurement

Measurement of service quality poses a serious challenge to researchers and has been an important concern for service providers. It is imperative that SQ attributes affecting customer behaviour are identified and their importance established (Mazulla and Eboli, 2006). In the literature there are many techniques for measuring SQ and customer satisfaction, for public transport as in other service industries. The evaluation of service quality and customer satisfaction can be obtained according to different methods: by asking customers the perception/satisfaction on service quality, by asking the expectation/importance, or by asking both perception and expectation; in addition, perception can be compared with the zone of tolerance of expectations (the range defined by the maximum desired level and minimum acceptable level of expectations). (Figini, 2003).

The techniques for measuring service quality and customer satisfaction can be identified in two different categories. The first one includes methods of statistical analysis, such as quadrant and gap analysis, factor analysis, scattergrams, bivariate correlation, cluster analysis, and conjoint analysis. Some of these provide an evaluation of the individual service attributes, others provide the relationship of attributes with overall satisfaction. Many authors have introduced some indexes for measuring overall satisfaction or service quality. On the basis of the method introduced by Kano (Kano, 1984), some indexes (Better, Worse and Quality Improvement) were proposed by Berger (Berger et al., 1993). One of the best-known indexes is the SERVQUAL, a service quality evaluation method developed by marketing academics. It produces a subjective measure of the gap between expectations and perceptions in five service quality dimensions common to all services. (Zeithaml et al., 1986). SERVQUAL comprises 22 items (Likert-type) with five dimensions namely- tangibles, reliability, responsiveness, assurance and empathy. Each item in SERVQUAL instrument is of two types. One to measure expectations about firms in general within an industry and the other measures perceptions regarding the particular company whose service is being assessed. Among other tools to measure SQ, SERVPERF, MORI model, Normed Quality and Zone of Tolerance have been used.

In the "Handbook for Measuring Customer Satisfaction and Service Quality", published by the Transportation Research Board, the "impact score" technique is described (TRB, 1999). "Impact score" is the impact of each service quality attribute on global customer satisfaction. For each attribute, the sample is divided into two categories, those respondents who have not recently experienced a problem with the attribute and those respondents who have had a recent problem with it. The mean satisfaction rating of each attribute of the two groups of respondents are compared. The difference between the two mean satisfaction rates, called "gap score", is multiplied by the percentage of passengers who have had a problem with an attribute.

A Customer Satisfaction Index (CSI) was adopted by Bhave; this index is calculated by using an importance weighting based on an average of 1. The customers assign a rate of importance (weighting) and a rate of satisfaction (score) to each service attribute. Each weighting is divided by the average of the weightings expressed by customers. In this way, average weightings based on an average of 1 are obtained. Then, a weighted score is calculated for each attribute as a product of score and average weighting. Finally, the CSI is the sum of all weighted scores. (Bhave, 2002).

The second category of techniques includes modelling for estimation of coefficients by relating global SQ (dependent variable) to some attributes (independent variable). Linear models such as multiple regression models and non-linear models such as structural equation model (SEM) and logit models.

Eboli and Mazzulla (2007) made use of the SEM to explore the impact of the relationship between global customer satisfaction and service quality attributes based on needs and expectations expressed by the customers of public transport services. The public transport service analyzed is the bus service used by University of Calabria students to reach the campus from the urban area of Cosenza (southern Italy). Data was collected through survey among sample of students.

Prioni and Hensher (2000) developed a stated preference model of service quality choice that provides the set of indicators required to represent a user-based measure of service quality. The service quality index (SQI) provides an operationally appealing measure of service effectiveness to assist regulators in administering and monitoring a performance assessment management and operators in improving customer service.

Tyrinopoulos and Antoniou (2008) propose a methodology based on the combination of factor analysis and ordered logit modelling. The method analyses variation in users' behavior and their level of satisfaction from the use of diverse transit systems. This methodology is applied to five different transit systems in Greece; survey respondents were asked to rate 23 selected attributes according to importance and satisfaction criteria. The data collected from the first set of questions were used as input for the factor analysis, while the second set of data was used as input for the ordered logit models. The objective of the factor analysis is to try to discern and recognize the underlying unobserved factors that the respondents perceive.

The models discussed above require input variables to be provided into the system which are the attributes of service quality affecting customer behavior. Many researchers have used large number of attributes (TRB 1999; Prioni and Hensher, 2000) to model a specific problem but that creates the problem of inputting too many variables into the system. Zeithaml et al (1988) suggested the use of a generic list of attributes for determining SQ in any field of service but the idea did not gain much appreciation from fellow researchers. Many are in agreement that various situation calls for separate analysis of each problem in hand and attributes selected accordingly. Mazulla and Eboli, (2006) suggested that all the attributes be grouped in macro-factors defined by one or more attributes. Examples of these are transport network design (e.g. number and regularity of bus stops, having stops near destination), service supply and reliability (e.g. frequency, regularity and punctuality of rides), comfort (e.g. availability of seats on bus, bus overcrowding), fare (e.g. fairness/consistency of fare structure, ease of paying fare), information (e.g. availability of information on schedules/maps, explanation and announcement of delays), safety (e.g. safe and competent drivers, security against crimes), relationship with personnel (e.g. friendly, courteous personnel), customer preservation (e.g. repayment, complaint number), environmental protection (e.g. use of vehicles with low environmental impact), quality of system (quality of stops furniture, cleanliness of bus exterior).

2.4 Artificial Neural Network

To analyze the non-linear relations between the attributes and user's satisfaction, estimation of coefficients by modeling has become more popular for the last few decades. In this technique, to find out the effects of each attributes, coefficients are estimated by relating the SQ attributes (independent variables) with the user's satisfaction (dependent variable). Numerous studies have been performed using this technique. Lai and Chen (2011) and de Oña et al. (2013) proposed multi-attribute approaches using SEM to identify the latent factors influencing the service and the relationships between these factors and the overall SQ. Eboli and Mazzulla (2008) proposed a Logit model to calculate SQ index based on user stated preferences which was concerned with a particular user group (student). As a result, that model was not much effective in measuring service quality of public transport. Many researchers used neural networks for measuring the performance of public transport services. A multi-layer perceptron (MLP) neural network was proposed by Costa and Markellos (1997) for public transport SQ measuring purpose which was a nonparametric and stochastic approach. That model was more flexible to practice and claimed as a superior technique than any other traditionally applied techniques. Davies et al. (1999) used SEM as a parametric model and MLP neural network as a non-parametric model to analyze customer satisfaction on banking service. That comparison study concluded that, a neural network analysis may be more useful in establishing a pattern where the relations between attributes and customer satisfaction are yet to be understood. Gan et al. (2005) compared the consumer choice prediction capabilities of the Logistic regression model and two types of neural network models, namely multi-layer feed-forward neural networks (MLFN) and probabilistic neural network (PNN). Acknowledging the constraints of ANN, this study concluded that both ANN models (MLFN and PNN) exhibited a higher overall percentage correct on consumer choice predictions than the logistic model. In addition, the PNN demonstrated to be the best predictive NN model.

2.5 Fuzzy Inference System

Since the introduction of fuzzy sets (Zadeh 1965), fuzzy approaches have been applied to many areas including civil engineering. It has been mainly used in control engineering, decision science, and management. The strength of fuzzy set theory is in its ability to establish numerical inputs from subjective and ambiguous information, to analyze or evaluate the information, and to produce numerical outputs from those procedures. Due to those strengths, it is especially useful for the representation of imprecise and subjective knowledge of the type that is prevalent in human concept formation and reasoning (Yager, 1986). Indeed, the fuzzy approach has already been used in many areas related to human perception, such as the evaluation of service quality, the analysis of workload and risk in the workplace, and decision making processes. In areas related to civil engineering, there are studies evaluating pavement condition and qualitative measurements including transportation service quality using the fuzzy approach. Three main topics, which apply fuzzy set theory, were reviewed including the applications of fuzzy sets in transportation engineering, decision making processes, and evaluation of service quality.

Early on, fuzzy set theory was mainly applied in transportation engineering for traffic control (Robertson 1979, Favilla et.al 1993) and accident prediction. Another researcher who indicated the importance of applying the fuzzy sets in transportation engineering was Spring (2000). He mentioned that fuzzy sets are able to represent vague and imprecise concepts in transportation engineering, such as the service quality of transportation facilities. Ndoh and Ashford applied fuzzy sets to evaluate airport terminal service quality in their 1995 study. They indicated that conventional methods to evaluate the transportation service quality are quantitative measures and are reasonably simple to measure but these measures are deficient in representing the qualitative nature of service quality for transportation facilities. These methods may not be able to incorporate directly users' perceptions of LOS. To remedy this situation, they developed a methodology for establishing LOS measures based on users' perception and then applied the method to evaluate airport terminal service quality. Fang et al. (2003) tried to incorporate user perception in defining the LOS categories using a fuzzy C-means clustering technique. They stated that the fuzzy set is an instrument that makes use of human knowledge and the deductive processes.

In the literature there are many models and methods available to measure SQ in any field of service but each method has its own inherent limitations and disadvantages. De Oña et al. (2012) mentioned that each model has its own assumptions and basic relationships unique to the problem in hand and demonstrated application of data mining technique and decision tree model. ANN closely resembles the advantages of the tree model and have been in use for modelling the SQ of public transportation systems (Garrido et al. 2014). Adaptive neuro-fuzzy inference system brings the advantages of both ANN and fuzzy inference system in one. After generated input-output by training, the ANFIS can be used to recognize data that is similar to any of the examples shown during the training phase. The adaptive neuro-fuzzy inference system has been well documented in civil engineering field to solve many problems (Abdulkadir et al., 2006; Akbulut et al., 2004; Fonseca el at., 2008;

Tesfamariam & Najjaran, 2007). Other application of ANFIS include Breast cancer detection (Elif, 2008); Determination of the relative magnetic permeability by using ANFIS and 2D-FEM (Mohdeb and Mekideche, 2010); Use of ANFIS model to estimate the marginal walking time (Kim and Lee, 2008) and many others.

2.6 Summary

This chapter reviews the available literature and previous researches on bus service and its quality analysis, artificial intelligence and its application on transportation system. Moreover, the present state of public transport, prevailing bus routes and number of buses operating at those routes in Dhaka city are also discussed in this chapter. The most significant recent change in the bus fleet composition in Dhaka city is the increases in the number of large buses. In the literature, there are many models and methods available to measure SQ in any field of service but each method has its own inherent limitations and disadvantages. Those limitations and disadvantages have also been addressed here.

Chapter 3

Artificial Neural Network

3.1 Introduction

Level of Service of Bus is a quantitative way of measuring the bus service quality which depends on users' perception. For this regards, it is essential to use such tool that can simulate the users' psychology and decision making process. Moreover, a tool is required which can learn the procedure of measuring the SQ of bus. Artificial Neural Network (ANN) is found to be the most suited technique for fulfilling that purpose. This chapter presents the overall knowledge regarding to ANN and its application on the analysis of bus service quality. Subsequently, some adaptive forms of ANN are described that have been used in this research.

3.2 Artificial Neural Network

Thinking and making decisions are done by the human brain. More specifically, Neuron is the smallest unit of brain that receives information and generates decision basing on that information. To simulate the decision making procedure of human brain, the activities and network of neurons are simulated artificially in the Artificial Neural Network.

3.2.1 Biological Neuron

Neural networks are models of biological neural structures. Figure 3.1 shows such a biological neuron. A neuron operates by receiving signals from other neurons through connections, called *synapses*. The combination of these signals, in excess of a certain threshold or activation level, will result in the neuron firing, that is sending a signal on to other neurons connected to it. Some signals act as excitations and others as inhibitions to a neuron firing. What we call thinking is believed to be the collective effect of the presence or absence of firings in the pattern of *synaptic connections* between neurons.

This sounds very simplistic until we recognize that there are approximately one hundred billion (100,000,000,000) neurons each connected to as many as one thousand (1,000) others in the human brain. The massive number of neurons and the complexity of their interconnections results in a "thinking machine", your brain.

Each neuron has a body, called the *soma*. The soma is much like the body of any other cell. It contains the cell nucleus, various bio-chemical factories and other components that support ongoing activity.

Surrounding the soma are *dendrites*. The dendrites are receptors for signals generated by other neurons. These signals may be excitatory or inhibitory. All signals present at the dendrites of a neuron are combined and the result will determine whether or not that neuron will fire.

If a neuron fires, an electrical impulse is generated. This impulse starts at the base, called the *hillock*, of a long cellular extension, called the *axon*, and proceeds down the axon to its ends.

The end of the axon is actually split into multiple ends, called the *boutons*. The boutons are connected to the dendrites of other neurons and the resulting interconnections are the previously discussed synapses. (Actually, the boutons do not touch the dendrites; there is a small gap between them). If a neuron has fired, the electrical impulse that has been generated stimulates the boutons and results in electrochemical activity which transmits the signal across the synapses to the receiving dendrites.

At rest, the neuron maintains an electrical potential of about 40-60 millivolts. When a neuron fires, an electrical impulse is created which is the result of a change in potential to about 90-100 millivolts. This impulse travels between 0.5 to 100 meters per second and lasts for about 1 millisecond. Once a neuron fires, it must rest for several milliseconds before it can fire again. In some circumstances, the repetition rate may be as fast as 100 times per second, equivalent to 10 milliseconds per firing. Compare this to a very fast electronic computer whose signals travel at about 200,000,000 meters per second (speed of light in a wire is 2/3 of that in free air), whose impulses last for 10 nanoseconds and may repeat such an impulse immediately in each succeeding 10 nanoseconds continuously. Electronic computers have at least a 2,000,000 times advantage in signal transmission speed and 1,000,000 times advantage in signal repetition rate.

It is clear that if signal speed or rate were the sole criteria for processing performance, electronic computers would win hands down. What the human brain lacks in these, it makes up in numbers of elements and interconnection complexity between those elements. This difference in structure manifests itself in at least one important way; the human brain is not as quick as an electronic computer at arithmetic, but it is many times faster and hugely more capable at recognition of patterns and perception of relationships.

The human brain differs in another, extremely important, respect beyond speed; it is capable of "self-programming" or adaptation in response to changing *external stimuli*. In other words, it can learn. The brain has developed ways for neurons to change their response to new stimulus patterns so that similar events may affect future responses. In particular, the sensitivity to new patterns seems more extensive in proportion to their importance to survival or if they are reinforced by repetition.

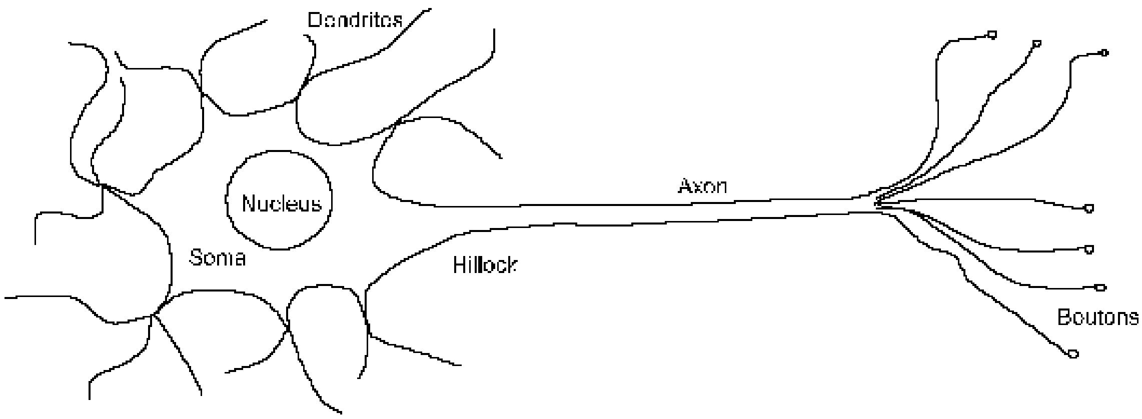


Figure 3.1: A Biological Neuron

3.2.2 Neural Network Structure

The starting point for most neural networks is a model neuron, as in Figure 3.2. This neuron consists of multiple inputs and a single output. Each input is modified by a *weight*, which multiplies with the input value. The neuron will combine these weighted inputs and, with reference to a threshold value and activation function, use these to determine its output. This behavior follows closely our understanding of how real neurons work.

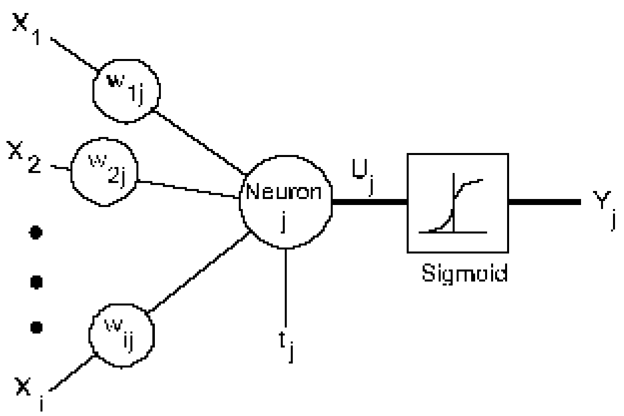


Figure 3.2: A Model Neuron

While there is a fair understanding of how an individual neuron works, there is still a great deal of research and mostly conjecture regarding the way neurons organize themselves and the mechanisms used by arrays of neurons to adapt their behavior to external stimuli. There are a large number of experimental neural network structures currently in use reflecting this state of continuing research. In our case, we will only describe the structure, mathematics and behavior of that structure known as the *backpropagation network*. This is the most prevalent and generalized neural network currently in use.

To build a backpropagation network, proceed in the following fashion. First, take a number of neurons and array them to form a *layer*. A layer has all its inputs connected to either a preceding layer or the inputs from the external world, but not both within the same layer. A layer has all its outputs connected to either a succeeding layer or the outputs to the external world, but not both within the same layer. Next, multiple layers are then arrayed one succeeding the other so that there is an *input layer*, multiple *intermediate layers* and finally an *output layer*, as in Figure 3.3. Intermediate layers, that is those that have no inputs or outputs to the external world, are called *hidden layers*. Backpropagation neural networks are usually fully connected. This means that each neuron is connected to every output from the preceding layer or one input from the external world if the neuron is in the first layer and, correspondingly, each neuron has its output connected to every neuron in the succeeding layer.

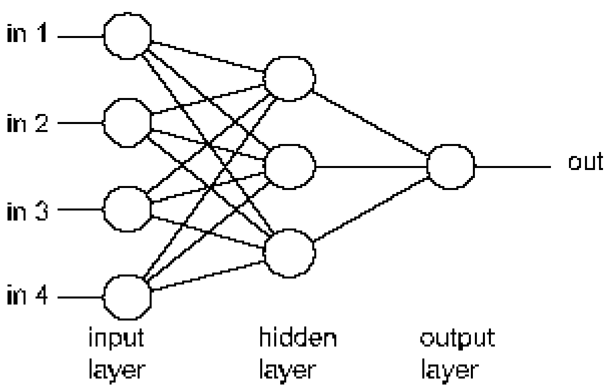


Figure 3.3: Backpropagation Network

Generally, the input layer is considered as distributor of the signals from the external world. Hidden layers are considered to be categorizers or feature detectors of such signals. The output layer is considered a collector of the features detected and producer of the response. While this view of the neural network may be helpful in conceptualizing the functions of the layers, you should not take this model too literally as the functions described may not be so specific or localized.

3.2.3 Neural Network Operation

The output of each neuron is a function of its inputs. In particular, the output of the j^{th} neuron in any layer is described by two sets of equations:

$$U_j = \sum (X_i \cdot w_{ij}) \quad \text{............ [Eqn 1]}$$

$$Y_j = F_{th}(U_j + t_j) \quad \text{............ [Eqn 2]}$$

For every neuron, j, in a layer, each of the i inputs, X_i, to that layer is multiplied by a previously established weight, w_{ij}. These are all summed together, resulting in the internal value of this operation, U_j. This value is then biased by a previously established threshold value, t_j, and sent through an activation function, F_{th}. This activation function is usually the sigmoid function, which has an input to output mapping as shown in Figure 3.4. The resulting output, Y_j, is an input to the next layer or it is a response of the neural network if it is the last layer. Neutralist allows other threshold functions to be used in place of the sigmoid described here.

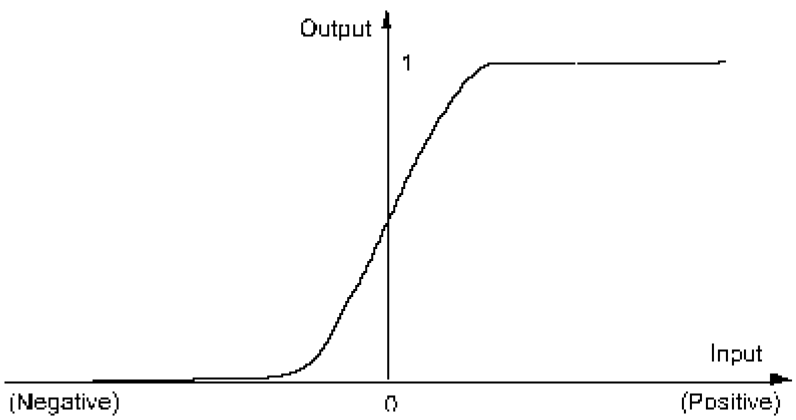


Figure 3.4. Sigmoid Function

In essence, Eqn 1 implements the combination operation of the neuron and Eqn 2 implements the firing of the neuron.

From these equations, a predetermined set of weights, a predetermined set of threshold values and a description of the network structure (that is the number of layers and the number of neurons in each layer), it is possible to compute the response of the neural network to any set of inputs.

3.2.4Neural Network Learning

Learning in a neural network is called *training*. Like training in athletics, training in a neural network requires a coach, someone that describes to the neural network what it should have produced as a response. From the difference between the desired response and the actual response, the *error* is determined and a portion of it is propagated backward through the network. At each neuron in the network the error is used to adjust the weights and threshold values of the neuron, so that the next time, the error in the network response will be less for the same inputs.

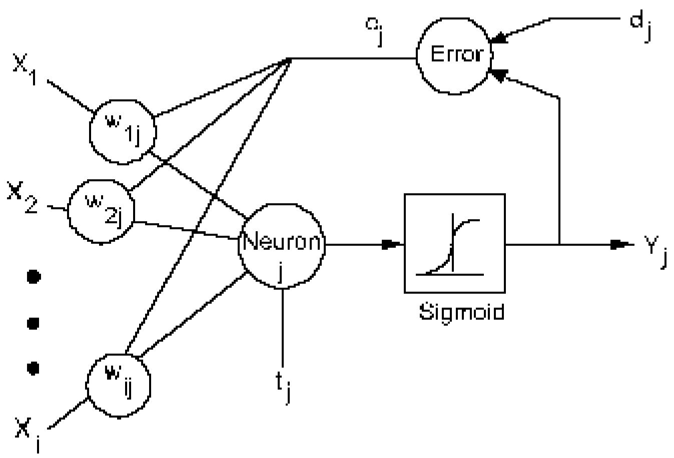


Figure 3.5: Neuron Weight Adjustment

This corrective procedure is called *backpropagation* and it is applied continuously and repetitively for each set of inputs and corresponding set of outputs produced in response to the inputs. This procedure continues so long as the individual or total errors in the responses exceed a specified level or until there are no measurable errors.

Backpropagation starts at the output layer with the following equations:

$$w_{ij} = w'_{ij} + LR \cdot e_j \cdot X_i \quad \text{............ [Eqn 3]}$$

$$e_j = Y_j \cdot (1 - Y_j) \cdot (d_j - Y_j) \quad \text{............ [Eqn 4]}$$

For the ith input of the j^{th} neuron in the output layer, the weight w_{ij} is adjusted by adding to the previous weight value, w'_{ij}, a term determined by the product of a learning rate, LR, an error term, e_j, and the value of the i^{th} input, X_i. The error term, e_j, for the j^{th} neuron is determined by the product of the actual output, Y_j, its complement, $1 - Yj$, and the difference between the desired output, d_j, and the actual output.

Once the error terms are computed and weights are adjusted for the output layer, the values are recorded and the next layer back is adjusted. The same weight adjustment process, determined by Eqn 3, is followed, but the error term is generated by a slightly modified version of Eqn 4. This modification is:

$$e_j = Y_j \cdot (1 - Y_j) \cdot \sum (e_k \cdot w'_{jk}) \quad \text{............ [Eqn 5]}$$

In this version, the difference between the desired output and the actual output is replaced by the sum of the error terms for each neuron, k, in the layer immediately succeeding the layer being processed times the respective pre-adjustment weights.

The learning rate, LR, applies a greater or lesser portion of the respective adjustment to the old weight. If the factor is set to a large value, then the neural network may learn more quickly, but if there is a large variability in the input set then the network may not learn very well or at all. In real terms, setting the learning rate to a large value is analogous to giving a child a spanking, but that is inappropriate and counter-productive to learning if the offense is so simple as forgetting to tie their shoelaces. Usually, it is better to set the factor to a small value and edge it upward if the learning rate seems slow.

In many cases, it is useful to use a revised weight adjustment process. This is described by the equation:

$$w_{ij} = w'_{ij} + (1 - M) \cdot LR \cdot e_j \cdot X_j + M \cdot (w'_{ij} - w''_{ij}) \qquad \text{............ [Eqn 6]}$$

This is similar to Eqn 3, with a *momentum factor*, M, the previous weight, w'_{ij}, and the next to previous weight, w''_{ij}, included in the last term. This extra term allows for momentum in weight adjustment. Momentum basically allows a change to the weights to persist for a number of adjustment cycles. The magnitude of the persistence is controlled by the momentum factor. If the momentum factor is set to 0, then the equation reduces to that of Eqn 3. If the momentum factor is increased from 0, then increasingly greater persistence of previous adjustments is allowed in modifying the current adjustment. This can improve the learning rate in some situations, by helping to smooth out unusual conditions in the training set.

3.3 Generalized Regression Neural Network (GRNN)

Generalized Regression Neural Network (GRNN) is an adaptation of radial basis network and used for function approximation (Funahashi 1989). It has a radial basis portion and a special linear portion. Figure 3.6 shows the GRNN architecture as an adaptive diagram for this research.

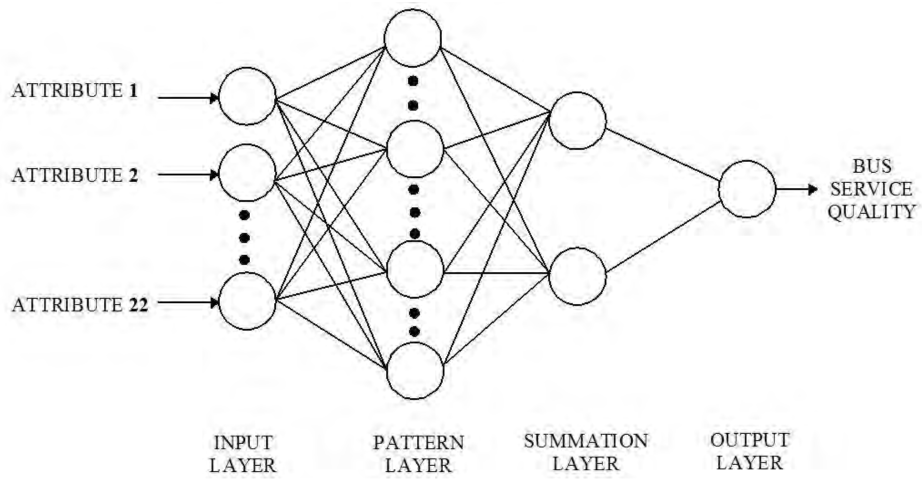


Figure 3.6: Architecture of GRNN and PNN

The GRNN architecture consists of four fully connected layers: input layer, pattern layer, summation layer and output layer. The input layer is merely a distribution unit, which provides all of the (scaled) measurement attributes to all of the neurons on the second layer, the pattern units. The pattern unit is dedicated to one exemplar or one cluster center. When a new vector is entered into the network, it is subtracted from the stored vector representing each cluster center. Either the squares or the absolute values of the differences are summed and fed into a nonlinear activation function. The activation function normally used in the exponential which is shown in Eqn 7. Then the pattern unit outputs are passed on to the summation units. The summation units perform a dot product between a weight vector and a vector composed of the signals from the pattern units. In this portion, the summation unit that generates an estimate of function of input sums of the outputs of the pattern units weighted by the number of observations each cluster center represents. The summation unit that estimates input attributes multiplies each value from a pattern unit by the sum of samples output associated with cluster center. The output unit yields the desired estimate of Y_i (i.e. bus SQ). However, it is found that the addition of one element in the output vector requires only one summation neuron and one output neuron.

$$\left.\begin{aligned} u &= 1/N\sum_{i-1}^{N}(x_i) \\ d &= \sqrt{\left\{(x_i-u_i)^T(x_i-u_i)\right\}} \\ h_i &= \exp\ (-d_i^{\,2}/(2b^2)) \end{aligned}\right\} \text{ .... Eqn [7]}$$

Where, $N =$ sample size; $x_i =$ estimator input vector; $u_i =$ unit weight vector in hidden layer; $d =$ distance between the input vector x_i and the training vector u_i ; $b =$ smoothing factor, decides the shape of basic functions in the pattern layer, $b > 0$.

$$\left.\begin{aligned} S &= \textstyle\sum_{i=1}^{n}(x_i) \\ Y_i &= \textstyle\sum_{i=1}^{n} h_i W_{ij} / S \end{aligned}\right\} \text{ .... Eqn [8]}$$

Where, $W_{ij} =$ connection weight corresponding to input training vector x_i and output Y_i.

3.4 Probabilistic Neural Network (PNN)

Probabilistic Neural Network (PNN) is an adaptation of radial basis network and used for classification problems. It has a radial basis portion and a competitive portion. PNN architecture consists of four layers: input layer, pattern layer, summation layer and decision layer. The Figure 1 shows a PNN structure that recognizes classes to determine bus SQ from a set of user attributes. The first layer shows the input layer that contains the independent variables. This layer does not perform any computation and simply distributes the values of input variables to the neurons in the succeeding layer. The second layer is pattern layer comprising with a number of nodes. The number of nodes is equal to the number of training instances. The input layer is fully connected to the pattern layer. The third layer is summation layer which also consists of nodes. The number of nodes in this layer is equal to the number of classes in the training instances. 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 of training pattern.

The network creation process initiates by multiplying the example vector and the input vector. Then, these activations are summed for each class node. The pattern node activation, 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).

$$h_i = E_i F \qquad \text{……….. Eqn [9]}$$

The class output activations are then defined as:

$$C_j = \frac{\sum_{i=1}^{N} e^{\frac{(h_i - 1)}{\gamma^2}}}{N} \qquad \text{……….. Eqn [10]}$$

Where,

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

3.5Pattern Recognition Neural Network (PRNN)

Pattern Recognition Neural Network (PRNN) is a type of Feed Forward Neural Network. During the learning process of the network, a set of data is fed along with their targeted output. A four layered PRNN is implemented for this study. These are an input layer, two hidden layers and an output layer (Figure 3.7). The values always flow from the input layer to the output layer through the neurons. The input values are weighted and biased at each neuron, and passed through an activation function. Using Back propagation algorithm, the neurons update their synaptic weight values by iteration until the resolved output tends to be the targeted value. Learning process of the network can be accelerated by defining Learning ratio and Momentum parameters (Hagan et al. 1996). Number of assigned neurons influences the accuracy in resolving output. Therefore, an optimum number of neuron is selected such that the error between resolved output and targeted value becomes least.

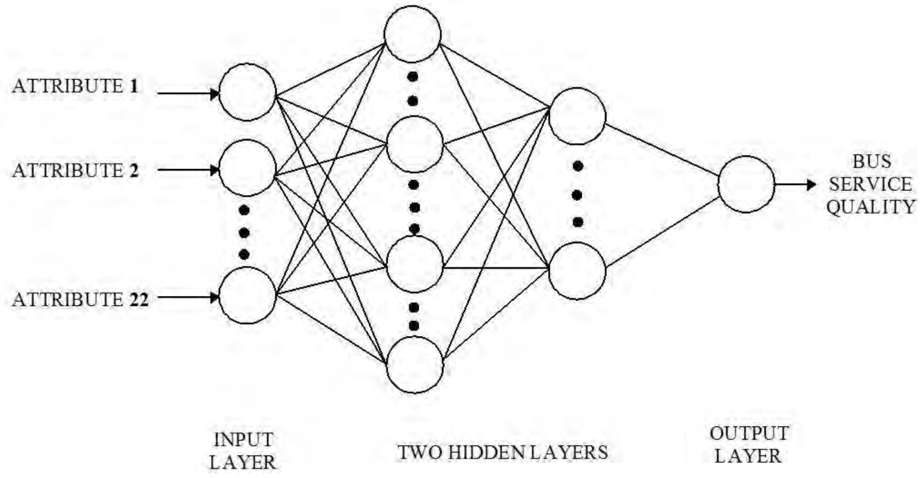


Figure 3.7: Architecture of PRNN

To determine bus SQ from the provided values of user attributes, each neuron of PRNN applies the following equations:

$$\left.\begin{aligned} U_j &= \sum (X_i . w_{ij}) \\ Y_j &= F(U_j + t_j) \end{aligned}\right\} \quad \text{………… Eqn [11]}$$

For every neuron, j, in a layer, each of the i inputs, X_i, to that layer is multiplied by a formerly established weight, w_{ij}. For a particular neuron these are all summed together, resulting in the internal value of this operation, U_j. This value is then biased by a formerly established threshold value, t_j, and sent through a tan-sigmoid function, F. The resulting output, Y_j, is an input to the next layer or it is a final output if it is the last layer.

3.6 Summary

This chapter presents the overall knowledge regarding to ANN and its application on the analysis of bus service quality. Subsequently, some adaptive forms of ANN are described that have been used in this research. The fundamental of ANN is, it is the model of biological neural structure. The input of an ANN model is modified by some *weights* and *biases* and passed through some *activation functions* which results an output. This output is the prediction of ANN. Three types of ANN are discussed here: GRNN, PNN and PRNN. The GRNN and PNN consist of four fully connected layers: input layer, pattern layer, summation layer and output layer. Whereas, the PRNN consists of an input layer, one or more hidden layers and an output layer.

Chapter 4

Fuzzy Inference System

4.1 Introduction

To solve real-life problems, linguistic information is often encountered by limitation that is frequently hard to quantify using 'classical' mathematical techniques. This linguistic information represents subjective knowledge. Since we are unable to quantify some linguistic information, different assumptions are made in the models. Through the assumptions made by the analyst when forming the mathematical model, the linguistic information is very often ignored. On the other hand, a wide range of traffic and transportation engineering parameters are characterized by uncertainty, subjectivity, impression and ambiguity. Human operators, dispatchers, drivers and passengers use this subjective knowledge or linguistic information on a daily basis when making decisions. When solving real-life traffic and transportation problems we should not use only objective knowledge (formulae and equations) or only subjective knowledge (linguistic information). We simply cannot and should not ignore the existence of linguistic information, i.e. subjective knowledge. Fuzzy logic is an extremely suitable concept with which to combine subjective knowledge and objective knowledge.

4.2Fuzzy Logic and Fuzzy Sets

Fuzzy logic was first introduced by Lotfi A. Zadeh, a professor at the University of California at Berkley. Zadeh (1965) established the idea that data can occupy partial set membership rather than crisp set membership of non-membership. Professor Zadeh in his paper reasoned that people do not require precise, numerical information input, and yet they are capable of highly adaptive control. Basically, FL is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers (Chennakesava, 2000).

Fuzzy Set theory introduced by Professor Lotfi Zadeh in 1965 is an extension of the classical set theory. In classical set theory an element either belongs to or does not belong to a set but in fuzzy set elements can take partial membership and sets are not necessarily bound by fixed boundaries or consist of binary membership characteristics. Human like interpretation and decision making processes are hard to simulate in machines as often these include some sort of vagueness and uncertainty. Fuzzy set was particularly invented to represent such uncertain and vague notions. (Agarwal, 2015).

Some of the essential characteristics of fuzzy logic relate to the following:

- In fuzzy logic, exact reasoning is viewed as a limiting case of approximate reasoning.
- In fuzzy logic, everything is a matter of degree
- In Fuzzy logic knowledge is interpreted a collection of elastic or, equivalent, fuzzy constraint on a collection of variables.
- Inference is viewed as a process of propagation of elastic constraints.
- Any logical system can be fuzzified.

The basis of the theory lies in making the membership function lie over a range of real numbers from 0.0 to 1.0. The fuzzy set is characterized by (0.0, 0, and 1.0). Real world is vague and assigning rigid values to linguistic variables means that some of the meaning and semantic value is invariably lost. Fuzzy logic operates on a concept of membership such as the statement Jane is old can be translated as Jane is a member of the set of old people and can be written symbolically as m(OLD), where m is the membership function that can return a value between 0.0 and 0.1 depending on the degree of membership.

The fuzzy set theory attempts to follow more closely the vagueness that is inherent in most natural language and in decision-making processes. In a conventional logic approach, this inherent fuzziness of membership and categorization is not incorporated. Fuzzy logic has found many real-world applications that involve imitating or modeling human behavior for decision-making in the real world. Development of intelligent systems incorporating the basics of fuzzy set theory have helped advance techniques for handling imprecision in soft computing. The primary idea in soft computing is to mimic human reasoning through building models of natural language variables, human interpretation and reasoning and it has found numerous applications in business and finance sectors, mobile robotics and also in social and behavioral sciences. The dynamics and complexity of social systems are being explained and modeled through the use of fuzzy theory.

The fuzzy inference system (FIS) is based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning. FIS is a very popular technique and has been widely applied in different fields like data classification, automatic control, expert system, decision making, robotics, time series analysis, pattern classification, system identification etc. The basic structure of a fuzzy inference system consists of three principal components: a rule base comprising of the selected fuzzy rules, a database defining the membership functions of the fuzzy rules, and a reasoning mechanism which performs a fuzzy reasoning inference with respect to the rules so as to derive a reasonable output or conclusion.

4.2.1 Analysis with Fuzzy Inference System

For the analysis of a fuzzy system whose inputs and outputs are described by linguistic variables, the following steps have to be carried out:

- **Fuzzification**: The linguistic variables of the fuzzy rules are expressed in the form of fuzzy sets where these variables are defined in terms of degree of their associated membership functions. This method of calculating the degree of belongingness of the crisp input in the fuzzy set is called the fuzzification. The membership functions may be triangular, trapezoidal, gaussian or bell shaped.
- **Aggregation**: After the degree of each linguistic statement is evaluated, they are combined by logical operators such as AND and OR. The conjunction of these linguistic statements is carried out by logical t-norm and the t-conorm operator to a large number of linguistic statements. Max and Min operators are used for classification task.
- **Activation**: Here the degree of rule fulfilment is used to calculate the output activations of the rules.
- **Accumulation**: In this step the output activations of all the rules are joined together to give rise to the fuzzy output of the system.
- **Defuzzification**: If a crisp value of the system is required, the final fuzzy output has to be defuzzified. This can be done by different methods like center of gravity, bisector of area, mean of maximum (mom), smallest (absolute) of maximum (som) and largest (absolute) of maximum (lom).

4.2.2 Types of Fuzzy Inference System

A fuzzy system may be of three principal types, namely:

- **Mamdani fuzzy system**: Also known as linguistic fuzzy system.
- **Singleton Fuzzy system**: The complexity of defuzzification of a linguistic fuzzy system can be simplified by restricting the output to a singleton membership function. Since no integration has to be carried out numerically, this results in reducing the computational demand for the evaluation and learning of the fuzzy system. Therefore, a singleton fuzzy system is most widely applied in industry.

- **Takagi-Sugeno Fuzzy system**: This system may be considered to be an extension of the singleton fuzzy system. Here the function f is not a fuzzy set. But the premise of a Takagi-Sugeno fuzzy system (1988) is linguistically interpretable. For a dynamic process modelling the Takagi- Sugeno models possess an excellent interpretation. A singleton fuzzy system can be recovered from a Takagi-Sugeno fuzzy system if the function f is chosen to be a constant. As the constant can be seen as a zeroth order Taylor series expansion of the function f, it is also called the zeroth order Takagi-Sugeno fuzzy system. However, in most of the applications, the first order Takagi-Sugeno fuzzy system is more common.

The fuzzy if-then rules contain the structured knowledge representation of the fuzzy inference system. But this does not provide the adaptive capability to the fuzzy inference system for dealing with the changing external environment which is found in a neural network.

4.3 Similarities between Fuzzy Logic and Neural Network

There are similarities between Fuzzy Logic (FL) and Neural Networks (NN):

- estimate functions from sample data
- do not require mathematical model
- are dynamic systems
- can be expressed as a graph which is made up of nodes and edges
- convert numerical inputs to numerical outputs
- process inexact information inexactly
- have the same state space
- produce bounded signals
- a set of n neurons defines n-dimensional fuzzy sets
- learn some unknown probability function

- can act as associative memories
- can model any system provided the number of nodes is sufficient.

The main dissimilarity between fuzzy logic and neural network is that FL uses heuristic knowledge to form rules and tunes these rules using sample data, whereas NN forms "rules" based entirely on data.

Table 4.1: Properties of neural networks and fuzzy systems (Fuller, 2000)

Skills	Type	Fuzzy Systems	Neural Network
Knowledge acquisition	Inputs	Human experts	Sample sets
	Tools	Interaction	Algorithms
Uncertainty	Information	Quantitative and Qualitative	Quantitative
Reasoning	Cognition	Heuristic approach	Perception
	Mechanism	Low	Parallel Computation
	Speed	Low	High
Adaption	Fault-tolerance	Low	Very high
	Learning	Induction	Adjusting weights
Natural language	Implementation	Explicit	Implicit
	Flexibility	High	Low

4.4 Adaptive Neuro Fuzzy Inference System

A neuro-fuzzy technique called Adaptive network based fuzzy inference system (ANFIS) (Jang, Sun, & Mizutani, 1997; Jang and Sun, 1995; Jang 1993) has been used as a prime tool in the present work. In ANFIS the parameters can be estimated in such a way that both the Sugeno and Tsukamoto fuzzy models (Tsukamoto et al, 1979) are represented by the ANFIS architecture. This ANFIS methodology comprises of a hybrid system of fuzzy logic and neural network technique. The fuzzy logic takes into account the imprecision and uncertainty of the system that is being modeled while the neural network gives it a sense of adaptability. Using this hybrid method, at first an initial fuzzy model along with its input variables are derived with the help of the rules extracted from the input output data of the system that is being modeled. Next the neural network is used to fine tune the rules of the initial fuzzy model to produce the final ANFIS model of the system.

4.4.1 ANFIS architecture

ANFIS is a hybrid multilayer feed forward network, which is used to plot an output space deriving from an input space. It uses neural network learning algorithms and fuzzy reasoning of linguistic expressions to get more strategic system (Jang, 1993). This is because, while neural network is trained, it can simultaneously be self-learned and self-improved; whereas, the fuzzy inference system can deal with linguistic expressions. Thus, ANFIS can adjust the membership functions' parameters and linguistic rules directly from training data with the aim at improving the system performance.

To generate fuzzy rules by means of a given input-output dataset, ANFIS implements a Sugeno fuzzy inference system for a logical approach (Negnevitsky, 2005). In the modeling process of ANFIS, the first step is the identification of the input and output variables. In a first-order Sugeno fuzzy inference system, two typical IF/THEN fuzzy rules can be expressed when a set of two inputs (x, y) and one output (f) is considered:

Rule 1: IF x is $A_1$and y is B_1, THEN $f_1=p_1x+q_1y+r_1$
Rule 2: IF x is $A_2$and y is B_2, THEN $f_2=p_2x+q_2y+r_2$

Where, p1, p2, q1, q2, r1 and r2 are linear parameters; A_1, A_2, B_1 and B_2 are nonlinear parameters. The ANFIS architecture consists of five-layers: fuzzification, fuzzy AND, normalization, defuzzification and output layer as shown in figure 4.1. These layers are connected to each other through direct links and nodes. Nodes are the process units that comprise of some adaptive and fixed parameters. Adaptive parameters can be changed by setting learning rules and thus, the membership functions are reformed.

First layer is the fuzzy layer, in which all nodes are adaptive nodes. The membership relationship between the output and input functions of this layer can be expressed as:

$$O_i^1 = \mu_{A_i}(x);\ i = 1, 2$$

$$O_j^1 = \mu_{B_j}(y);\ j = 1, 2$$

Here, x and y are the input of nodes A_i and B_j respectively. A_i and B_j are the linguistic labels used in the fuzzy theory for dividing the membership functions.

In the second layer, all the nodes are fixed nodes. They perform as a simple multiplier and are labeled with *M*. The outputs of this layer are firing strengths which can be represented as:

$$O_i^2 = w_i = \mu_{A_j}(x)\mu_{B_j}(y)\ ;\ i = 1, 2$$

In the third layer, the nodes are also fixed nodes. They are labeled with *N*, indicating that they perform as a normalizer to the firing strengths from the previous layer. The outputs of this layer are called as normalized firing strengths which can be represented as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum w_i};\ i = 1, 2$$

In the fourth layer, the nodes are adaptive nodes. For a first order Sugeno model, the output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial. Hence, the outputs of this layer are given by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i);\ i = 1, 2$$

In the fifth layer, the only one single fixed node performs the summation of all incoming signals that is labeled with $\sum$. Hence, the overall output of the model that comes from fifth layer can be expressed by:

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{(\sum_{i=1}^{2} w_i f_i)}{\sum w_i};\ i = 1, 2$$

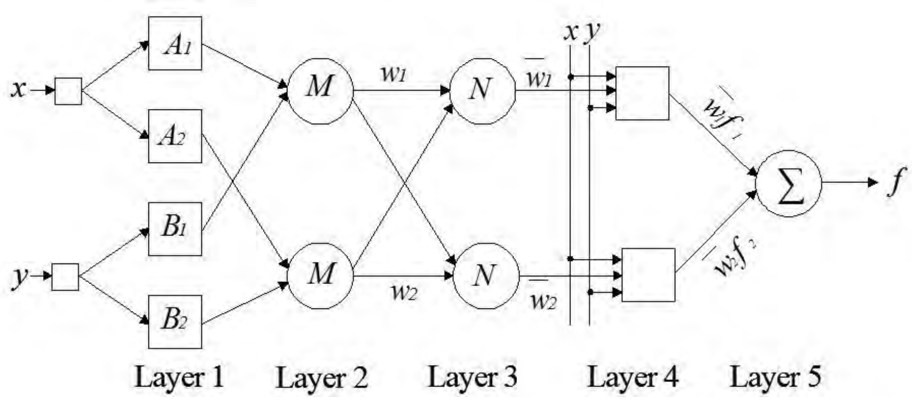


Figure 4.1: Architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993)

4.4.2 Learning Algorithm

In the ANFIS structure, it is observed that given the values of premise parameters, the final output can be expressed as a linear combination of the consequent parameters. The output f in Figure 4.1 can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \overline{w_1} f_1 + \overline{w_2} f_2$$

$$= (\overline{w_1}\, x)p_1 + (\overline{w_1}\, y)q_1 + (\overline{w_1})r_1 + (\overline{w_2}\, x)p_2 + (\overline{w_2}\, y)q_2 + (\overline{w_2})r_2$$

where f is linear in the consequent parameters (p_1, q_1, r_1, p_2, q_2, r_2).

In the forward pass of the learning algorithm, consequent parameters are identified by the least squares estimate. In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm (Haykin, 2003; Hagan et al., 1996).

Table 4.2: Two passes in the hybrid learning algorithm for ANFIS

	Forward Pass	**Backward Pass**
Premise Parameters	Fixed	Gradient Descent
Consequent Parameters	Least-squares estimator	Fixed
Signals	Node outputs	Error Signals

Backpropagation requires a known, desired output for each input value in order to calculate the loss function gradient. It is therefore usually considered to be a supervised learning method, although it is also used in some unsupervised networks such as autoencoders. It is a generalization of the delta rule to multi-layered feedforward networks, made possible by using the chain rule to iteratively compute gradients for each layer. Backpropagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable.

The backpropagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps:

- Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
- Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas (the difference between the input and output values) of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse the following steps are followed:

- Multiplying its output delta and input activation to get the gradient of the weight.
- Subtracting a ratio (percentage) of the gradient from the weight.
- This ratio (percentage) influences the speed and quality of learning; it is called the learning rate. The greater the ratio, the faster the neuron trains; the lower the ratio, the more accurate the training is. The sign of the gradient of a weight indicates where the error is increasing, this is why the weight must be updated in the opposite direction.

Phase 1 and 2 is repeated until the performance of the network is satisfactory.

As the algorithm's name implies, the errors propagate backwards from the output nodes to the input nodes. Technically speaking, backpropagation calculates the gradient of the error of the network regarding the network's modifiable weights. This gradient is almost always used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Often the term "backpropagation" is used in a more general sense, to refer to the entire procedure encompassing both the calculation of the gradient and its use in stochastic gradient descent. Backpropagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

Backpropagation networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers: a multilayer network using only linear activation functions is equivalent to some single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function, and the gaussian function. The backpropagation algorithm for calculating a gradient has been rediscovered a number of times, and is a special case of a more general technique called automatic differentiation in the reverse accumulation mode. It is also closely related to the Gauss–Newton algorithm, and is also part of continuing research in neural backpropagation.

4.4.3 Derivation of the Initial Fuzzy Model

As described earlier, in ANFIS based system modeling for a set of rules with fixed premise parameters, identification of an optimal fuzzy model with respect to the training data reduces to a linear least-squares estimation problem. A fast and robust method for identification of fuzzy models from input-output data was proposed by S.L.Chiu (1996). This method selects the important input variables when building a fuzzy model from data by combining cluster estimation method with a least squares estimation algorithm. The method follows in two steps:

1. First step involves extraction of an initial fuzzy model from input output data by using a cluster estimation method incorporating all possible input variables.
2. In the next step the important input variables are identified by testing the significance of each variable in the initial fuzzy model.

4.4.4 Extracting the initial fuzzy model

In order to start the modeling process, an initial fuzzy model has to be derived. This model is required to find the number of inputs, number of linguistic variables and hence the number of rules in the final fuzzy model. The initial model is also required to select the input variables for the final model and also the model selection criteria, before the final optimal model can be derived. This initial fuzzy model can be selected based on the fuzzy rules framed by either using the subtractive clustering technique (Chiu 1994) or the grid partitioning method (Jang and Sun 1995) (Jang et al. 1997; Jang 1993).

4.4.5 Subtractive Clustering Technique

As a first step towards extracting the initial fuzzy model by subtractive clustering, this technique is applied to the input output data pairs, which are obtained from the system which is to be modeled.

The cluster estimation technique helps in locating the cluster centers of the input output data pairs. This in turn helps in the determination of the rules which are scattered in input output space, as each cluster center is an indication of the presence of a rule. In addition to this it also helps to determine the values of the premise parameters. This is important because an initial value, which is very close to the final value, will eventually result in the quick convergence of the model towards its final value during the training session with neural network. In this clustering technique the potentials of all the input output data points are calculated as functions of their Euclidian distances from all the other data points. The points having a potential above a certain preset value are considered as cluster centers. After the cluster centers are ascertained the initial fuzzy model can be subsequently extracted as the centers will also give an indication of the number of linguistic variables.

4.4.6 Grid Partitioning Technique

The second method which can be used for framing the rules of the initial fuzzy model is by grid partitioning. This method is used when the number of inputs and their membership functions are less. Here, the input spaces are partitioned into a number of fuzzy regions to form the antecedents of the fuzzy rules. The Grid partitioned fuzzy space for a two input model, with each input having three membership functions each is shown in Figure 4.2. The two dimensions represent the abscissa and the ordinate of the input space. The rules obtained from either of the two methods are then optimized by using ANFIS methodology developed by Jang (1993). This method involves optimization of the premise membership functions by gradient descent algorithm combined with optimization of the consequent equations by linear least squares estimation.

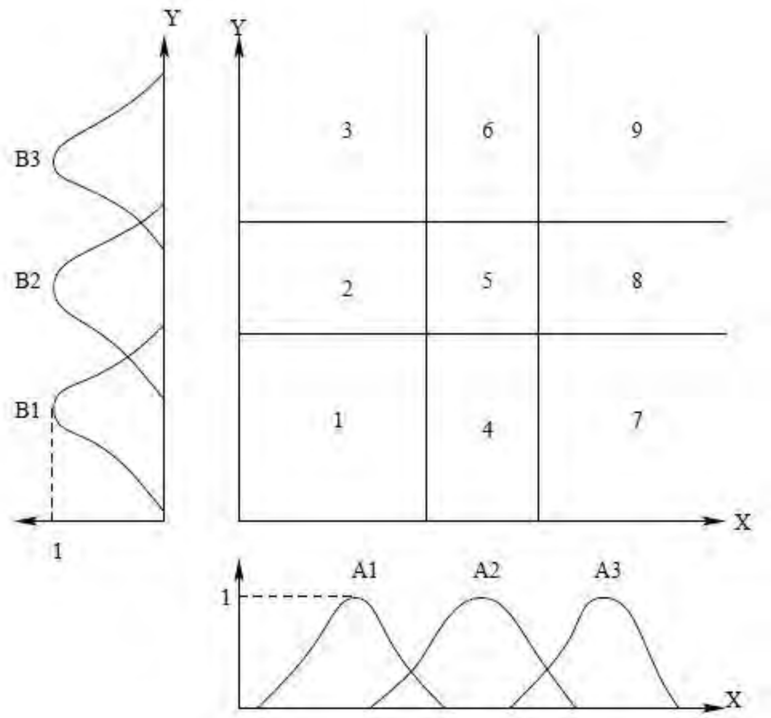


Figure 4.2: Grid partitioned fuzzy subspaces for 2-input ANFIS

4.4.7 ANFIS in Matlab

“anfis” and the ANFIS Editor GUI apply fuzzy inference techniques to data modelling. The “anfis” function can be accessed either from the command line or through the ANFIS Editor GUI. Using a given input/output data set, the toolbox function “anfis” constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted using either a backpropagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data they are modelling.

4.4.7.1 Training Data

The training data, *trnData*, is a required argument to anfis. Each row of trnData is a desired input/output pair of the target system that is to be modelled. Each row starts with an input vector and is followed by an output value. Therefore, the number of rows of trnData is equal to the number of training data pairs, and, because there is only one output, the number of columns of trnData is equal to the number of inputs plus one.

4.4.7.2 Input FIS Structure

The input FIS structure can be obtained from any of the following fuzzy editors:

- The Fuzzy Logic Designer
- The Membership Function Editor
- The Rule Editor from the Neuro-Fuzzy Designer (which allows an FIS structure to be loaded from a file or the MATLAB® workspace)
- The command line function, genfis1 (for which you only need to give numbers and types of membership functions)

The FIS structure contains both the model structure, (which specifies such items as the number of rules in the FIS, the number of membership functions for each input, etc.), and the parameters, (which specify the shapes of membership functions).

There are two methods that anfis learning employs for updating membership function parameters:

1. Backpropagation for all parameters (a steepest descent method)
2. A hybrid method consisting of backpropagation for the parameters associated with the input membership functions, and least squares estimation for the parameters associated with the output membership functions

As a result, the training error decreases, at least locally, throughout the learning process. Therefore, the more the initial membership functions resemble the optimal ones, the easier it will be for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting up these initial membership function parameters in the FIS structure.

The genfis1 function produces an FIS structure based on a fixed number of membership functions. This structure invokes the so-called curse of dimensionality, and causes excessive propagation of the number of rules when the number of inputs is moderately large, that is, more than four or five. Fuzzy Logic Toolbox offers a method that provides for some dimension reduction in the fuzzy inference system: FIS structure using the clustering algorithm. To use the clustering algorithm, the Sub. Clustering option needs to be selected in the Generate FIS portion of the Neuro-Fuzzy Designer before the FIS is generated. This subtractive clustering method partitions the data into groups called clusters, and generates an FIS with the minimum number rules required to distinguish the fuzzy qualities associated with each of the clusters. Since this method occupies much less computational memory compared to the grid partitioning technique, esp. when the number of inputs is very high (22 attributes), the selection of sub. Clustering technique is justified.

4.4.7.3 Training Options

The Neuro-Fuzzy Designer tool allows desired error tolerance and number of training epochs to be chosen. The training process stops if the designated epoch number is reached or the error goal is achieved, whichever comes first.

4.4.7.4 Method

'anfis' apply either a backpropagation form of the steepest descent method for membership function parameter estimation, or a combination of backpropagation and the least-squares method to estimate membership function parameters. The choices for this argument are hybrid or backpropagation. These method choices are designated in the command line function, anfis, by 1 and 0, respectively.

4.4.7.5 Model Validation using Testing and Checking Data Sets

Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. Data set selected for model validation should be both representative of the data the trained model is intended to emulate and sufficiently distinct from the training data set so as not to render the validation process trivial. Collecting a large amount of data contains all the necessary representative features, so the process of selecting a data set for checking or testing purposes is made easier. The testing data set allows checking of the generalization capability of the resulting fuzzy inference system. The idea behind using a checking data set for model validation is that after a certain point in the training, the model begins overfitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that overfitting begins, and then the model error for the checking data suddenly increases. Overfitting is accounted for by testing the FIS trained on the training data against the checking data, and choosing the membership function parameters to be those associated with the minimum checking error if these errors indicate model overfitting.

4.5 Summary

Fuzzy logic is an extremely suitable concept with which to combine subjective knowledge and objective knowledge. It uses both the neural network learning algorithms and fuzzy reasoning of linguistic expressions to get more strategic system. This is because, while neural network is trained, it can simultaneously be self-learned and self-improved. The prediction capability of ANFIS is greatly biased by various parameters like- membership function, transfer function, learning algorithm and so on. To get more accurate prediction, these parameters should be altered. Model validation is done by the input vectors from input/output data sets on which the FIS was not trained. The more and accurate is the training data, the better it performs.

Chapter 5

Methodology

5.1 Introduction

There are mainly two categories of service quality attributes: subjective and objective (Eboli & Mazulla, 2011). Futhermore attributes can be classified as operational, which aim to indicate the performance aspects of serivce utilities, and physical that are used to evaluate the service attributes related to design. There has been numerous researches in last few years which uses attributes of all these categories and classification as service quality indicators. In the following chapter the attribute selection procedure has been outlined leading to data collection and finally the model development.

5.2 Selection of SQ attributes

The selection of concise sets of attributes is a challenging task and the reasons for this as given by Mahmoud et al. (2011) are: wide range of indicators available in the literature, and the variation in definition associated with different indicator sets. Litman (2007) concluded that a single perception based evaluation always leads to biased results, and the tradeoff between consistency and comprehensiveness in selecting quality indicators should consider all stakeholders associated with bus transit. The Transportation Research Board, through the Transit Cooperative Research Program, developed interesting researches about service quality measures, summarized in some reports in which the different transit service aspects are widely and fully described (Transportation Research Board, 1999, 2003a, 2003b). In these reports five categories of service quality measures are defined: availability in terms of passengers' ease of access and use of transit service, service monitoring, travel time, safety and security in terms of real and perceived chances of being involved in an accident or being the victim of a crime while using transit, and maintenance and construction. For each service quality aspect some examples of objective measures are suggested.

Another challenge is to identify and combine both commuter satisfaction and transit performance measures. A methodology suggested by Tyrinopoulos and Aifadopoulou (2008) for the quality control of passenger services in the public transport business. Essentially the work provides an overview of the methodology developed by the Hellenic Institute of Transport to assess the levels of quality and performance of public transport services. Here 39 indicators are analyzed, classified in the following seven categories: safety–comfort–cleanliness; information–communication with the passengers; accessibility; terminals and stop points performance; lines performance; general elements of the public transport system; compound indicators based on the results of the indicators of the previous categories. Among the compound indicators, a customer satisfaction measure is considered in order to take into account customer perceptions. In fact, the authors suggest using factor analysis and multinomial logistic regression for investigating the influence of the operational performance indicators of the transportation system on customer satisfaction.

The following list provides some recent studies and the no. of indicators used by the respective researchers:

Table 5.1: Quality Indicators available in the literature

Author	Source	No. of indicators
Eboli & Mazulla (2011)	A methodology for evaluating transit service quality based on subjective and objective measures from the passenger's point of view	13
Dell'Olio, Ibeas, & Cecin. (2010)	Modelling user perception of bus transit quality	6

Dell'Olio, Ibeas, & Cecin. (2011)	The quality of service desired by public transport	10
Lai & Chen (2010)	Behavioral intentions of public transit passengers - The roles of service quality, perceived value, satisfaction and involvement	18
Tyrinopoulos & Antoniou (2008)	Public transit user satisfaction: Variability and policy implications	23
Hensher & Stanley, (2003)	Service quality—developing a service quality index in the provision of commercial bus contracts.	13
CEN (2002)	Transportation – Logistics and services – public passenger transport – service quality definition, targeting and measurement	103
TRB (1999)	Transportation Research Board; a handbook for measuring customer satisfaction and service quality.	48

After a detailed investigation and study on the current situation of Dhaka city and its public bus service scenario, a concise set of 22 SQ attributes were selected to carry out the study. The procedure followed was suggested by Mahmoud et al. (2011) as illustrated in the figure 5.1. It includes analysis of bus transit users' demands and the analysis of transit experts' views towards service quality indicators. When considering user demand characteristics, current and potential users must be taken into account. Expert panel analysis includes individual indicator analysis by academics, operators, policy makers, and local authorities.

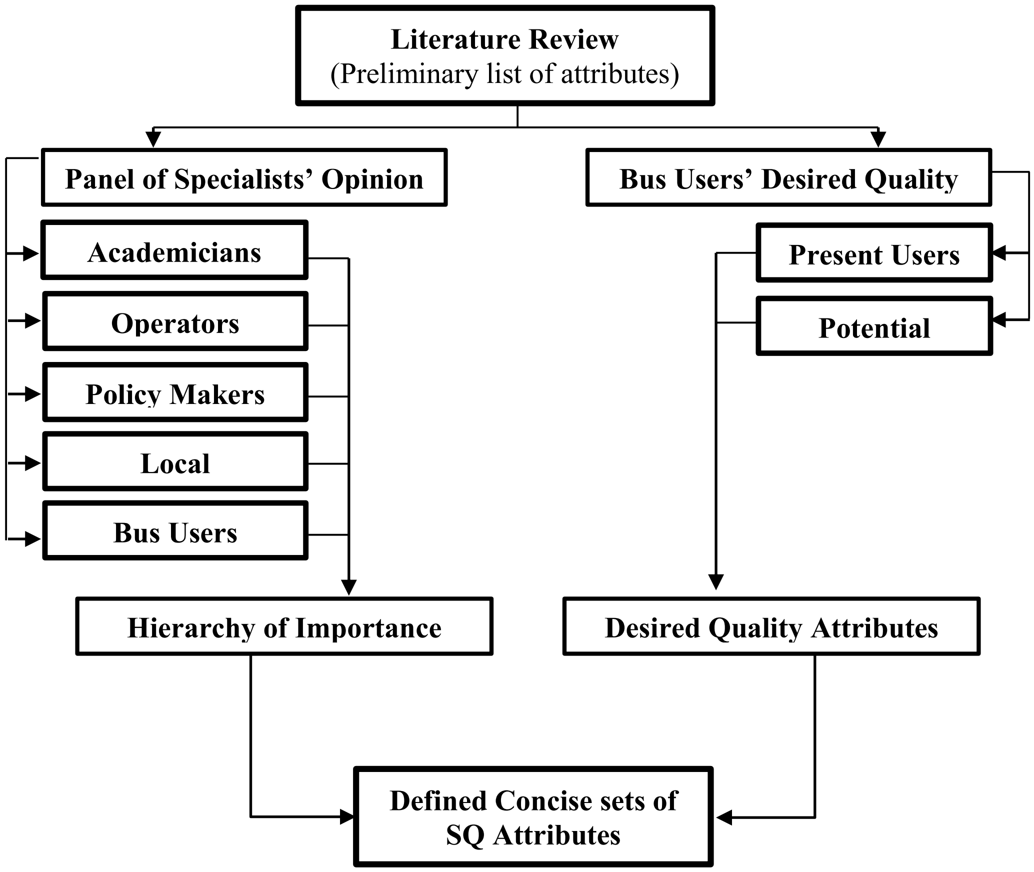


Figure 5.1: Framework for SQ attributes selection

The attributes analyzed and listed as below:

Table 5.2: List of service quality attributes

No.	Attributes	Description
1	*Proximity from Home*	Time taken to travel from home to bus stops
2	*Proximity from Workplace*	Time taken to travel from workplace to bus stops
3	*Commuting Frequency (daily)*	Number of times commuters travel by bus on daily basis
4	*Service Frequency*	Interval between consecutive bus arrivals
5	*Commuting period (weekdays)*	Time spent in bus travel during weekdays
6	*Commuting period (weekends)*	Time spent in bus travel during weekends
7	*Ticketing system*	System to pay bus fare

8	*Fare Expenditure (daily)*	Daily amount paid in bus travels
9	*Punctuality and Reliability*	Reliability of buses and whether they're on schedule
10	*Seat Availability*	Availability of seats in buses
11	*Seat Comfort*	Comfortability of seats provided
12	*Accessibility to/from bus*	Ease of getting into and alighting a bus
13	*Air Ventilation system*	Provision of necessary ventilation
14	*On-board security*	Safety against crimes on buses
15	*Female Harassment*	Disturbance faced by female commuters
16	*On-time Performance*	Smoothness of bus travel
17	*Bus Staffs Courtesy*	Helpfulness and behavior of bus personnel
18	*Structural condition*	Structure and attractiveness of the vehicle
19	*Interior Cleanliness*	Cleanliness of interior, seats and windows
20	*Noise Level*	Level of noise during travel
21	*Commuting Experience*	Experience of travel
22	*Route Information*	Clarity of the information provided regarding the route the bus uses

5.3 Data Collection and Preparation

The users of metropolitan public transport services operating in Dhaka, Bangladesh are the targeted study components of this research. 30 expert enumerators were involved to carry out face-to-face interviews at main bus stops and on-board survey around Dhaka city throughout the month of December, 2014. The target sample was 1000 according to the demography and standard sample size practice. However, unwillingness of the commuters, rush hour office/home movement, and other impending situations have restricted the random data samples to 850. After filtering the anomalies, the remaining sample size was 655.

The qualitative survey was transformed to quantitative form. The selected option among the alternatives for each attributes were labeled as corresponding number. Thus an excel sheet was prepared in such a manner that can be used to input training and testing data into the models. The entire set of sample was randomly divided into two sub-sets containing 524 (80% of whole sample set) and 131 (20% of whole sample set) observations, respectively.

The survey questionnaire (Appendix A) is subdivided into four sections. The first section aims to acquire information regarding socioeconomic characteristics of passengers (gender, age, occupation) and reason for travelling. The second section focuses on 22 SQ attributes provided in a close ended layout with pertinent alternatives. The respondents were asked to mark the checkboxes from their point of view and assess the present situation of the service. The third section focuses on collecting benchmark points at a quantitative scale of 1 to 5 to rate the SQ for a particular service on a route, where 1 and 5 corresponds to very poor and excellent, respectively. The fourth section provides the option to the users to select the most important 12 attributes out of the 22 which they think affected their decision of the rating that they have given for the service. This was done to collect information regarding users' perception on relative importance of the attributes so that a comparison can be established with the attribute ranking obtained from the model.

5.4 Model Development

The out-of-sample forecasting technique is applied to examine the predictive power of the model. Accordingly, the sample is randomly divided into two sub-samples: a training sample consisting of 80% (524) of whole sample set and a forecasting sample which includes 20% (131) of the sample set. Neural network models are developed using GRNN, PNN, PRNN and ANFIS GUI tools of MATLAB 14. The steps for developing and validating the models are outlined in the following sections.

5.4.1 Generalized Regression Neural Network

A generalized regression neural network (GRNN) is often used for function approximation. It has a radial basis layer and a special linear layer. It is similar to the radial basis network, but has a slightly different second layer.

The first layer operates just like the radial basis layer. The *bias* is set to a column vector of 0.8326/*spread*. Each neuron's weighted input is the distance between the input vector and its weight vector, calculated with *dist*. Each neuron's net input is the product of its weighted input with its bias, calculated with *netprod*. Each neuron's output is its net input passed through *radbas*. If a neuron's weight vector is equal to the input vector (transposed), its weighted input will be 0, its net input will be 0, and its output will be 1. If a neuron's weight vector is a distance of spread from the input vector, its weighted input will be *spread*, and its net input will be sqrt(−log(.5)) (or 0.8326). Therefore, its output will be 0.5.

A larger *spread* leads to a large area around the input vector where layer 1 neurons will respond with significant outputs. Therefore, if *spread* is small the radial basis function is very steep, so that the neuron with the weight vector closest to the input will have a much larger output than other neurons. The network tends to respond with the target vector associated with the nearest design input vector.
newgrnn function is used to create a GRNN in MATLAB.

5.4.2 Probabilistic Neural Network

Probabilistic neural network is used for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities.

Finally, a compete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes.

newpnn function is used to create a PNN in MATLAB.

5.4.3 Pattern Recognition Neural Network

Pattern Recognition Neural Network is used to classify inputs into a set of target categories. The PRNN tool helps to select data, create and train a network, and evaluate its performance using cross-entropy and confusion matrix. *nprtool* is used to initiate PRNN in MATLAB which opens the following window:

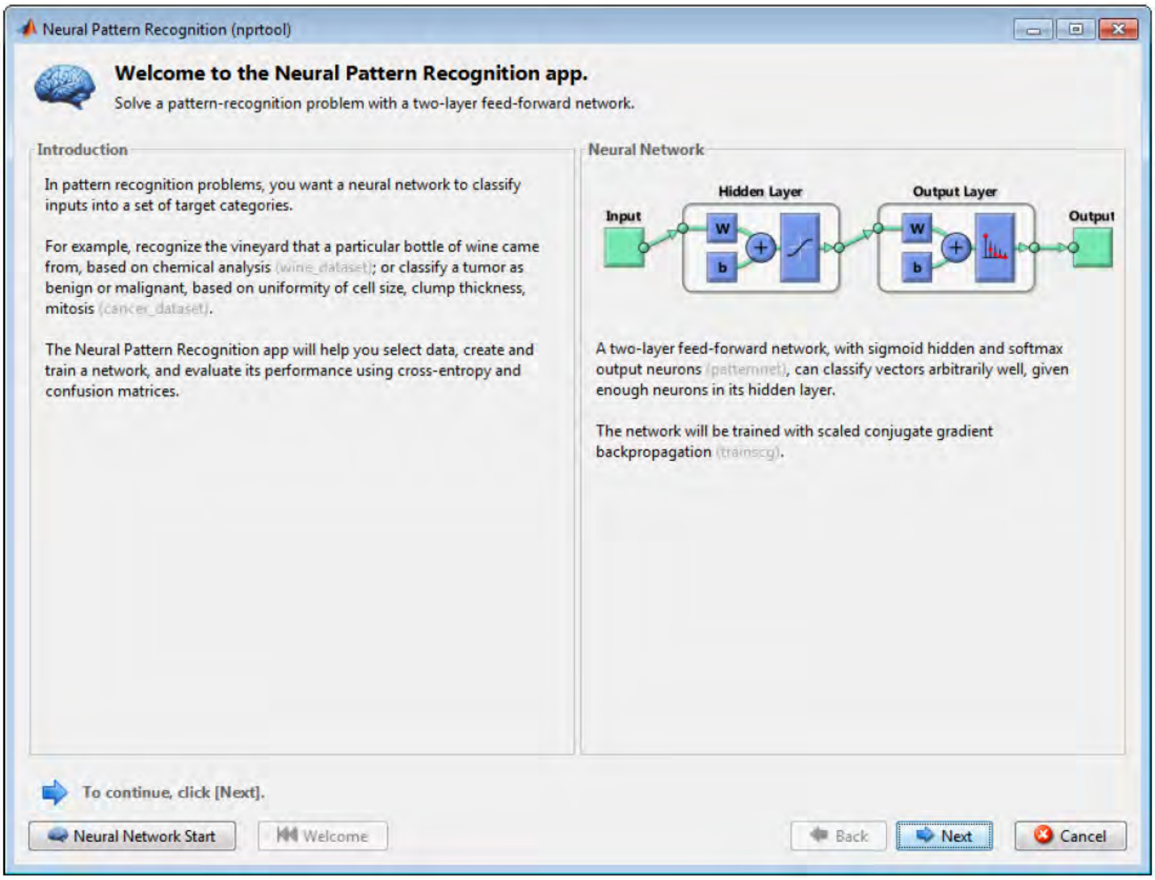


Figure 5.2: PRNN tool in MATLAB

5.4.4Adaptive Neuro Fuzzy Inference System

The GUI can be accessed by typing in *anfisedit* command which brings up the ANFSIS editor. There are functions to generate, train, test and check the model.

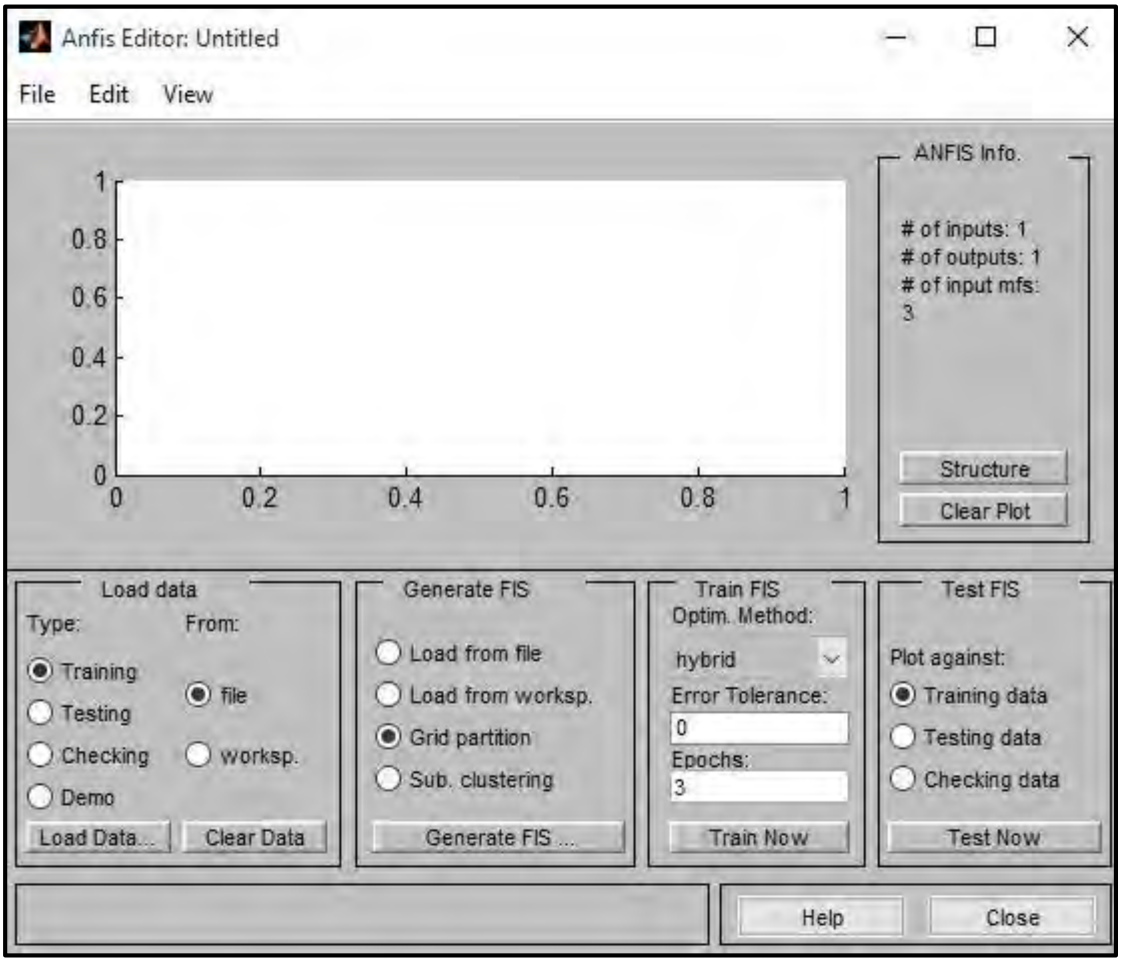


Figure 5.3: ANFIS Editor GUI in MATLAB

The first step in developing the model is Initialization. Initializing includes the following steps:

- Loading the train data either as a .DAT file or from the workspace variable. Training data is a matrix with N+1 columns where the first N columns contain data for each FIS input and the last column contains the output data.
- Specifying an initial FIS model structure by choosing the sub. clustering partitioning technique which generates an initial model for ANFIS training by first applying subtractive clustering on the data. This generates the FIS faster compared to grid partitioning technique and occupies lesser computational memory. The result using this technique was satisfactory to justify its use. The other parameters needed for this techniques (such as radius of influence, squash factor, accept ratio, etc) are kept as default values since with the default values the result was satisfactory.

(Detailed discussion on grid partitioning and sub-clustering in Section 4.4.5 and 4.4.6)

After loading the training data and generating the initial FIS structure, the training is done in following steps:

- In **Optim. Method**, **hybrid** or **backpropagation** needs to be selected as the optimization method. The optimization methods train the membership function parameters to emulate the training data. Backpropagation consumes lesser computational memory and hence justifies its selection.
- **Training Epochs** and the training **Error Tolerance** is set as stop criteria for training. The training process stops whenever the maximum epoch number is reached or the training error goal is achieved.
- Next the **Train Now** is pressed to start training the FIS. This action adjusts the membership function parameters and displays the error plots.

Table 5.3: Parameters for ANFIS for Bus SQ prediction model

ANFIS parameters	
Number of input variables	*22*
Number of layers	*5*
Number of Membership Functions	*430*
MF type	*Gaussian*
Transfer function of hidden layer	*tansigmoid*
Scaling method	*normalization*
Transfer function of output layer	*linear*
Training algorithm	*back-propagation*
Training cycles, epochs	*10*
Training goal	*0.01*

5.5 Model Evaluation

There are several ways to evaluate the model performance. However, the performance evaluation techniques used in this study are: confusion matrix, root-mean-square error (RMSE), correlation co-efficient (R). These are explained in the following sections.

5.5.1 Confusion Matrix

A confusion matrix, also known as a contingency table or an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class (or vice-versa). The name stems from the fact that it makes it easy to see if the system is confusing two classes (i.e. commonly mislabeling one as another). Confusion matrix is used to check the one-to-one matching between output classes (1 to 5) and target classes (1 to 5). The diagonal green boxes show the amounts and percentages that are identical in both output and corresponding target classes. The red boxes show the amounts of misclassifications. The right-bottom blue box shows the total correct classifications (green) and misclassifications (red) in percent (%).

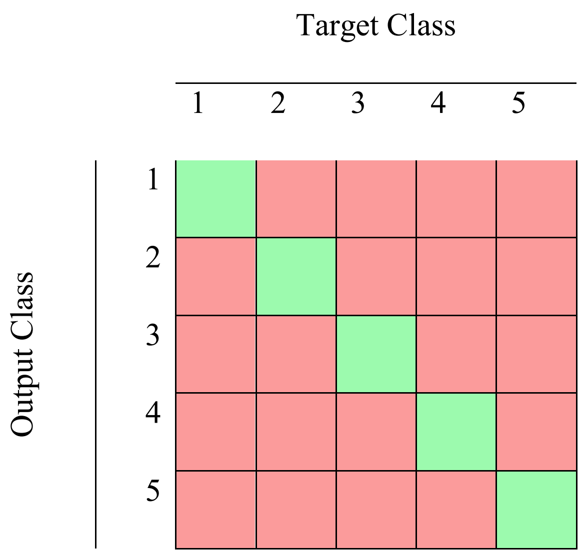


Figure 5.4: Illustration of a confusion matrix used for the evaluation of the model

5.5.2 Correlation co-efficient (R)

A correlation coefficient is a coefficient that illustrates a quantitative measure of some type of correlation and dependence, meaning statistical relationships between two or more random variables or observed data values. There are few types of correlation coefficient but in the model development, Pearson product-moment correlation coefficient (R) is used. It is a measure of the linear correlation between two variables X and Y, giving a value between +1 and −1 inclusive, where 1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation. It is widely used in the sciences as a measure of the degree of linear dependence between two variables. Correlation coefficient (R) is defined as:

$$R = \frac{\sum_{i=1}^{N}\left(O_i - O_{avg}\right)\left(P_i - P_{avg}\right)}{\sqrt{\sum_{i=1}^{N}\left(O_i - O_{avg}\right)^2}\sqrt{\sum_{i=1}^{N}\left(P_i - P_{avg}\right)^2}}$$

Where,

O_{avg} = mean of target classes; P_{avg} = mean of predicted classes;

O_i = i^{th} target class; and P_i = i^{th} predicted class.

5.5.3 Root-mean-square error

Root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample and population values) predicted by a model or an estimator and the values actually observed. The RMSE represents the sample standard deviation of the differences between predicted values and observed values. These individual differences are called residuals when the calculations are performed over the data sample that was used for estimation, and are called prediction errors when computed out-of-sample. The RMSE serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSE is a good measure of accuracy, but only to compare forecasting errors of different models for a particular variable and not between variables, as it is scale-dependent. RMSE is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - P_i)^2}{N}}$$

Where, N = total number of observations.

5.6 Attributes Ranking

The study includes 22 attributes in AI models to estimate the bus SQ. As the relationship between input variables (SQ attributes) and the output variable is indistinct, ranking of these SQ attributes can be performed by analytical techniques (Maier & Dandy, 2000). Cross-correlation, principal component analysis (PCA), connection weights and stepwise approach are some of the analytical techniques. However, this study implements connection weights and stepwise approach. In addition, public opinion is also considered to rank the attributes.

5.6.1 Connection Weights

The synaptic weights of the trained ANN models are used for quantifying the contributions of each input attribute. For each attribute, the weights of every neuron are summed. According to Olden and Jackson (2002), the greater the sums for given input neurons, the greater the relative importance of the corresponding attribute on Bus SQ. Then the sum of the connection weights is normalized and termed as 'relative contribution'.

5.6.2 Stepwise Approach

In stepwise approach, cases are formed by dropping one of the attributes consecutively from input variable matrix. Separate networks are trained with the 'training sample' for each new case. The predictions of these networks for the 'forecasting sample' are estimated. After that, model performances are assessed for each case. Although, model performance can be assessed by calculating the dissimilarity between actual and predicted results through average percentage error, co-efficient of determination (R^2), root-mean-square error (RMSE) and correlation coefficient (R), this study used the last two measures to evaluate the effects of attributes. Here, the lesser the value of 'R' and greater the value of 'RMSE', the corresponding excluded attribute is more significant and vice versa.

5.6.3 Public Opinion

To determine the relative importance of the attributes, all the respondents are asked to select at least 12 out of 22 attributes that affect mostly the bus SQ. Note that these public opinion data is independent of the data used for model development. The percentages of public inclination to each attribute have been normalized and compared with each other termed as 'Relative Importance'. Equation for Normalization is given below:

$$X_{i,\ 0\,to\,1} = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Where,

X_i = Each data point i

X_{min} = The minima among all data points

X_{max} = The maxima among all the data points

$X_{i,\,0\,to\,1}$ = The data point i normalized between 0 to 1

5.7 Summary

Bus SQ can be determined from two different approaches: Objective measurement and Subjective measurement. In the context of Dhaka city, Subjective measurement is followed which is derived from the judgment of the users. With a view to assessing the quality of service provided by the bus transit system, this study has conducted field survey basing on 22 attributes and some demographic variables. These attributes have been selected by analyzing users' demand and the transit experts' view towards service quality indicators. After conducting the stated preference survey, a set of 655 samples has been prepared for analyzing with Artificial Intelligence (AI) models. Analysis has been performed using GRNN, PNN, PRNN and ANFIS tools.

Chapter 6

Results and Discussions

6.1 Introduction

This chapter presents the general characteristics of bus users of Dhaka city. It also shows the results of different models and the comparison among the predictive capabilities of those models. Moreover, the relative importance of the attributes influencing the bus SQ have also been determined in this chapter.

6.2 General Characteristics of Bus Users

The strategy followed in this survey was to assess the opinion of different age groups, gender and occupation type. The target sample was 1000 according to the demography and standard sample size practice. However, unwillingness of the commuters, rush hour office/home movement, and other impending situations have restricted the random data samples to 850. After filtering the anomalies, the remaining sample size was 655. 70% of the respondents were male and 30% were female. In case of income (in BDT) distribution, 68 percent of the respondents' income was less than 10000, 19 percent was in between 10000 to 30000, 9 percent was in between 30000 to 50000, and 4% was more than 50000. Age distribution shows that 23%, 40%, 28% and 9% of the respondents fall in the category of 18 to 25 years, 26 to 35 years, 36 to 45 years, and more than 45 years, respectively. Occupation type revealed that 56 percent of the respondents was job holder, 30 percent was student, 12 percent was businessman and 2 percent was teacher. Commuters' response towards reason for travel showed that 75 percent travel for work purpose, 9 percent travel for entertainment and 16 percent for saving money. 3 percent of the respondents indicated the SQ as 5 (very good); 21 percent people indicated level of service as 4 (good); 42 percent people indicated level of service as 3 (average); 22 percent people indicated level of service as 2 (poor); 13 percent people indicated level of service of bus as 1 (very poor).

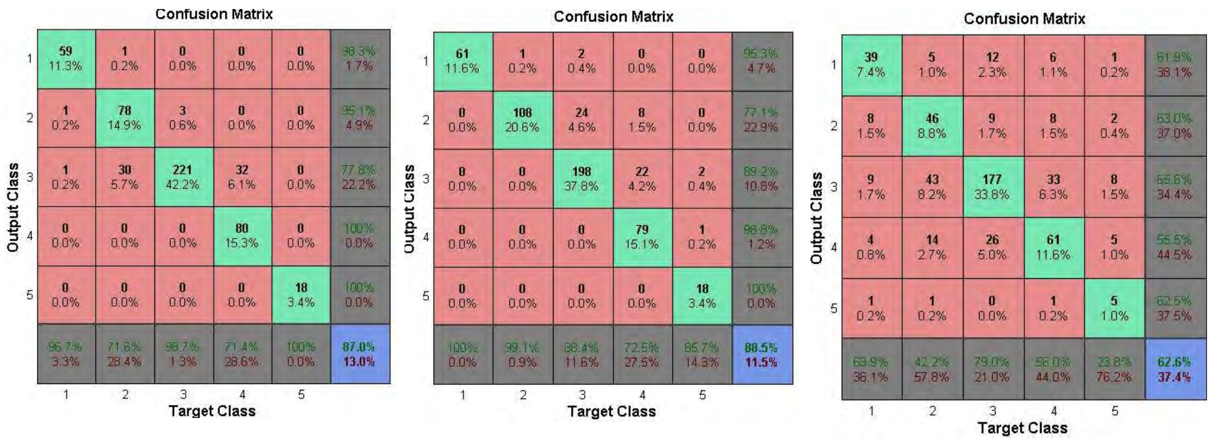
6.3 Models Evaluation

Earlier studies show that Adaptive Neuro Fuzzy Inference System is superior than other Neural Network models. So, in this research, model evaluation has been done in two stages: firstly, the best model among the Neural Network models has been determined; and secondly, that model has been compared with ANFIS.

6.3.1 Evaluation of Neural Network models

6.3.1.1 Training Stage

To verify the performance of networks during training stage, predicted SQs are compared with the surveyed SQs for the training data set. Confusion matrices are prepared to show the similarity of each of the predicted classes to the target classes shown in Figure 6.1. The horizontal axes of Confusion matrices show the surveyed SQ whereas the vertical axes show the simulated SQ. Confusion matrix of GRNN (Figure 6.1a) reveals that 11.3% prediction matches with actual SQ for output Class 1 (very poor). And, Similarly, 14.9%, 42.2%, 15.3% and 3.4% prediction match with actual SQ for class 2 (poor), class 3 (average), class 4 (good) and class 5 (excellent), respectively. For GRNN, 87% prediction matched and 13% didn't comply with actual SQ. Similarly, 88.5% and 62.6% prediction matched with actual SQ in PNN and PRNN, respectively.

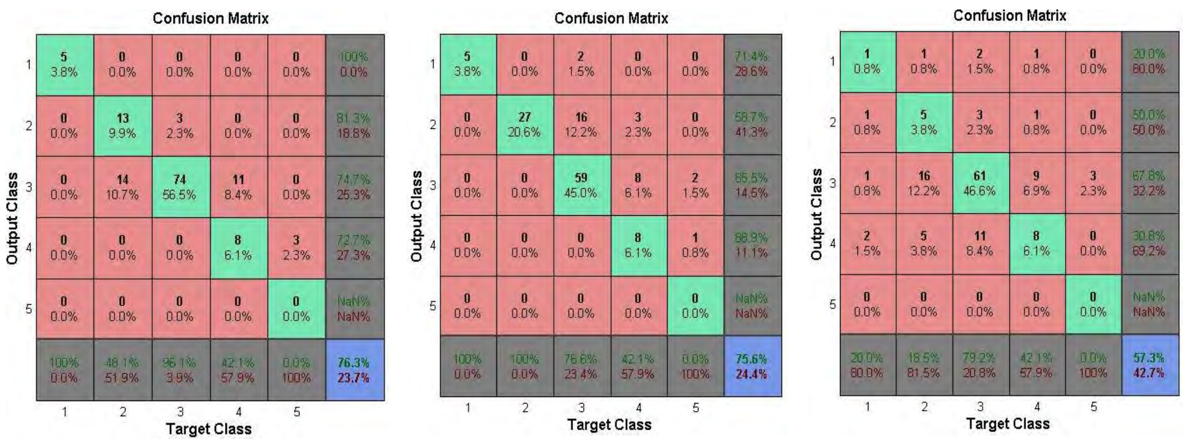


(a) (b) (c)

Figure 6.1: Confusion matrices at training stage for (a) GRNN, (b) PNN and (c) PRNN

6.3.1.2 Testing Stage

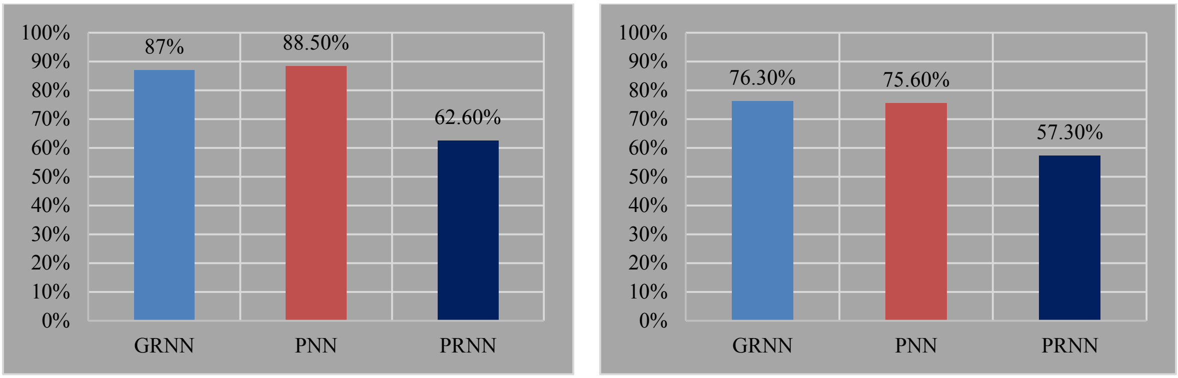
The predicted SQs are compared with the actual SQs using the forecasting data set. Confusion matrices of GRNN, PNN and PRNN are shown in Figure 6.2. From these matrices it is shown that 76.3%, 75.6% and 57.3% predictions matched with actual SQ in GRNN, PNN and PRNN, respectively.



(a) (b) (c)

Figure 6.2: Confusion matrices at testing stage for (a) GRNN, (b) PNN and (c) PRNN

Figure 6.3 shows that among the three models, PNN has highest accuracy at training stage whereas GRNN shows highest accuracy at testing stage. However, these two models predict considerably more accurate than PRNN model. Therefore, GRNN and PNN can be inferred as competent NN tools for bus SQ prediction.



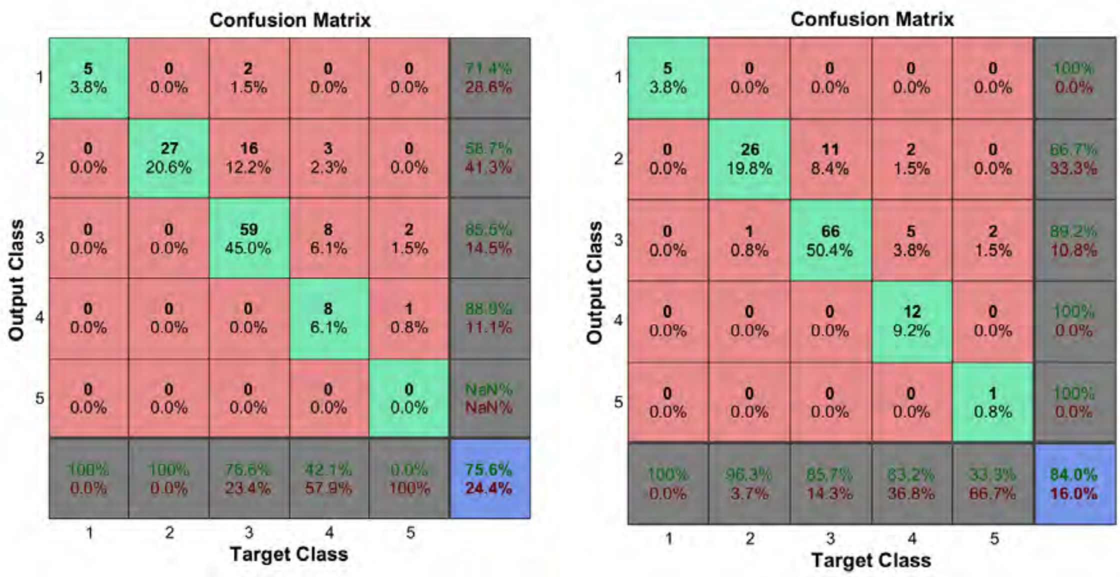
(a) Prediction accuracy at training stage

(b) Prediction accuracy at testing stage

Figure 6.3: Prediction accuracy of the ANN models

6.3.2 Comparison Between PNN and ANFIS

The predicted classifications of developed PNN and ANFIS models are shown in figure 6.4 by means of confusion matrix. It can be seen that, PNN and ANFIS have 75.6% and 84.0% accuracy in prediction, respectively. That is, a total of 99 predictions out of 131 match with the actual SQ value in PNN. Whereas, in ANFIS, a total of 110 predictions out of 131 match with the actual SQ value.



(a) (b)

Figure 6.4: Confusion matrix for model evaluation: (i) PNN; and (ii) ANFIS

Also, analyzing R and RMSE values between the predicted and actual SQ of the forecasting sample (131 data), comments can be made on the model performances. The R values of PNN and ANFIS prediction are 0.70788 and 0.79932, respectively. Whereas, the RMSE values for those models are 0.63607 and 0.50190, respectively. It can be seen that R value of ANFIS model is greater than PNN model. Whereas, RMSE value of ANFIS model is smaller than PNN model. It indicates that based on user stated preferences, ANFIS performs better than PNN in bus SQ prediction.

6.4 Attributes Ranking

This study used 22 attributes in AI models to estimate the bus SQ. As the relationship between input variables (SQ attributes) and the output variable is obscure, analytical techniques are more suitable than other techniques for the ranking of these SQ attributes. Cross-correlation, principal component analysis (PCA), stepwise approach, and connection weights are some of the analytical techniques. However, this study evaluates connection weights of input neurons in case of Neural Network models to rank the importance of each attribute. Whereas, Stepwise method has been followed in case of ANFIS model. In addition, public opinion is also considered to rank the attributes.

6.4.1 Connection weights

The synaptic weights of the trained ANN models are used for quantifying the contributions of each input attribute. For each attribute, the weights of every neuron are summed. According to Olden and Jackson (2002), the greater the sums for given input neurons, the greater the relative importance of the corresponding attribute on the output. Then the sum of the connection weights is normalized and termed as 'relative contribution'. Table 6.1 shows the relative contribution for each SQ attribute. According to GRNN and PNN models, the highest connection weight is assigned to 'Punctuality and reliability' since its relative contribution is 1.00. On the other hand, PRNN shows highest relative contribution of 'Service frequency'.

Table 6.1: Attributes ranking comparison among GRNN, PNN and PRNN

ATTRIBUTES	GRNN		PNN		PRNN	
	Relative Contribution	Rank	Relative Contribution	Rank	Relative Contribution	Rank
Proximity from Home	0.40373	13	0.40373	13	0.42431	15
Proximity from Workplace	0.41236	12	0.41236	12	0.42845	14
Commuting Frequency (daily)	0.39941	15	0.39941	15	0.34013	16
Service Frequency	0.92337	2	0.92337	2	1.00000	1
Commuting period (weekdays)	0.64843	7	0.64843	7	0.62753	5
Commuting period (weekends)	0.15686	21	0.15686	21	0.61738	7
Ticketing System	0.71969	5	0.71969	5	0.59219	9
Fare Expenditure (daily)	0.33895	16	0.33895	16	0.09336	20
Punctuality and Reliability	1.00000	1	1.00000	1	0.97711	2
Seat Availability	0.85715	3	0.85715	3	0.80907	4
Seat Comfort	0.66787	6	0.66787	6	0.60574	8
Accessibility to/from bus	0.16118	20	0.16118	20	0.29203	18
Air Ventilation system	0.00000	22	0.00000	22	0.48229	12
On-board Security	0.42748	11	0.42748	11	0.45596	13
Female Harassment	0.16334	19	0.16334	19	0.30003	17
On-time performance	0.44907	10	0.44907	10	0.19190	19
Bus Staffs Courtesy	0.40013	14	0.40013	14	0.02878	21
Structural condition	0.62612	8	0.62612	8	0.62507	6
Interior Cleanliness	0.28569	17	0.28569	17	0.55508	10
Noise Level	0.18997	18	0.18997	18	0.49193	11
Commuting Experience	0.79526	4	0.79526	4	0.83701	3
Route Information	0.51816	9	0.51816	9	0.00000	22

6.4.2 Stepwise Approach

In stepwise approach, cases are formed by dropping one of the attributes consecutively from input variable matrix. Separate networks are trained with the 'training sample' for each new case. The predictions of these networks for the 'forecasting sample' are estimated. After that, model performances are assessed for each case. Although model performance can be assessed by calculating the dissimilarity between actual and predicted results through average percentage error, co-efficient of determination (R^2), root-mean-square error (RMSE) and correlation coefficient (R). However, this study used the last two measures to evaluate the effects of attributes. These criteria are compared for both PNN and ANFIS models in table 6.2. Here, the lesser the value of 'R' and greater the value of 'RMSE', the corresponding excluded attribute is more significant and vice versa. As an example, in case of the model developed by excluding 'Punctuality and Reliability', the prediction is the most inaccurate. Because, among all the other models, this model has the least R value and the largest RMSE. It means, this variable has significant control on the bus SQ determination. Conversely, 'Commuting Period (weekends)' is less important due to the corresponding R and RMSE values.

Table 6.2: Attributes ranking comparison between PNN and ANFIS

		PNN			*ANFIS*		
Sl. No.	**Excluded attribute**	**R**	**RMSE**	**Rank**	**R**	**RMSE**	**Rank**
1	Proximity from Home	0.45685	0.85605	13	0.40703	0.90377	12
2	Proximity from Workplace	0.44569	0.87806	12	0.39091	0.92050	11
3	Commuting Frequency (daily)	0.54212	0.80552	15	0.57723	0.77163	15
4	Service Frequency	0.05790	1.19477	2	0.15452	1.23251	3
5	Commuting period (weekdays)	0.23759	1.10516	7	0.16227	1.20114	5
6	Commuting period (weekends)	0.69393	0.65963	21	0.77681	0.52422	21
7	Ticketing System	0.17312	1.09475	5	0.18427	1.19157	6
8	Fare Expenditure (daily)	0.55845	0.78146	16	0.59264	0.75159	16
9	Punctuality and Reliability	0.05398	1.15910	1	0.13416	1.27812	1
10	Seat Availability	0.08405	1.17220	3	0.14655	1.26612	2
11	Seat Comfort	0.19997	1.13245	6	0.27965	1.16567	7

12	Accessibility to/from bus	0.66690	0.68238	20	0.79031	0.50190	22
13	Air Ventilation system	0.70537	0.64204	22	0.72882	0.57955	19
14	On-board Security	0.40590	0.90377	11	0.44291	0.86932	13
15	Female Harassment	0.62217	0.71516	19	0.63332	0.69896	17
16	On-time performance	0.35688	0.99618	10	0.35688	0.99618	10
17	Bus Staffs Courtesy	0.48098	0.84257	14	0.50169	0.83803	14
18	Structural condition	0.24548	1.07717	8	0.29986	1.05208	9
19	Interior Cleanliness	0.57173	0.77163	17	0.68781	0.63607	18
20	Noise Level	0.58848	0.76667	18	0.76364	0.53859	20
21	Commuting Experience	0.08580	1.15910	4	0.15757	1.22006	4
22	Route Information	0.28725	1.06291	9	0.28626	1.06649	8

6.4.3 Public Opinion

To determine the relative importance of the attributes, all the respondents are asked to select at least 12 out of 22 attributes that affect mostly the bus SQ. Note that these public opinion data is independent of the data used for PNN and ANFIS models development. Figure 6.5 shows the percentages of public opinion corresponding to all the attributes. According to 74.66% respondents, ‘Punctuality and reliability’ is one of the most important attribute. Around 70-74% opined that ‘Service Frequency’, ‘Commuting Experience’, ‘Seat availability’, ‘Ticketing System’, ‘Comfort Level of Seats’, ‘Average travel time (weekdays)’ are also important and have significant impact on the SQ.

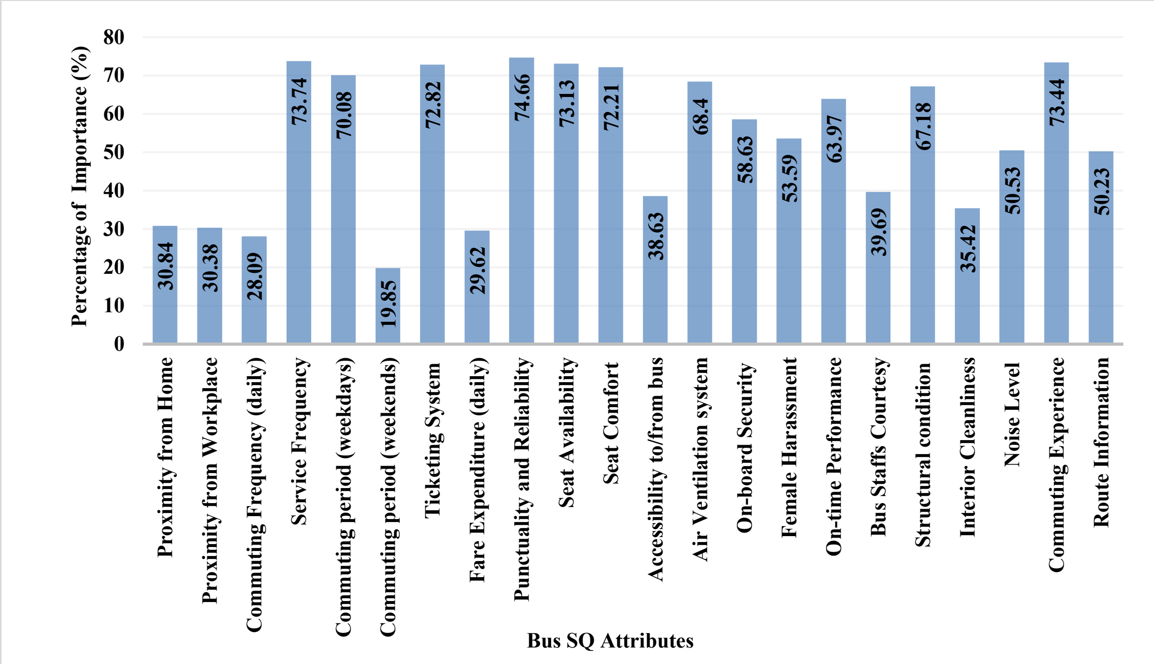


Figure 6.5: Percentages of Public Opinion for each of the Attributes

Table 6.3: Attribute ranking by Public Opinion

ATTRIBUTES	PUBLIC OPINION	
	Relative Contribution	**Rank**
Proximity from Home	0.20056	18
Proximity from Workplace	0.19220	19
Commuting Frequency (daily)	0.15042	21
Service Frequency	0.98329	2
Commuting period (weekdays)	0.91643	7
Commuting period (weekends)	0.00000	22
Ticketing System	0.96657	5
Fare Expenditure (daily)	0.17827	20
Punctuality and Reliability	1.00000	1
Seat Availability	0.97214	4
Seat Comfort	0.95543	6
Accessibility to/from bus	0.34262	16
Air Ventilation system	0.88579	8
On-board Security	0.70752	11
Female Harassment	0.61560	12

ATTRIBUTES	PUBLIC OPINION	
	Relative Contribution	Rank
On-time performance	0.80501	10
Bus Staffs Courtesy	0.36212	15
Structural condition	0.86351	9
Interior Cleanliness	0.28412	17
Noise Level	0.55989	13
Commuting Experience	0.97772	3
Route Information	0.55432	14

6.5 Summary

The overall condition of bus service quality in Dhaka city is as follows:

3 percent of the respondents indicated the SQ as very good; 21 percent people indicated level of service as good; 42 percent people indicated level of service as average; 22 percent people indicated level of service as poor; 13 percent people indicated level of service of bus as very poor.

In SQ prediction, PNN and ANFIS performs better than other models having 75.6% and 84.0% accuracy, respectively. Also, R and RMSE values between the predicted and actual SQ of the forecasting sample are observed. The R values of PNN and ANFIS prediction are 0.70788 and 0.79932, respectively. Whereas, the RMSE values for those models are 0.63607 and 0.50190, respectively. It can be seen that R value of ANFIS model is greater than PNN model. Whereas, RMSE value of ANFIS model is smaller than PNN model. It indicates that based on user stated preferences, ANFIS performs better than PNN in bus SQ prediction.

According to all the models and public opinion, 'Punctuality and Reliability' is found to be the most significant attribute that affect the bus SQ. 'Seat Availability', 'Service Frequency' and 'Commuting Experience' are found to be the next three most significant attributes.

Chapter 7

Conclusions and Recommendations

7.1 Introduction

Artificial Intelligence is a strong tool to mimic the human decisions to assess the quality of services depending on some attributes. Therefore, three NN models and an ANFIS model are developed to estimate bus SQ. The results of this study shows the significant bus SQ attributes as well as the most suitable AI model for bus SQ prediction.

7.2 Conclusions

Predicting service quality based on users' perception is a non-linear process. Artificial neural network is a dependable tool in case of non-linear relationship. Four of the most advanced and popular techniques of artificial neural network: GRNN, PNN, PRNN and ANFIS have been implemented in this study to predict bus service quality based on selected SQ attributes. This study is conducted with two main objectives: i) comparison of prediction capability of GRNN, PNN, PRNN and ANFIS, and ii) evaluation of bus SQ attributes according to their importance.

To reach the goals, four models are constructed using GRNN, PNN, PRNN and ANFIS structure involving all the 22 attributes. From the results, it is found that ANFIS outperforms all the models in SQ prediction capability with 84% accurate prediction. ANFIS stands superior to other ANN in prediction because, ANFIS executes the combined algorithm of both neural network and fuzzy inference system; whereas NNs use only neural network algorithm.

Most influential attributes are ranked from 1 to 22 using all the models. To have a better understanding, the SQ attributes are also ranked based on relative importance from the questionnaire survey. Findings of this study support the user stated preferences collected from the survey. According to all the models and public opinion, 'Punctuality and Reliability' is found to be the most significant attribute that affect the bus SQ. 'Seat Availability', 'Service Frequency' and 'Commuting Experience' are found to be the next three most significant attributes. 'Ticketing System', 'Commuting period (weekdays)' and 'Structural condition' are the also important factors. This model reflects users' perceptions about the provided quality of bus service. From the result, the first attribute to prioritize is the Punctuality of the bus service, that is the arrival time and departure time in every bus stop must be maintained properly. And, Reliability, that is the certainty with which the service will help the users to reach the destination in time. Service frequency is the second most important attribute which can be improved by introducing more public buses and reducing the travel time in desired routes. This will also increase the Seat availability. Similarly, an in depth examination of the results presented in Chapter 6 will help to initiate a multitude of possible initiatives to increase the satisfaction levels of the users and thereby increase the number of PT users.

From the above discussion, the following specific conclusions may be drawn:

- ANFIS outperforms all the models in SQ prediction capability with 84% accurate prediction. This is because, ANFIS executes the combined algorithm of both neural network and fuzzy inference system; whereas NNs use only neural network algorithm.
- For all the models, Connection weights, Stepwise approach and Public opinion reveals that 'Punctuality and Reliability' is the most significant bus SQ attribute. It implies that commuters are greatly concerned about the arrival and departure time of bus. In addition, they want to rely on the bus service to reach the destination in time.
- 'Seat Availability', 'Service Frequency' and 'Commuting Experience' are found to be the next three most significant attributes. Finally, an in depth analysis of the attribute ranking

will provide a direction to the bus authority about the relatively important features that should be improved to attract the bus users.

7.3 Recommendations

Intra city bus transport network of Dhaka city is selected for this study. Because, bus is the most dominant among all travel modes and represents 31% of all trips within the city. Nonetheless traffic congestion is ever on the rise as the number of private car users are increasing day by day. With only 6 percent car ownerships among the urban population, private vehicles are occupying more than half of the available road areas. Therefore, passengers should be attracted to public buses rather than private transports. The outcome of this study will convey some valuable suggestions to the service providers, operators, policy makers and transportation authorities about how to improve the bus SQ in view of attracting more passengers. However, due to shortcomings in resources of developing countries like Bangladesh, it is merely impossible to improve all the SQ attributes at once. This research provides a platform for staged development with the most significant attributes to start with.

7.4 Future Research

The more an AI model is trained, the more it predicts accurately. So, further research may be performed with a larger data set to get a better AI model for bus SQ analysis.

Since, from this study, ANFIS model is found to be the best approach in bus SQ estimation. Therefore, this approach can be applied to other cities reliably. However, the model parameters need to be calibrated for that particular scenario.

The prediction capability of ANFIS is greatly biased by various parameters like- membership function, transfer function, learning algorithm and so on. To get more accurate prediction, further researches may be carried out utilizing other membership functions which may be triangular, trapezoidal, sigmoidal or other shapes. Learning algorithm may also be improved to get better performance.

Many previous researches show that ANN is one of the most commonly and proficiently used machine learning algorithms. Hence, more researches have to be done on bus service quality incorporating AI for further improvements in prediction. Different algorithms like decision trees, case-based learning and so on may be used for further improvements. Another fact is the limitations of using connection weights inside the NN. Each contributing variable in the models cannot be evaluated to the same extent that traditional statistics-based models allow. The weights in the input layer can provide some information about the significance (weight) of each variable; however, this is not a practical solution. Because, the effects of weights of neurons in the input layer might be altered by the effects of weights applied in other hidden layers, or output layer might totally change the significance of contributing variables. This type of debates should be eliminated by further researches. The author expects to develop further refined models of bus SQ prediction that would be afar of this debate.

References

1. Abdulkadir, A., Ahmed, T., & Murat, Y. (2006). Prediction of Concrete Elastic Modulus Using Adaptive Neuro-Fuzzy Inference System. Journal of Civil Engineering and Environmental Systems, 23(4), 295-309.
2. Agarwal, P. (2015, September 4). Lofti Zadeh: Fuzzy logic-Incorporating Real-World Vaguness by Pragya Agarwal. Retrieved from Center for Spatially Integrated Social Science: http://www.csiss.org/classics/content/68
3. Akbuluta, S., Samet, H., & Pamuk, S. (2004). Data Generation for Shear Modulus and Damping Ratio in Reinforced Sands Using Adaptive Neuro-Fuzzy Inference System. Journal of Soil Dynamics and Earthquake Engineering, 24(11), 805-814.
4. Berger, C., Blauth, R., Boger, D., Bolster, C., Burchill, G., DuMouchel, W., . . . Walden, D. (1993). Kano's methods for understanding customer-defined quality. The Center for Quality Management Journal, 2(4).
5. Bhave, A. (2002). Customer Satisfaction Measurement. Quality & Productivity Journal.
6. Chennakesava, R. A. (2000). Fuzzy Logic and Neural Networks, Basic Concepts and Application. Hyderabad: New Age International (P) Limited.
7. Chiu, S. (1994). A cluster estimation method with extension to fuzzy model identification. in Proc. 3rd IEEE Conf. on Fuzzy Syst. World Congress in Comput. Intell, 1240-1245.
8. Chiu, S. (1996). Selecting input variables for fuzzy models. J. Intell. and Fuzzy Syst, 4(4), 243-256.
9. Costa Á, Markellos RN (1997) Evaluating public transport efficiency with neural network models. Transportation Research Part C: Emerging Technologies, Vol. 5, No. 5, pp. 301-312.
10. Davies F, Goode M, Mazanec J, Moutinho L (1999) LISREL and neural network modelling: two comparison studies. Journal of Retailing and Consumer Services, 6(4): 249-261.
11. De Oña, J., De Oña, R., & Calvo, F. (2012). A Classification Tree Approach to Identify Key Factors of Transit Service Quality. Expert Systems with Applications, 39, 11164-11171.
12. Dell'Olio, L., Ibeas, A., Cecin. P. (2011). The quality of service desired by public transport, Transport Policy, Vol. (18), Issue 1, 217-227.
13. Eboli L, Mazzulla G (2008) A stated preference experiment for measuring service quality in public transport. Transportation Planning and Technology, Vol. 31, No. 5, pp. 509-523.

14. Eboli, L., & Mazulla , G. (2011). A methodology for evaluating transit service quality based on subjective and objective measures from the passenger's point of view. Transport Policy, 18, 172-181.
15. Eboli, L., & Mazzulla, G. (2007). Service quality attributes affecting customer satisfaction for bus transit. Journal of Public Transportation, 10(3), 21-34.
16. European Committee for Standardization (CEN) (2002). Transportation – Logistics and services – public passenger transport – service quality definition, targeting and measurement, BS EN 13816.
17. Fang, F., Elefteriadou, K., Pecheux, & Pietrucha, M. (2003). Using Fuzzy Clustering of User Perception to Define Levels of Service at Signalized Intersections. Journal of Transportation Engineering, Vol. 129(6), 657-663.
18. Favilla, J., Machion, A., & Gomide, F. (1993). Fuzzy Traffic Control: Adaptive Strategies. IEEE International Conference on Fuzzy Systems. San Francisco: CA
19. Figini, M. D. (2003). valore alle esigenze dei clienti e dei dipendenti dell’azienda. Franco Angeli.
20. Fonseca, E., Vellasco, S., & Andrade, S. (n.d.). A Neuro-Fuzzy Evaluation of Steel Beams Patch Load Behaviour. Journal of Advances in Engineering Software, 39(7), 535-555.
21. Fuller, R. (2000). Introduction to Neuro-Fuzzy Systems. Advances in Soft Computing Series. Springer-Verlag Berlin Heidelberg.
22. Gan C, Limsombunchai V, Clemes M, Weng A (2005) Consumer choice prediction: Artificial neural networks versus logistic models. Lincoln University. Commerce Division. Chicago.
23. Garrido , C., De Oña, R., & De Oña, J. (2014). Expert Systems with Applications. An International Journal, 41(15), 6830-6838.
24. Hagan MT, Demuth HB, Beale MH (1996) Neural network design. Campus Publishing Service. Colorado University Bookstore. ISBN 0-9717321-0-8
25. Haykin, S. (2003). Neural Networks- A Comprehensive Foundation. Pearson Education (Singapore) Pvt. Ltd. Indian Branch.
26. Hensher, D.A., Stanley, J. (2003). Performance-based quality contracts in bus service provision, Transportation Research Part A, Vol. (37), 519–538.
27. Hossain, M. (2006). The issues and realities of BRT planning initiatives in developing Asian cities. Journal of Public Transportation, 69-87.
28. Jang, J. (1993). ANFIS: Adaptive-network-based fuzzy inference system. IEEE Trans. on Syst, Man and Cybern, Vol. 23(no. 3), 665-684.
29. Jang, J. R., & Sun, C. T. (1995). Neuro Fuzzy Modelling and control. Proc. EEE, 37-406.
30. Jang, J. R., Sun, C. T., & Mizutani, E. (1997). Neuro Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice Hall Inc. 1997.

31. Khan, S. M., & Hoque, M. S. (2013). Traffic Flow Interruptions in Dhaka City: Is Smooth Traffic Flow Possible?. Journal of PU, 46-48.
32. Kim, K., & Lee, D. (2008). A Model to Estimate the Marginal Walking Time of Bus Users by using Adaptive Neuro-Fuzzy Inference System. KSCE Journal of Civil Engineering, 12(3), 197-204.
33. Lai WT, Chen CF (2011) Behavioral intentions of public transit passengers—The roles of service quality, perceived value, satisfaction and involvement. Transport Policy, Vol. 18, No. 2, pp. 318-325.
34. Lai, W.T., Chen, C.F. (2010). Behavioural intentions of public transit passengers - The roles of service quality, perceived value, satisfaction and involvement, Transport Policy, Vol. (18), Issue 2, 318-325.
35. Litman, T. (2007). Developing Indicators for Comprehensive and Sustainable Transport Planning. Transportation Research Record 2017, 10-15.
36. Mahmoud, M., J. Hine, and A. Kashyap. Bus transit service quality monitoring in UK: A methodological framework. Proceedings of the ITRN, 2011. www.itrn.ie/uploads/sesD2_ID75.pdf. Accessed June 20, 2015.
37. Maier, H., & Dandy, G. (2000). Neural Networks for the prediction and forecasting of water resources variables: A review of modelling issues and applications. Environmental modelling & software, 15(1), 101-124.
38. Mazulla, G., & Eboli, L. (2006). A Service Quality experimental measure for public transport. European Transport n.34, 42-53.
39. Mohdeb, N., & Mekideche, M. (2010). Determination of the Relative Magnetic Permeability by using and Adaptive Neuro-Fuzzy Inference System and 2D-FEM. Progress in Electromagnetics Research B, 22, 237-255.
40. Ndoh, N. N., & Ashford, N. J. (1994). Evaluation of Transportation Level of Service Using. Transportation Research Record, 1461, 31-37.
41. Negnevitsky, M. (2005). Artificial intelligence: a guide to intelligent systems. Pearson Education.
42. Olden JD, Jackson DA (2002) Illuminating the “black-box”: a randomization approach for understanding variable contributions in artificial neural networks. Ecological Modeling 154: 135-150.
43. Prioni, P., & Hensher, D. (2000). Measuring service quality in scheduled bus services. Journal of Public Transportation, 3(2), 51-74.
44. Rahman, M. (2011). Service level of public bus in Dhaka city, Bangladesh. Presented in 24th World Road Congress (PIARC). Mexico.

45. Robertson, D. (1979). Traffic Models and Optimum Strategies of Control: A Review. Proceedings of the International Symposium on Traffic Control Systems. Vol. 1, pp. 262-288. University of California.
46. Spring, G. (2000). Integration of Safety and the Highway Capacity Manual. Transportation Research Circular, E-C018.
47. Takagi, T., & Sugeno, M. (1983). Derivation of fuzzy control rules from human operator's control action. in Proc. IFAC Symp. Fuzzy Inform. Knowledge Representation and Decision Analysis, 55-60.
48. Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. IEEE Trans. Syst., Man and Cybern, 15, 116-132.
49. Tesfamariam, S., & Naijjaran, H. (2007). Adaptive Network-Fuzzy Inferencing to Estimate Concrete Strength Using Mix Design. Journal of Materials in Civil Engineering, 19(7), 550-560.
50. Transport Research Board. (1999). A Handbook for Measuring Customer Satisfaction and Service Quality. TCRP Report 47.
51. Transportation Research Board. (2003a). A Guidebook for Developing a Transit Performance-Measurement System. TCRP Report 88.
52. Transportation Research Board. (2003b). Transit Capacity and Quality of Service Manual. TCRP Report 100.
53. Tsukamoto, Y., Gupta, M., Ragade , R., & Yager , R. (1979). An approach to fuzzy reasoning method. In R. K. Madan M. Gupta, Advances in Fuzzy Set Theory and Applications (pp. 137-149). Amsterdam: North-Holland.
54. Tyrinopoulos, Y., & Aifadopoulou, G. (2008). A complete methodology for the quality control of passenger services in the public transport business. European Transport, 38, 1-16.
55. Tyrinopoulos, Y., & Antoniou, C. (2008). Public transit user satisfaction: Variability and policy implications. Transport Policy, 15, 260-272.
56. Yager, R. R. (1986). An Introduction to Fuzzy Theory. In Applications of Fuzzy Set Theory in Human Factors. Amsterdam: Elsevier Science.
57. Zadeh, L. (1965). Fuzzy Sets. Information Control 8, 338-353.
58. Zeithaml, A., Parasuraman, V., & Berry, L. (1990). Delivering Quality Service: Balancing Customer Perceptions and Expectations. New York: The Free Press.
59. Zeithaml, V., Parasuraman, A., & Berry, L. L. (1986). Servqual: a multiple item scale for measuring perceptions of service quality. Marketing Science Institute.

Appendix A

Questionnaire Survey

This Information obtained in this survey will be accorded confidential treatment and will be utilized for academic research purposes only. We also assure the anonymity of the information you provide.

Survey Pre-Detail

The objective of this questionnaire survey is to determine service quality of the bus network system in Dhaka city, integrating commuter's attitude and predilections toward prevalent service parameters in different routes. The survey form consists of a series of general questions with accommodated choice assemblage. The general set of questions is followed by a numerical perception rating survey to evaluate the existing service condition of the bus system. Moreover, an optimized survey to opt requisite and desirable service quality parameters suitable in Dhaka city situation is supplemented to substantiate the level of service designation.

Person interviewed: .... Occupation: ....

Date: .... Address: ....

Contact Number: .... Email: ....

Age: ………………… Gender: Male / Female; Office/Institution: ……………………………………………………….

Income: ………………………… BDT Purpose for travelling by bus: Work / Recreation / Saving money

General Questions

Service Quality Parameter	Preferential – 1	Preferential – 2	Preferential – 3	Preferential – 4	Preferential – 5	Comments
1. **Proximity from home**	☐ 100	☐ 500	☐ 1000	☐ 1500	☐ 2000	
2. **Proximity from workplace**	☐ 100	☐ 500	☐ 1000	☐ 1500	☐ 2000	
3. **Commuting frequency (daily)**	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	
4. **Service frequency**	☐ 5	☐ 10	☐ 20	☐ 30	☐ 60	
5. **Commuting period (weekdays)(min)**	☐ 10	☐ 20	☐ 30	☐ 60	☐ 120	
6. **Commuting period (weekends) (min)**	☐ 10	☐ 20	☐ 30	☐ 60	☐ 120	
7. **Ticketing system**	☐ On counter and convenient	☐ On board and convenient	☐ On counter and inconvenient	☐ On board and inconvenient	☐ Other	
8. **Fare expenditure (daily) (tk)**	☐ <10	☐ <20	☐ <50	☐ <100	☐ >100	
9. **Punctuality and reliability**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor	
10. **Seat Availability**	☐ Available	☐ Not available in peak period	☐ Broken seat	☐ Not available		

11. **Seat Comfort**	☐ Very comfortable	☐ Medium comfort	☐ Low comfort	☐ Very poor	☐ Not enough leg room and side space
12. **Accessibility to/from bus**	☐ Comfortable	☐ Low comfort	☐ Risky due to boarding height	☐ Discomfort in alighting situation	☐ Both discomfort and risky
13. **Air ventilation system**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor
14. **On-board security**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor
15. **Female Harassment**	☐ No harassment	☐ Almost not	☐ Sometimes	☐ Very often	☐ Always
16. **On-time performance**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor
17. **Bus staff courtesy**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor
18. **Structural condition**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor
19. **Interior cleanliness**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor
20. **Noise level**	☐ Silent	☐ Almost silent	☐ Tolerable	☐ Noisy	☐ Intolerable
21. **Commuting experience**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor
22. **Route information**	☐ Excellent	☐ Good	☐ Average	☐ Poor	☐ Very poor

Numerical Rating Survey

Provide a tick mark underneath the preference

Bus Service	**Excellent (6)**	**Good (5)**	**Satisfactory (4)**	**Average (3)**	**Poor (2)**	**Very Poor (1)**
____________	☐ 6	☐ 5	☐ 4	☐ 3	☐ 2	☐ 1

Rationale of Numerical Rating

For any bus, mark 12 items out of 22 given in the followings, considering the ones you think best affect your riding quality.

1. **Proximity from home** ☐
2. **Proximity from workplace** ☐
3. **Commuting frequency (daily)** ☐
4. **Service frequency** ☐
5. **Commuting period (weekdays)** ☐
6. **Commuting period (weekends)** ☐
7. **Ticketing system** ☐
8. **Fare expenditure (daily)** ☐
9. **Punctuality and reliability** ☐
10. **Seat Availability** ☐
11. **Seat Comfort** ☐
12. **Accessibility to/from bus** ☐
13. **Air ventilation system** ☐
14. **On-board security** ☐
15. **Female Harassment** ☐
16. **On-time performance** ☐
17. **Bus staff courtesy** ☐
18. **Structural condition** ☐
19. **Interior cleanliness** ☐
20. **Noise level** ☐
21. **Commuting experience** ☐
22. **Route information** ☐

Appendix B

Related Publications

Followings are the list of publications resulted from the Author’s M.Sc. Thesis:

1. Islam, M. R., Hadiuzzaman, M., Banik, R., Hasnat, M. M., Musabbir, S. R., & Hossain, S. (2016). Bus service quality prediction and attribute ranking: a neural network approach. Public Transport, 8(2), 295-313.
2. Islam, M. R., Musabbir, S. R., Ahmed, I. U., Hadiuzzaman, M., Hasnat, M., & 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.
3. Islam, M. R., Hasnat, M. M., Hadiuzzaman, M., Ahmed, I. U., & Hossain, S. (2016). Application of Probabilistic Neural Network and Adaptive Neuro Fuzzy Inference System for Predicting Bus Service Quality and Attribute Ranking. In Transportation Research Board 95th Annual Meeting (No. 16-2720).