ANALYSIS OF CLASSROOM SPEECH INTELLIGIBILITY USING FUZZY LINEAR REGRESSION MODEL

ABSTRACT

Speech is defined as a process of producing sounds confirming to an accepted code by the human vocal apparatus. These sounds are perceived by the ear-brain system with the primary purpose of conveying thoughts. The intelligibility of speech refers to the accuracy with which a normal listener can understand a spoken word or phrase. In a classroom, a teacher talks to a group of students who are intended to hear everything the teacher says. The achievements and behavior of the students inside the classroom is mainly influenced by the speech intelligibility factor. For achieving the highest possible speech intelligibility, the acoustical design of classrooms should be based on all the listeners in the classroom. This research work investigates the effect of Signal to Noise Ratio (SNR) on speech intelligibility in University classrooms. The speech intelligibility level of a classroom depends on the room volume, source receiver distance, back ground noise level, RT, SNR. A set of Malay words with CVC format is complied and a speech signal data base is created. In a classroom, the speech signal is presented at a level of 47 to 72 dB with +/- 2dB and the noise at levels of 55, 60 and 63 dB are electrically mixed to yield a signal-to-noise ratio of -16 to +16 dB. The sound pressure levels are then measured at different classroom positions. From the measured sound pressure level, the speech intelligibility at various listeners' positions is determined and a simple neural network model is developed to predict the speech intelligibility at various listeners' positions of a classroom for various speech levels.

1.1 INTRODUCTION

Classrooms provide an environment to students to obtain knowledge through hearing and understanding the lectures delivered by teachers where a very high level of acoustical quality is required. Most of the time, noisy and reverberant classrooms may act as a barrier to this learning process. It is necessary to provide the optimum condition for speech intelligibility in classrooms that are used for delivering the lectures such as background noise that will not interfere with the hearing of lectures and the reverberation time that should approach the optimum characteristic are very related to speech intelligibility.

The problems occur when the speech is unintelligible in classrooms not because of lack of power but because lack of intelligibility.This is usually due to two factors, which are the signal to noise ratio (S/N) at the listener's positons and room acoustic characteristics. Test results collected over the years show that speech intelligibility is reduced by the increased of background noise (or decrease of signal – to – noise ratio) and by increase of the reverberation time. In this research work, Speech Clarity and (SC) Speech Transmission Index (STI) are used as a criterion to predict the speech intelligibility in a classroom. Neural network models are developed to predict the SC and STI for various speech sound levels at different seating locations.

1.1 Need for the project

Classrooms are places of learning where speaking and listening are the primary communication modes. Until recently neither university planners nor the general public were aware of the significant negative effect of noise and excessive reverberation on the learning process which affects the classroom speech intelligibility. Learning spaces have poor speech intelligibility level because of the outside noise, noise generated by heating, ventilating and air conditioning systems, noise emanated from halfway, adjacent spaces and the re-emergence of open classrooms architecture (large rooms with partitions dividing the room for multiple classes) and the presence of too many hard reflective surfaces. In this research work, an Intelligent System for Speech Intelligibility Measurement software package are developed to measure the speech intelligibility in the classrooms. The system will record the background noise level and speech level in dB in a classroom. On receiving the classroom dimension information from the user, the system predicts and provides the speech intelligibility mapping of the classroom. The system will be useful for the architect, School designer and also lecturers to measure speech intelligibility level in the classroom.

1.2 Scope and Objectives

One of the main aims of this work is to measure the reverberation time and background noise level in University classroom and predict the speech intelligibility level in a classroom. Classroom characteristic study is used as a sample in training the network. Method and setting up of experiments is explored and based on the Acoustical International Standard (ISO 9614 & ISO 3745)

The second aim of this research work is to propose software to predict the speech intelligibility level in any classroom based on the input from the user.

The objectives of this work can be summarized as follows:

i. To study and measure the reverberation time and background noise level and its effect on classroom speech intelligibility.
ii. To study and analyzed obtained data by using 01 dB software.
iii. To study, analyze and obtain the speech intelligibility using frequency spectrum method.
iv. To propose different neural network architecture to predict speech intelligibility in university classrooms
v. To compare the performance of the different types of neural network architecture.

2.0 EXPERIMENTAL SETUP

2.1 Equipment used for measuring RT and Background Noise

a) Orchestra
b) Noise generator
c) Microphones
d) 01 dB Calibrator
e) Amplifier

2.2 Measurement Procedures and Setup

The reverberation time and background noise are measured for a frequency range of 63 to 8000 Hz at intervals of 1/3 octave. The microphone standard calibration value is 94 dB and it is calibrated using 01dB calibrator. The calibrated microphone is connected to Orchestra and placed at the distance of 1.2m from the noise generator.

The RT and background noise has been measured under 4 different test conditions as listed below;

a) *With furniture and ventilation on*
-The RT and background noise are measured with furniture kept inside the Classroom and the Air Conditioner is on.

b) *With furniture and ventilation off*
- The RT and background noise are measured with furniture kept inside the classroom and the Air Conditioner is off

c) *Without furniture and ventilation on*
- The RT and background noise are measured in the empty classroom (all furniture are removed) and the Air Conditioner is on.

(d) *Without furniture and ventilation off*
- The RT and background noise are measured in the empty classroom (all furniture are removed) and the Air Conditioner is on.

Table 1 – RT with furniture and ventilation on

Classrooms	Frequency Bands(Hz)							
	250	**500**	**630**	**1000**	**1600**	**2000**	**4000**	**8000**
BKP1 (sec)	2.07	1.75	1.63	1.77	1.64	1.63	1.4	0.99
DKP2 (sec)	1.07	1.16	1.31	1.36	1.31	1.25	1.09	0.95
DKP3 (sec)	2.13	1.87	1.71	2.03	2.18	2.1	1.52	0.9
BKY (sec)	2.14	1.9	1.88	2.18	2.11	1.98	1.62	1.02
BTM1(sec)	1.52	1.54	1.56	1.88	1.86	1.75	1.4	0.96
DTM1(sec)	1.24	0.99	0.87	0.73	0.77	0.8	0.75	0.62
DKG3(sec)	1.21	1.26	1.34	1.43	1.47	1.52	1.27	0.89
DKG5(sec)	1.75	1.67	1.52	1.9	1.97	1.96	1.45	0.86

Table 2 – RT with furniture and ventilation off

Classrooms	Frequency Bands(Hz)							
	250	**500**	**630**	**1000**	**1600**	**2000**	**4000**	**8000**
BKP1 (sec)	2.41	2.17	2.05	2.1	2.02	1.93	1.58	1.14
DKP2 (sec)	1.18	1.18	1.33	1.35	1.36	1.22	1.11	0.95
DKP3 (sec)	2.22	2.01	1.87	2	2.19	2.2	1.57	0.89
BKY (sec)	2.17	1.99	1.82	2.28	2.21	2.02	1.67	1.02
BTM1(sec)	1.3	1.05	1.01	0.89	1.01	0.94	0.91	0.71
DTM1(sec)	1.42	1.05	0.83	0.8	0.79	0.82	0.75	0.6
DKG3(sec)	1.19	1.34	1.32	1.51	1.53	1.57	1.27	0.89
DKG5(sec)	2.13	1.83	1.52	1.95	2.1	2	1.45	0.87

Table 3 – RT without furniture and ventilation off

	Frequency Bands(Hz)							
Classrooms	250	500	630	1000	1600	2000	4000	8000
BKP1 (sec)	2.6	2.19	2.13	2.25	2.07	1.95	1.69	1.11
DKP2 (sec)	1.07	1.16	1.31	1.36	1.31	1.25	1.09	0.95
DKP3 (sec)	2.09	2.31	2.05	2.26	2.55	2.42	1.68	0.94
BKY (sec)	2.52	2.2	2.14	2.4	2.28	2.15	1.71	1.06
BTM1(sec)	1.55	1.64	1.59	1.78	1.86	1.77	1.37	0.97
DTM1(sec)	1.41	1.48	1.48	1.72	1.83	1.72	1.37	0.91
DKG3(sec)	1.21	1.37	1.66	1.76	1.87	1.79	1.44	0.98
DKG5(sec)	1.9	2.09	1.88	2.29	2.43	2.27	1.78	1.11

Table 4 – RT without furniture and ventilation on

Classrooms	Frequency Bands(Hz)							
	250	500	630	1000	1600	2000	4000	8000
BKP1 (sec)	2.1	1.59	1.59	1.53	1.66	1.65	1.47	1
DKP2 (sec)	1.89	2.25	2.49	2.78	2.52	2.4	1.78	1.2
DKP3 (sec)	2.09	2.31	2.05	2.26	2.55	2.42	1.68	0.94
BKY (sec)	2.59	2.17	2.16	2.47	2.54	2.29	1.77	1.04
BTM1(sec)	1.55	1.64	1.59	1.78	1.86	1.77	1.37	0.97
DTM1(sec)	1.56	1.51	1.52	1.62	1.71	1.73	1.34	0.81
DKG3(sec)	1.21	1.49	1.59	1.7	1.83	1.75	1.44	0.95
DKG5(sec)	2.1	2.05	1.82	2.29	2.44	2.25	1.76	1.11

Table 5 – Average value of Background noise in 8 classrooms

Background Noise Test Conditions	Average value (dB)
With furniture and ventilation on	46.1
With furniture and ventilation off	33.5
Without furniture and ventilation on	29.9
Without furniture and ventilation off	26.4

3.0 THE SPEECH INTELLIGIBILITY PARAMETERS MEASUREMENT

The measurement of speech intelligibility parameters are carried out in four different classrooms (BKP1, BTM1, DKG 3 and BKY).

3.1 Room Characteristic

A detailed study on the different types of material used for constructing the classrooms is carried out. The types of fabrication material and furniture available in the classrooms also have been studied. The typical room characteristics are shown in Table 6.

Table 6 – Typical room characteristic

Room Characteristics	BKP1	BTM1	BKY	DKG3
Width (m)	6.401	7.38	10.06	9.09
Height (m)	3.285	2.59	3.56	3.02
Length (m)	12.80	15.76	18.90	18.12
Reverberation Time (sec at 1 kHz)	1.77	0.92	1.51	0.83
Background Noise (dB at 1 kHz)	41.2	39.9	43.2	37.9
Seating Positions Identified	21	33	50	72

3.2. The Experimental Setup

The width, length and height of the classrooms are measured and the listener's positions in the classroom are identified. The listeners' positions in the classrooms are varied according to the size of the classroom. The distance between any two adjacent listeners position in the same row is chosen as 0.5m (D_1) and the distance between each row is chosen as 1m (D_2). The basic plan view of a classroom is shown in Figure 1.

The omni directional source is placed at the source position representing a lecturer at a height of 1.5m from the floor level. The microphones are placed at 1m from the floor level at each listeners seating position representing the human ear. Various pre-recorded Malay words arranged in Consonant Vowel Consonant (CVC) formats are played back at various speech and noise levels. The details of various speech and noise levels are shown in Table 7.

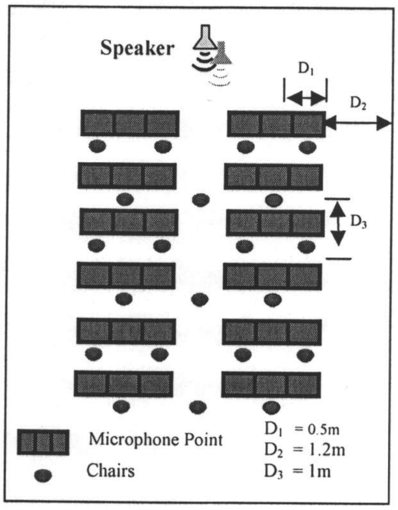


Figure 1 The basic plan view of the classrooms

3.3 The Measurement of Speech Intelligibility Parameters

In order to measure the SC and STI at each position in the classrooms, Malay words of CVC format recorded at different ranges of speech levels (from 47dB to 72 dB) and noise levels (55, 60 and 63 dB) are played back using a power amplifier and an omni directional speaker. The different sound level of the spoken word and the added noise levels are shown in Table 7. The speech level and noise are played simultaneously and recorded to yield signal to noise ratio from -8dB to +16dB.

The data obtained at each listener positions are analyzed using dBBati software and from the measured speech level, the speech intelligibility at each location is calculated.

Table 7 The different ranges of Speech Levels and Noise Levels

Range 1													
Noise(dB)	55												
Word(dB)	47	49	51	53	55	57	59	61	63	65	67	69	71
S/N	-8	-6	-4	-2	0	2	4	6	8	10	12	14	16
Range 2													
Noise(dB)	60												
Word(dB)	50	52	54	56	58	60	62	64	66	68	70	72	
S/N	-10	-8	-6	-4	-2	0	2	4	6	8	10	12	
Range 3													
Noise(dB)	63												
Word(dB)	47	49	51	53	55	57	59	61	63	65	67	69	71
S/N	-16	-14	-4	-2	0	2	4	6	8	10	12	14	16

4.0 NEURAL NETWORK TRAINING

Neural network models are developed to predict SC and STI of the classrooms at various seating positions. The architecture of neural network model to predict STI is shown in Figure 2. This network model consists of three input neurons to represent the sound pressure level in dB, X and Y coordinate of the listeners sitting position, width, length and height of the classroom, S/N and RT, and one output neuron to represent the STI. The performance of the network is observed by varying the number of hidden neurons. Through simulation, the neuron in the hidden layer is fixed as 30.

The second network model is developed to predict the SC of the classrooms. The network model consists of eight input neurons representing speech level in dB, X,Y coordinate of listeners seating position, width, length and height of the classroom, RT and S/N in dB. The second network model also has 1 hidden layer with 65 hidden neurons. The output neuron of this network represents the SC. Both networks are trained using back propagation algorithm with 2482 samples for training and 3546 samples for testing. The training result obtained for both network are tabulated in Table 8 and 9.

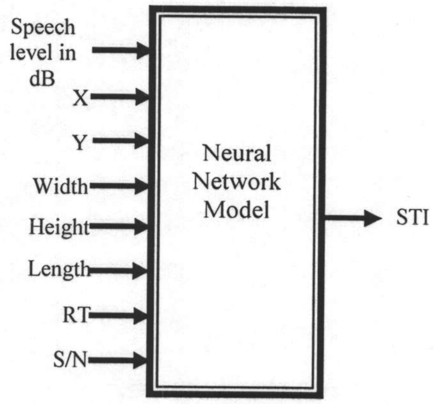


Fig. 2 The network Model for STI

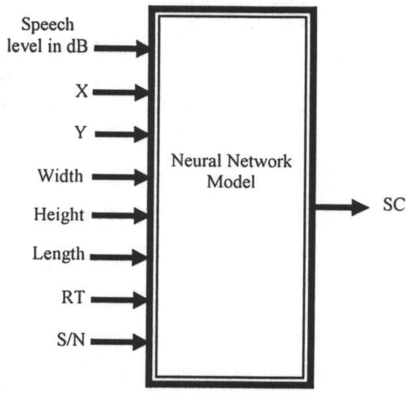


Fig 3. The network model for SC

Table 8 Prediction of SC using Backpropagation Method

Number of Input Neuron: 8 **Number of Output Neuron: 1**
Number of Hidden Neuron : 65 **Bias: 1,1**
Activation Function: $1/(1+e^{-x})$
Learning Rate: 0.005 **Momentum Factor: 0. 7**
Training tolerance: 0.005 **Testing Tolerance: 0.1**
Number of sample used for training: 2482
Number of sample used for testing: 3546

Trial No	Min Epoch	Max Epoch	Mean Epoch	Std. Dev	Min Training Time (sec)	Max Training Time (sec)	Mean Training Time (sec)	Std. Dev
1	111	950	248	158	37	323	84	53
2	91	949	268	188	30	321	90	63
3	86	673	237	143	28	328	86	49
4	108	979	246	155	36	331	82	52
5	116	735	254	141	39	247	85	47

Table 9 Prediction of STI using Backpropagation Method

Number of Input Neuron: 8
Number of Hidden Neuron : 30
Activation Function: ***1/(1+e^{-x})***
Learning Rate: 0.4
Training tolerance: 0.005
Number of sample used for training: 2482
Number of sample used for testing: 3546

Number of Output Neuron: 1
Bias: 1,1
Momentum Factor: 0.7
Testing Tolerance: 0.1

Trial No	Min Epoch	Max Epoch	Mean Epoch	Std. Dev	Min Training Time (sec)	Max Training Time (sec)	Mean Training Time (sec)	Std. Dev
1	38	2499	161	443	27	1055	77	185
2	50	1322	161	237	17	2689	144	489
3	50	3175	911	577	20	1461	538	2659
4	42	6604	442	1330	18	3298	224	670
5	41	3002	212	538.	17	1255	91	225

5. RESULTS & DISCUSSION

5.1 Speech Clarity (SC) Mapping

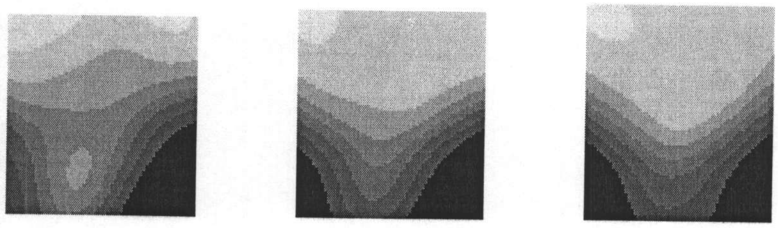
The speech intelligibility level at various listener's positions are determined using the trained neural network model. The resulting speech intelligibility level at different locations are represented in a gray scale mapping and shown in Figures 4, 5, and 6.

Figure 4, 5 and 6 shows the mapping result obtained for SC in 3 classrooms. From the Figures it can be inferred that as the signal to noise ratio is increased, the SC is reduced. In the mapping, the black area represents 0 (unintelligible) while the gray area represents 1 (intelligible). From the 3 classrooms, BKP 1 has a smallest size and the size of DKG5 is the largest.

The background noise in BKP 1 is 41.2 dB and RT is 1.77 sec. BKP1 has glass door at the back side of the classroom and a staircase on the right. Figure 4 (a, b and c) shows the mapping of SC at the speech level of 71 dB and the noise level of 55, 60 and 63 dB. It can be observed that the SC is almost uniform in the front side of the classroom and the SC at the back side and the right side of the classroom is poor. This is due to the glass door at the back side of the classroom and the stair case on the right of the classroom. As the signal to noise ratio increased, the SC clarity of the classroom is reduced this can clearly observed in Figure 4.

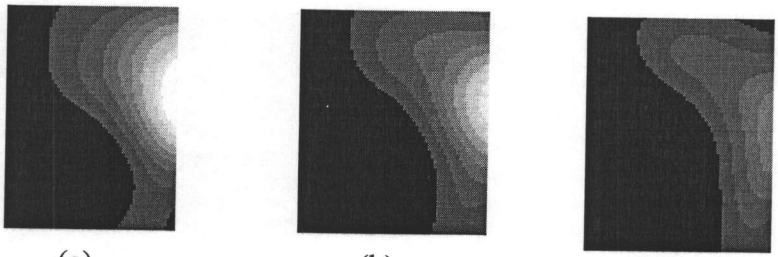
Further, Figure 5 represents the mapping for BTM1. The background noise for BTM 1 is 39.9 dB and this classrooms has the lowest RT (0.92 sec) compare to the otherclassrooms.

Figure 6 represents the mapping for DKG5. The classroom has the largest volume from the other 2 classrooms. The background noise of the classroom is 37.9 dB and the RT is 1.83 sec. Through out the left side of the classroom have black area which represent un intelligible. This is because the left side of the classroom has glass window which cause high reflection.



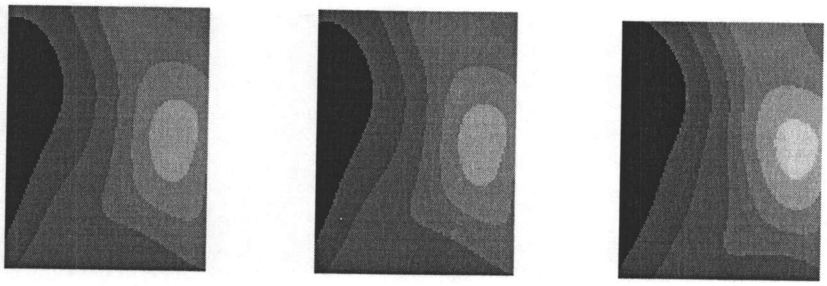
(a) (b) (c)

Fig.4.The SC mapping of BKP1 at speech level of 71dB and noise level of (a) 55dB, (b) 60dB, (c) 63dB with Background noise =41.2 dB and RT = 1.77 sec.



(a) (b) (c)

Fig.5. The SC mapping of BTM1 at speech level of 71dB and noise level of (a) 55dB, (b) 60dB, (c) 63dB with Background noise = 39.9 dB and RT = 0.92 sec.



(a) (b) (c)

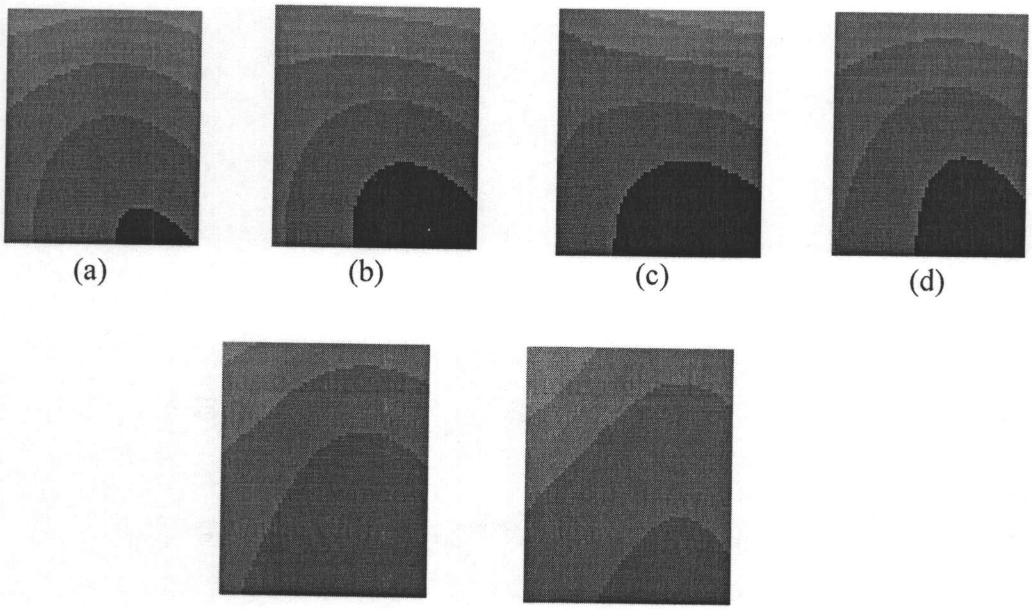
Fig.6.The SC mapping of DKG5 at speech level of 71dB and noise level of (a) 55dB, (b) 60dB, (c) 63dB with Background noise = 37.6 dB and RT = 1.83 sec.

5.2. Speech Transmission Index (STI) Mapping

The STI at various locations in the three classrooms are mapped. The STI mapping of three classrooms for different signal and noise levels are shown in Figure 7, 8 and 9.
The black area represents the speech unintelligibility (0) while the gray area represents the speech intelligibility (1). The mapping of the 3 classrooms clearly shows that as the signal to noise ratio increased, the speech intelligibility is reduced.
Figure 7 represent the mapping for BKP1. It can be observed that the back side of the classroom shows the poor intelligibility. This is because the back side of the classroom has a glass door.

The second classroom has a staircase at the bottom right. This affects STI considerably. The same result can be inferred in the Figure 8.

The third classroom has a glass window in the left half. The presence of the glass window affects the STI and this can be verified from the Figure 9.



(a) (b) (c) (d) (e) (f)

Fig 7. Mapping of STI for BKP1 – (a) Speech Signal level 65dB, S/N 10dB, (b) Speech Signal level 65dB, S/N 2 dB, (c) Speech Signal level 66 dB, S/N 6 dB, (d) Speech Signal level 71dB, S/N 16dB, (e) Speech Signal level71dB, S/N 12dB, (f) Speech Signal level 72 dB, S/N 12 dB, Background noise = 41.2 dB, RT = 1.77 sec.

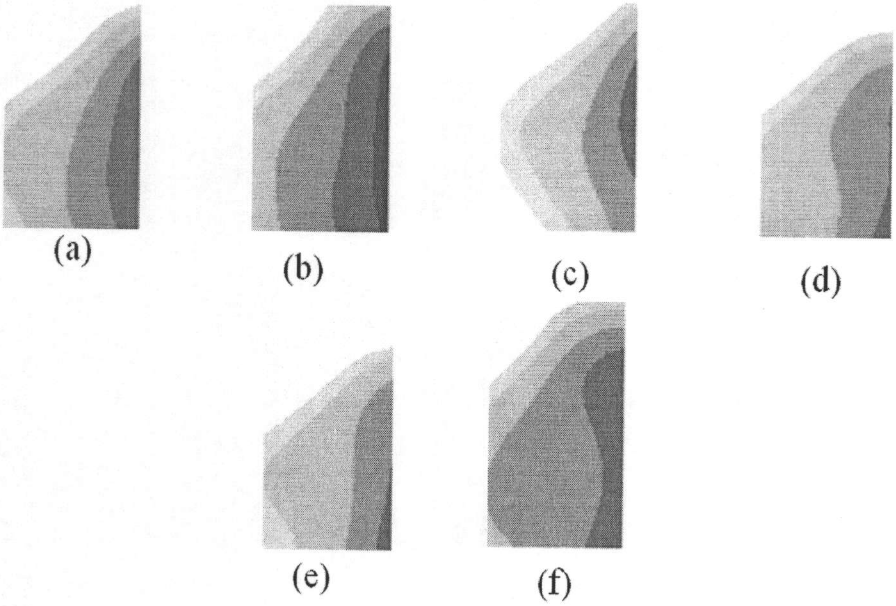


Fig 8: Mapping of STI for classroom 2 – (a) Speech Signal level 65dB, S/N10dB,(b) Speech Signal level65dB, S/N 2 dB, (c) Speech Signal level 66 dB, S/N 6 dB, (d) Speech Signal level 71dB, S/N 16dB, (e) Speech Signal level 71dB, S/N 12dB, (f) Speech Signal level 72 dB, S/N 12 dB, Background noise = 39.9 dB, RT = 0.92 sec.

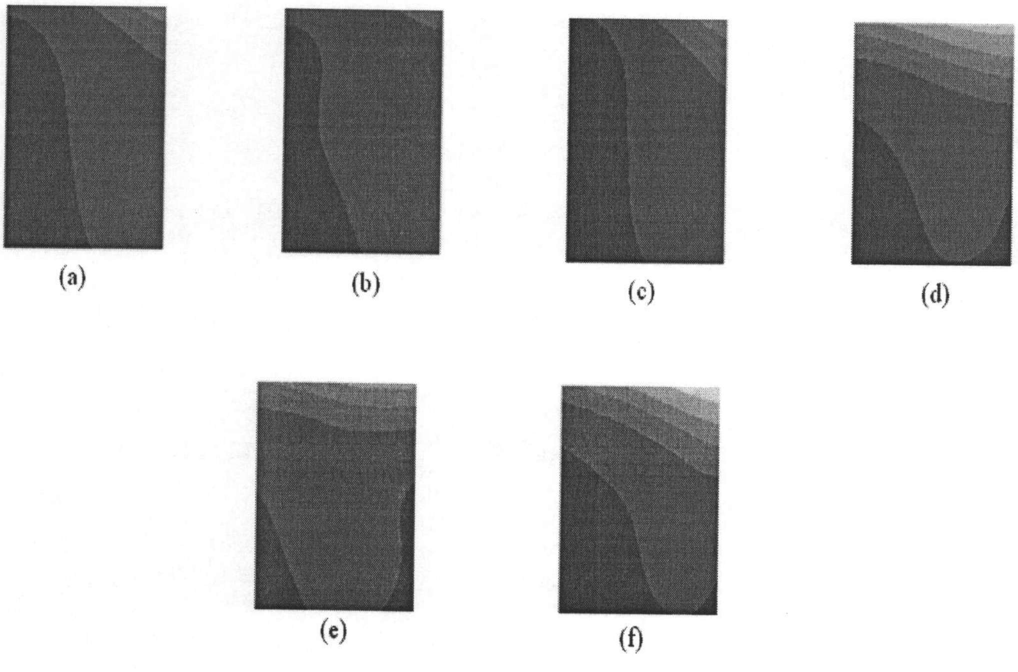


Fig 9: Mapping of STI for DKG5– (a) Speech Signal level 65dB, S/N 10dB,(b) Speech Signal level 65dB, S/N 2 dB, (c) Speech Signal level 66 dB, S/N 6 dB, (d) Speech Signal level 71dB, S/N 16dB, (e) Speech Signal level 71dB, S/N 12dB. (f) Speech Signal level 72 dB, S/N 12 dB, Background noise = 37.9 dB, RT = 1.83 sec.

5.3 Fuzzy Logic Modeling

5.3.1 Introduction

Over the past few decades, *fuzzy logic* has been used in a wide range of problem domains. Although the fuzzy logic is relatively young theory, the areas of applications are very wide process control, management and decision making, operations research, economies.

A *fuzzy set* is a set whose elements have degrees of membership. A element of a fuzzy set can be full member (100% membership) or a partial member (between 0% and 100% membership). That is, the membership value assigned to an element is no longer restricted to just two values, but can be 0, 1 or any value in-between. Mathematical function which defines the degree of an element's membership in a fuzzy set is called *membership function.* The natural description of problems, in *linguistic* terms, rather than in terms of relationships between precise numerical values is the major advantage of this theory. A simple procedure using fuzzy logic to predict the speech intelligibility in university classrooms is newly proposed in this report.

5.3.2 Algorithm

In this research work, *a priori* knowledge about spectral information of classroom characteristics are used in order to predict speech intelligibility level in fuzzy logic manner. More specifically,

a) Input (RT, S/N, Word dB, Listeners distance and classroom volume) and output variables (speech intelligibility) are introduced in Matlab's environment. b)

b) Membership functions are defined based on the input and output data range

c) Matlab's Fuzzy Logic Toolbox is used in defining the fuzzy logic inference rules,

d) These rules are tested and verified through the simulation of classification procedure at random sample areas.

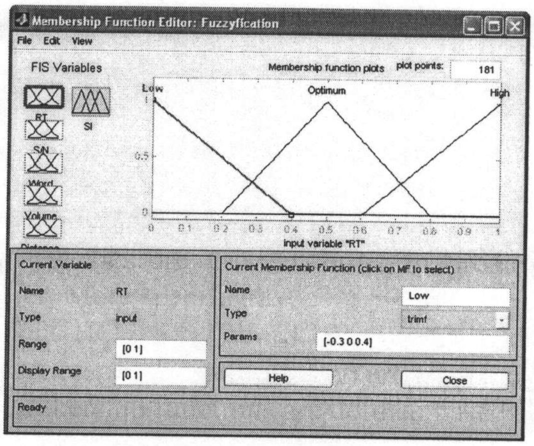


Fig10 – Membership function for input RT

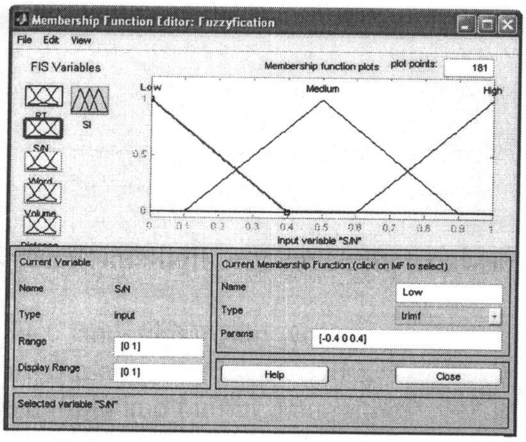


Fig 11- Membership function for input S/N

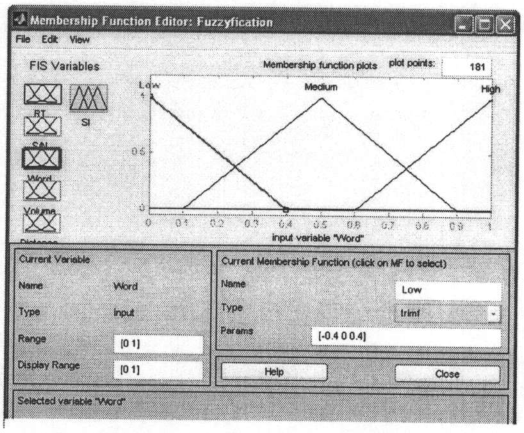


Fig 12 – Membership function for input Word dB

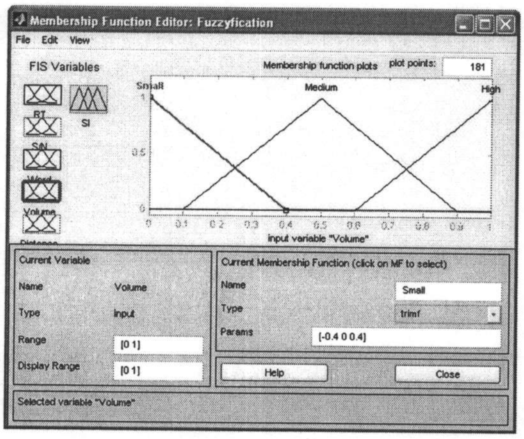


Fig 13 – Membership function for input Volume

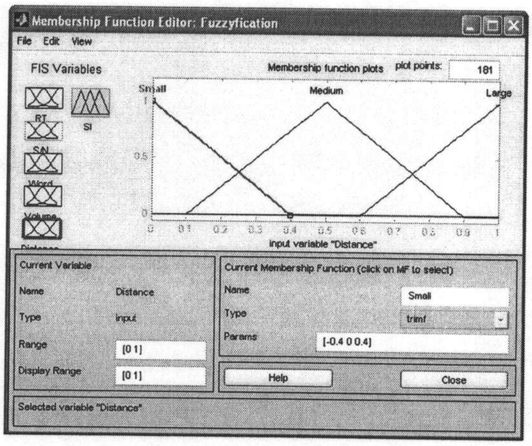


Fig 14 – Membership function for input Distance

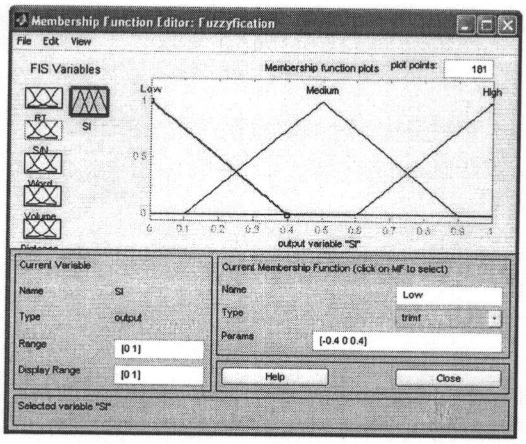


Fig 15 – Membership function for output Speech Intelligibility

5.3.3 Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping as set of input variables to a set of output variable using fuzzy logic. The process of fuzzy inference involves: *membership functions*, *fuzzy logic operators* and *if-then rules. The* fuzzy inference system that can be implemented using:

a) Mamdani-type and

b) Sugeno-type.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology and it expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant. This fuzzy inference system was introduced in 1985 and also is called Takagi-Sugeno-Kang.Sugeno output membership functions (z, in the following equation) are either linear or constant. A typical rule in a Sugeno fuzzy model has the following form: *If Input 1* = x *and Input 2* = y, *then Output is* z = ax + by + c model, the output level *z* is a constant *(a=b =0).*

5.3.4 Membership function

Membership function is the mathematical function which defines the degree of an element's membership in a fuzzy set.
The Fuzzy Logic Toolbox includes 11 built-in membership function types. These functions are built from several basic functions:
a) piecewise linear functions,
b) the Gaussian distribution function,
c) the sigmoid curve and
d) quadratic and cubic polynomial curve.

5.3.5 Fuzzy logic operators

The most important thing to realize about fuzzy logical reasoning is the fact that it is a superset of standard Boolean logic. In other words, if the fuzzy values are kept at their extremes of 1 (completely true) and 0 (completely false), standard logical operations will hold. That is, A AND M operator is replaced with minimum - *min* (A,M) operator, A OR M with maximum - *max* (A,M) and NOT M with 1-M. In this research work, the rules are set using AND operators

5.3.6 If-Then rules

Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. Usually the knowledge involved in fuzzy reasoning is expressed as rules in the orm: ***If RT is low and S/N is high is then Speech intelligibility is Medium*** **where RT and S/N** are fuzzy variables and low and high are fuzzy values. The if-part of the rule "RT is low and S/N is high" is called the *antecedent* or premise, while the then-part of the rule "*Speech intelligibility is medium*" is called the *consequent* or conclusion. Statements in the antecedent (or consequent) parts of the rules may well involve fuzzy logical connectives such as 'AND' and 'OR'. In the if-then rule, the word "is" gets used in two entirely different ways depending on whether it appears in the antecedent or the consequent part. In this research works, 18 rules have been formed and shown below.

1. IF (RT is Low) and (Volume is Small) then (SI is Medium) (1)
2. IF (RT is Optimum) and (Volume is Small) then (SI is High) (1)
3. IF (RT is High) and (Volume is Small) then (SI is Low) (1)
4. IF (RT is Low) and (Volume is Medium) then (SI is Low) (1)
5. IF (RT is Optimum) and (Volume is Medium) then (SI is High) (1)
6. IF (RT is High) and (Volume is Medium) then (SI is medium) (1)
7. IF (RT is Low) and (Volume is High) then (SI is High) (1)
8. IF (RT is Optimum) and (Volume is High) then (SI is High) (1)
9. IF (RT is High) and (Volume is High) then (SI is Low) (1)

10. IF (S/N is Low) and (Word is Low) then (SI is High) (1)
11. IF (S/N is Low) and (Word is Medium) then (SI is Medium) (1)
12. IF (S/N is Low) and (Word is High then (SI is High) (1)
13. IF (S/N is Medium) and (Word is Low then (SI is Low) (1)
14. IF (S/N is Medium) and (Word is Medium then (SI is Medium) (1)
15. IF (S/N is Medium) and (Word is High then (SI is High) (1)
16. IF (S/N is High) and (Word is Low then (SI is Low) (1)
17. IF (S/N is High) and (Word is Medium then (SI is High) (1)
18. IF (S/N is High) and (Word is High then (SI is High) (1)

5.3.7 Surface mapping

Based on the input, output, membership function and the derived rules, a fuzzy system is formulated. Using the fuzzy system, the variation of speech intelligibility with respect to volume and distance (keeping word dB, RT and S/N constant) is obtained and shown in Figure 16. In Figure 17, the variation of speech intelligibility is shown using RT and S/N (keeping word dB, volume and distance constant)

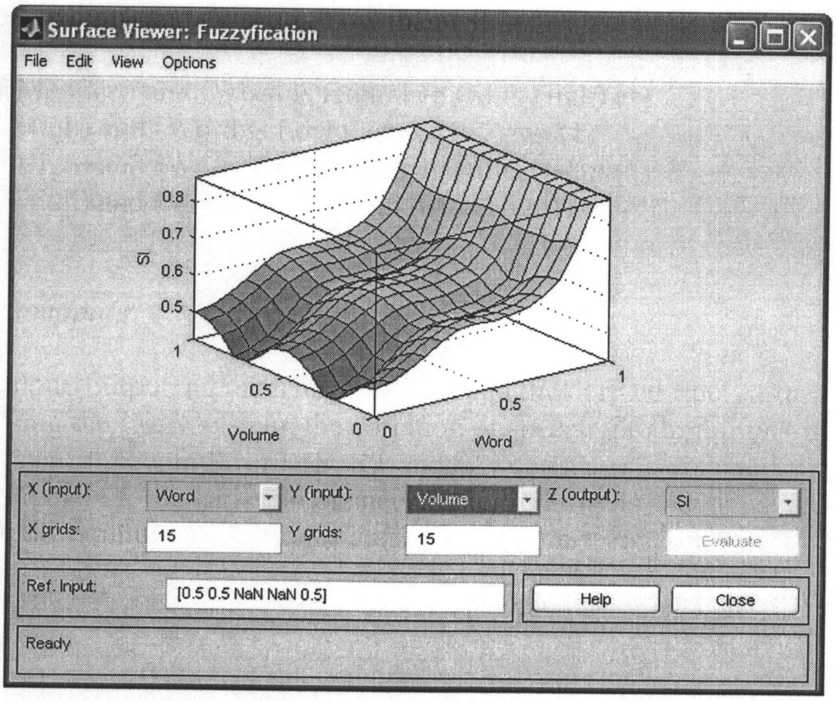


Fig16 – The variation of Speech Intelligibility using Volume and Word.

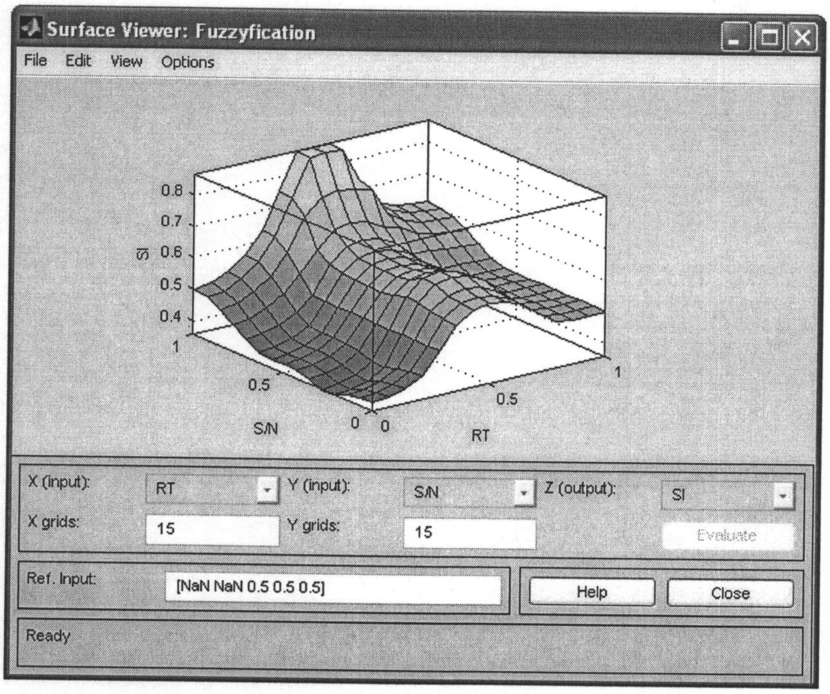


Fig 17 – The variation of Speech Intelligibility using S/N and RT

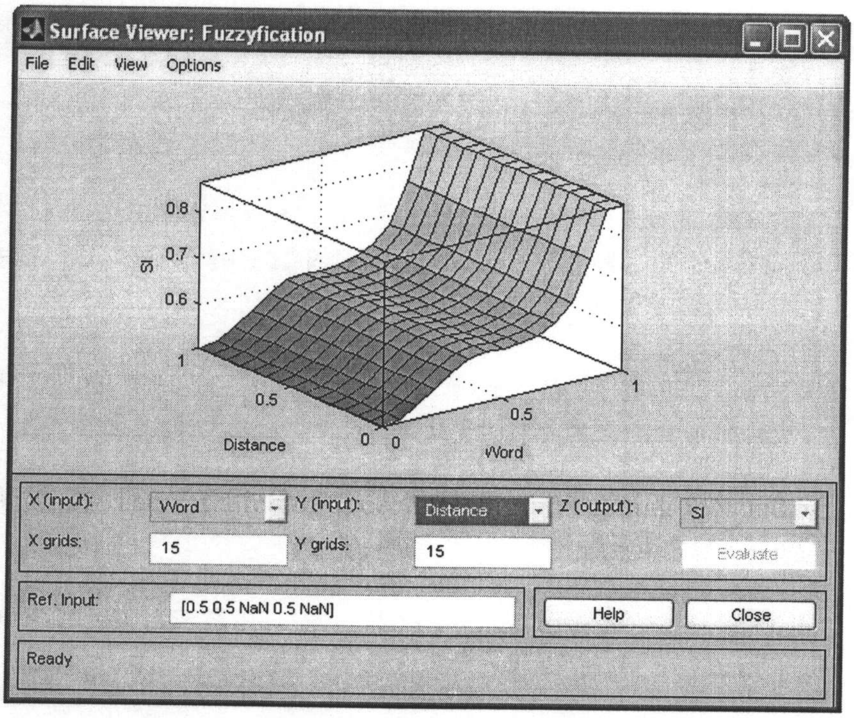


Fig 18 – The variation of Speech Intelligibility using Distance and Word

Further, in Figure 18, the speech intelligibility variation is observed by using Distance and Word as input and (keeping ***RT, Volume, and S/N as constant)***

5.4 Graphical User Interface

A graphical user interface (GUI) model has been developed for predicting the speech intelligibility and psychoacoustic parameters (loudness, sharpness and roughness) in any classroom.The system will record the background noise level and speech level in dB in a classroom. On receiving the classroom dimension information from the user, the system predicts and provides the speech intelligibility mapping of the classroom.

This system is user friendly and requires no expertise and useful to architect and classroom design engineers as a speech intelligibility measurement device to test and improve the speech intelligibility of the existing classroom with adjusting the classrooms parameters to obtain optimum speech intelligibility at all listeners seating position. This system is also useful for the lecturers to measure their sound pressure level in dB. Figure 19, 20 and 21 represent the interface of GUI model.

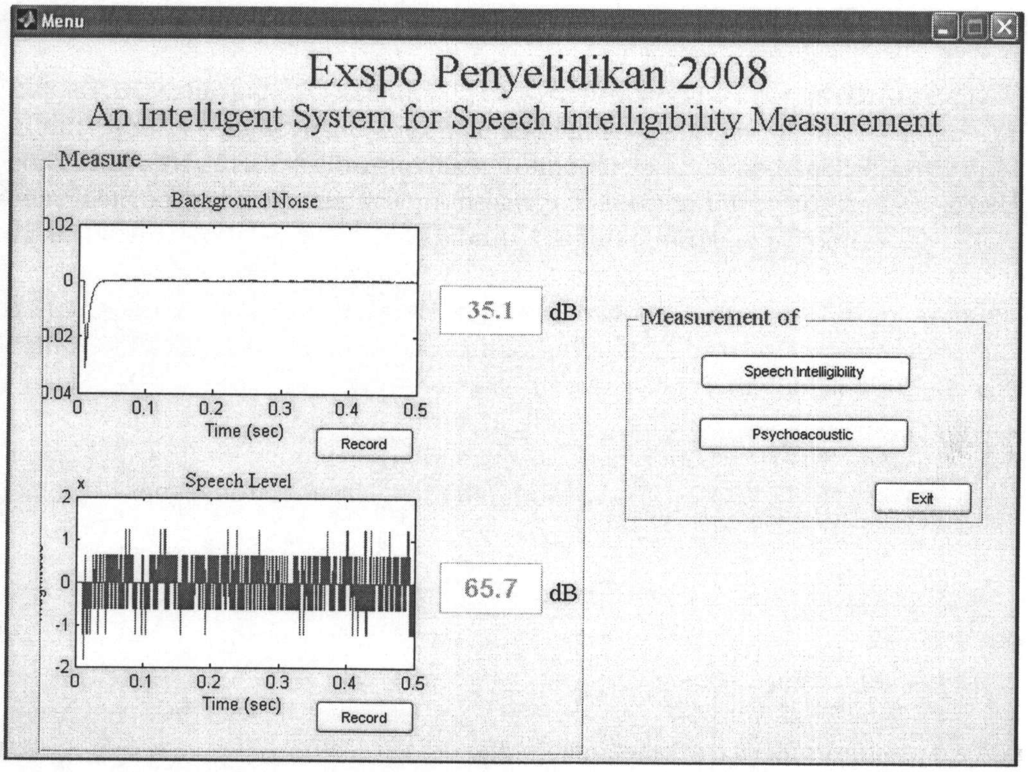


Fig 19 – First page (Menu) of the GUI Model

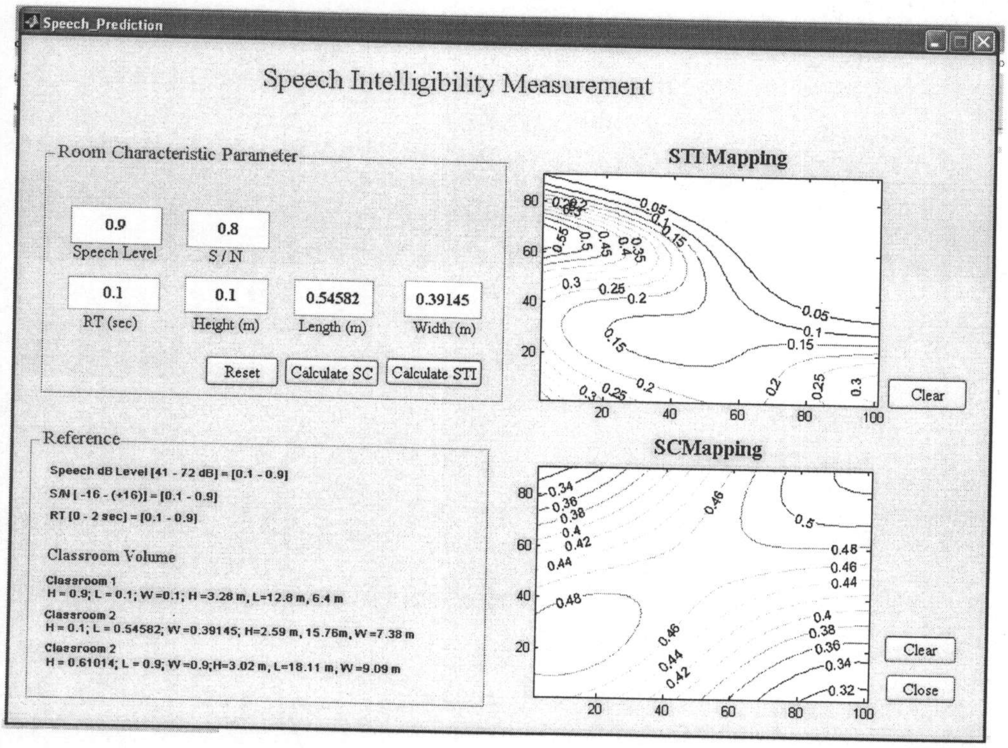


Fig 20 – Speech Intelligibility Measurement Model

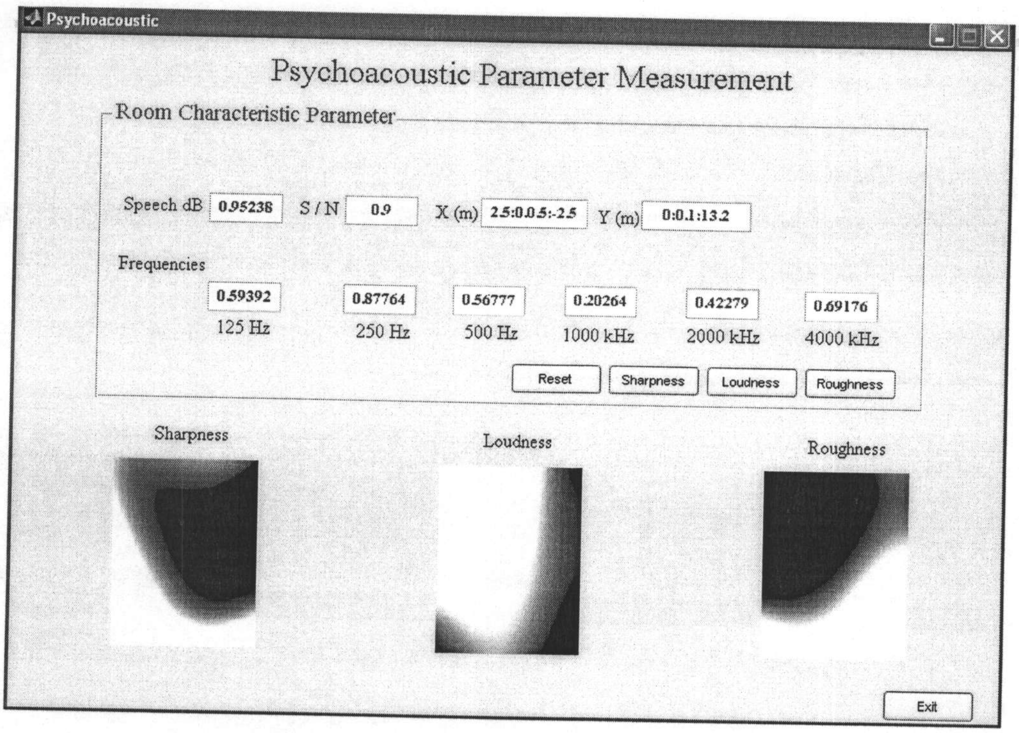


Fig 21 – Psychoacoustic Parameters Measurement Model

CONCLUSION

The classroom acoustic parameter measurements in eight classrooms are made. The time taken for the impulse signal to reduce by 60 dB for various frequency bands are measured and recorded. The above signals are analyzed and the reverberation times for the eight classrooms are calculated using dBBati software.

The measurements of speech intelligibility parameters in four different classrooms are made. From the observed measurements, simple neural network models and fuzzy models to predict STI and SC and RASTI are developed. Simulation is carried out and the effect of background noise and the speech signal levels on RASTI in the classrooms are observed. Based on the obtained result, a simple Graphical user Interface Model to predict SC, RASTI and Psychoacoustic parameters in the classrooms are developed

Publication

1.Paulraj M P, Sazali Yaacob,Ahmad Nazri, M. Thagirarani, **"Classroom Speech Intelligibility Prediction using Backpropagation Neural Network"**, International Conference on Modelling and Simulation , CITICOMS 2007, 27 – 29 August,2007, p 519-525.

2.Paulraj M P, Sazali Yaacob,Ahmad Nazri, M. Thagirarani, **"Prediction of Speech Clarity using Backpropagation Neural Network"**, Regional Conference on Noise, Vibration and Comfort(NVC-2007), pp. 481-488.Universiti Kebangsaan Malaysia(UKM), Malaysia,November 27-28,2007.

3.Paulraj M P, Sazali Yaacob, S N Sivanandam,Ahmad Nazri, M. Thagirarani, **"Neural Network Model for Speech Intelligibility Assessment in University Classrooms"**, Proceedings of International Conference on Resource Utilisation and Intelligent System, Kongu Engineering College,Erode, TamilNadu, India,January 1-2, 2008, pp 518-523

4.Paulraj M P, Sazali Yaacob, S N Sivanandam,Ahmad Nazri, M. Thagirarani, **"Prediction of Psychoacoustic Parameters using Radial Basis Functional Neural Network"**, International Conference on Intelligent System & Control, ISCO 2008, Karpagam College of Engineering, Coimbatoore, India. February 1-2,2008 (Published).

5.Paulraj M P, Sazali Yaacob,Ahmad Nazri, M. Thagirarani, **"Classroom Speech Intelligibility Prediction using Backpropagation Neural Network"**, 4th International Colloquium on Signal Processing and its Application (CSPA 08), 07 -09 March 2008. (Accepted for Publication)