Sound Can Go Faster than Light using S-Transform and Fuzzy Expert System

Prasannajit Dash
NM Institute of Techlogy
Sijua, Patrapada, Bhubaneswar, Odisha, India

ABSTRACT

This paper presents new approach for time series data classification using Fuzzy Expert System (FES). In the proposed study, the power disturbance signals are considered as time series data for testing the designed FES. Initially the time series data are pre-processed through the advanced signal processing tool such as S-transform and various statistical features are extracted, which are used as inputs to the FES. The FES output is optimized i1sing Particle Swann Optimization (PSO) to bring the output to distinct classification level. Both Gaussian and trapezoidal membership functions are selected for designing the proposed FES arid the performance measure is derived by comparing the classification rates for the time series data without noise and with noise up to SNR 20 db. The proposed algorithm provides accurate classification rates even under noisy conditions compared to the existing techniques, which shows the efficacy and robustness of the proposed algorithm fortime series data classification

Keywords

Time-series data, Fuzzy Expert System, S-transform, Particle Swarm Optimization

1. INTRODUCTION

The question of wave velocity has been studied since theadvent of Einstein's special theory of relativity.[1][2] A central issue is whether the speed of light in vacuum *c* constituted anupper limit to the group velocity—the velocity of the peak ofa wave packet. The consensus of much theoretical work[3][5] is that the group velocity is not limited and, in the past few years, a number of experiments [6][9] have confirmed that it is possible for optical or electrical wave pulses to travel through absorbing, attenuating, or gain materials with group velocities greater than *c*. Furthermore, under appropriate conditions, the group velocity can even become negative,[10][11] a circumstance in which the peak of the tunneled pulse emerges from the output of the medium before the peak of the incident pulse has reached the input. Al- though most wave propagation phenomena have been explored for electromagnetic waves, there is a history of theoryand experiment using ultrasonic acoustic waves.[3][14][15] Recently, it was predicted through numerical modeling[16] that faster-than-light phenomena should be observable for ultra- sound pulses. In this letter we demonstrate experimentally the transmission of audio-frequency acoustic pulses through an asymmetric loop filter with group velocities that exceed the speed of light. This work is significant for two reasons. First, we confirm the theoretical prediction that, under the appropriate conditions, sound pulses can exhibit group velocities that surpass the speed of light in vacuum. Second, we demonstrate a simple passive acoustic filter system that exhibits a negative group velocity.

The mechanism by which superluminal propagation arises involves rephrasing of the spectral components of a pulse by a medium that exhibits anomalous dispersion. Anomalous dispersion occurs over frequency intervals in which materials exhibit strong absorption, attenuation, orgain. The spectral components of a pulse traveling throughan anomalously dispersive medium recombine in a manner such that they replicate the shape of the original pulse but are moved forward closer to the leading edge of that pulse. Be- cause the tunneling pulse is fashioned from the leading edge of the incident pulse, it exits the sample earlier in time. The group velocity is defined by the length of the sample dividedby the time taken for the peak of a pulse to traverse the sample. If anomalous dispersion is sufficiently strong the group velocity can exceed the speed of light. If the transit time is zero, the peak of the transmitted pulse exits at the same time as the peak of the incident pulse reaches the input,and the group velocity is infinite. Finally, in the case of very strong dispersion, the peak of the transmitted pulse exits before the peak of the incident pulse reaches the input, and the group velocity is negative. It is now generally agreed that all of these superluminal phenomena do not violate special relativity or causality and, in particular, it has been shown that the speed of information transmission is subluminal[17][18] In all previous optical, microwave, or electrical demonstrations the individual spectral components of the pulse have velocities close to the speed of light and thus realizing sufficient rephrasing to achieve superluminal propagation is less surprising. In the experiments described here, however, the individual spectral components travel at the speed of sound, almost six orders of magnitude slower than the speed of light and yet still experience sufficient rephrasing to achieve super- luminal velocities.

Experiments were conducted in a one-dimensional acoustic waveguide system constructed from 1.9 cm diameter polyvinyl chloride (PVC) pipe. The filter element being characterized was an asymmetric loop filter, a type of acoustic interference filter modeled on a similar device used in electrical measurements in coaxial cable waveguides[12]. The design and dimensions of the acoustic loop filter are shown in Figures below. The loop was created from the same type of 1.9 cm diameter PVC pipe used for the waveguide and it was connected together using commercially available right-angle and T junctions. The asymmetric loop splits the guided sound signal along two unequal length paths designated as dL and dS (long and short, respectively). By analogy with the electrical results reported in Ref. [12], there are two mecha- organisms by which the asymmetric loop filter results in dips in transmission. The first mechanism is due to destructive inteference that results when the path length $\Delta L = d_L - d_S$ betweenthe long and short arms differs by one-half wavelength. The second mechanism occurs due to standing wave resonances around the whole length of the loop $L = d_L + d_S$.

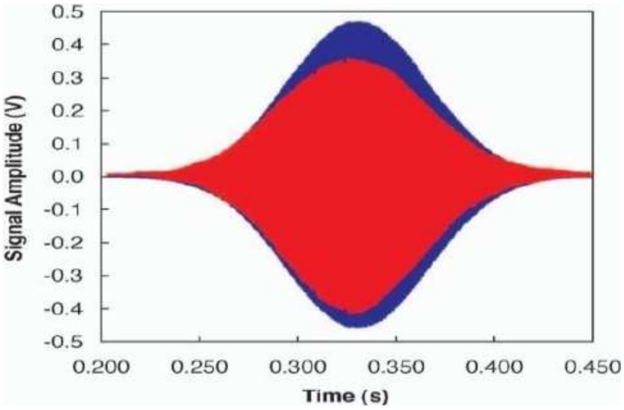


Figure 1 (Color) Plots of Gaussian wave packet centered at 2414 Hz after transmission through straight waveguide (blue) and through a single loop filter (red). The red trace has been scaled up by a factor of 10.

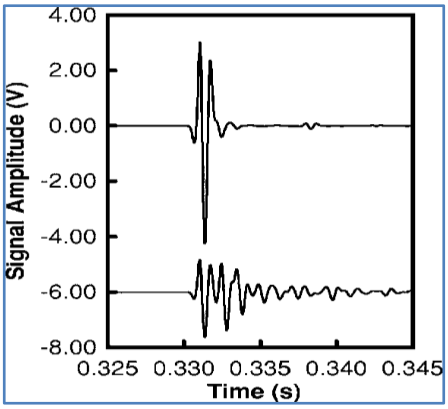


Figure2 Signal Amplitude Vs. Time(s)

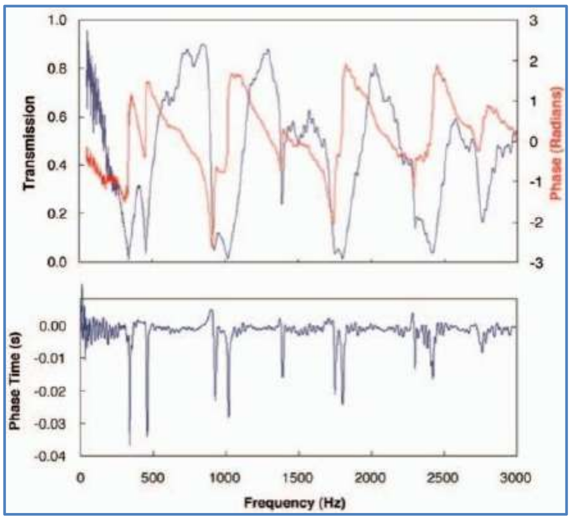


Figure 3 Phase Time and Transmission vs. Frequency

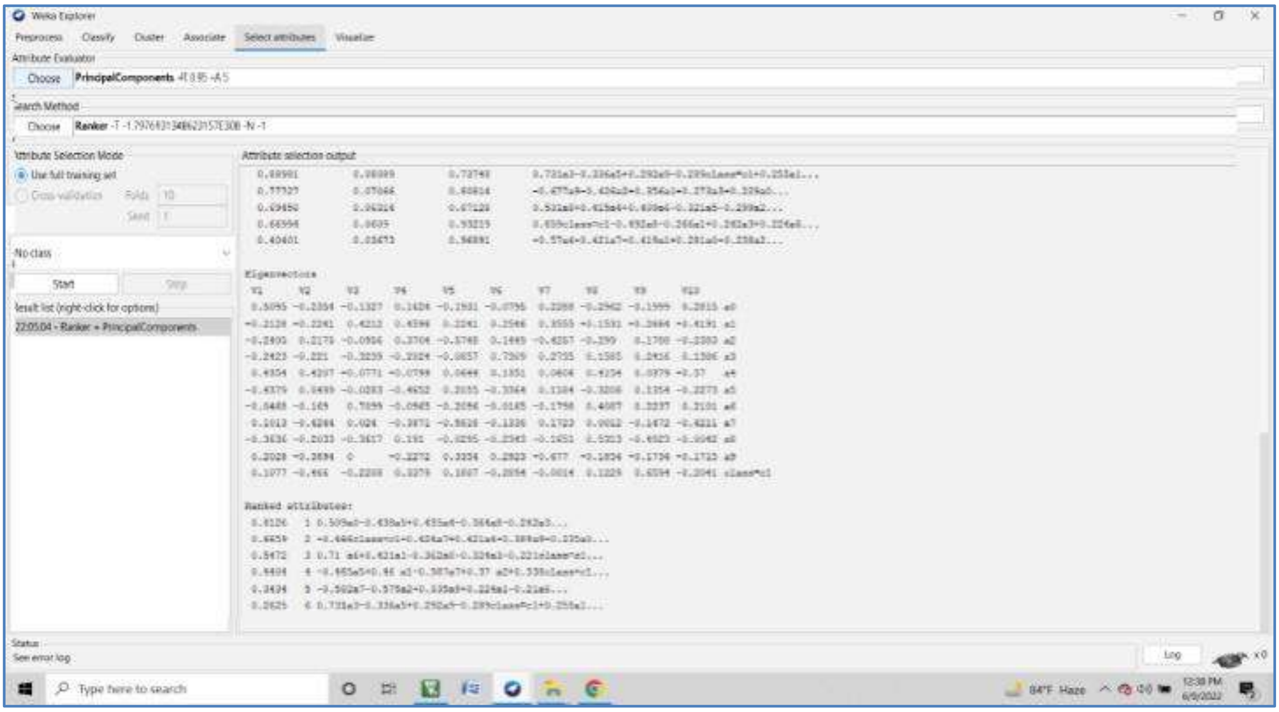


Figure 4 Principal Component Analysis(PCA) with Ranking

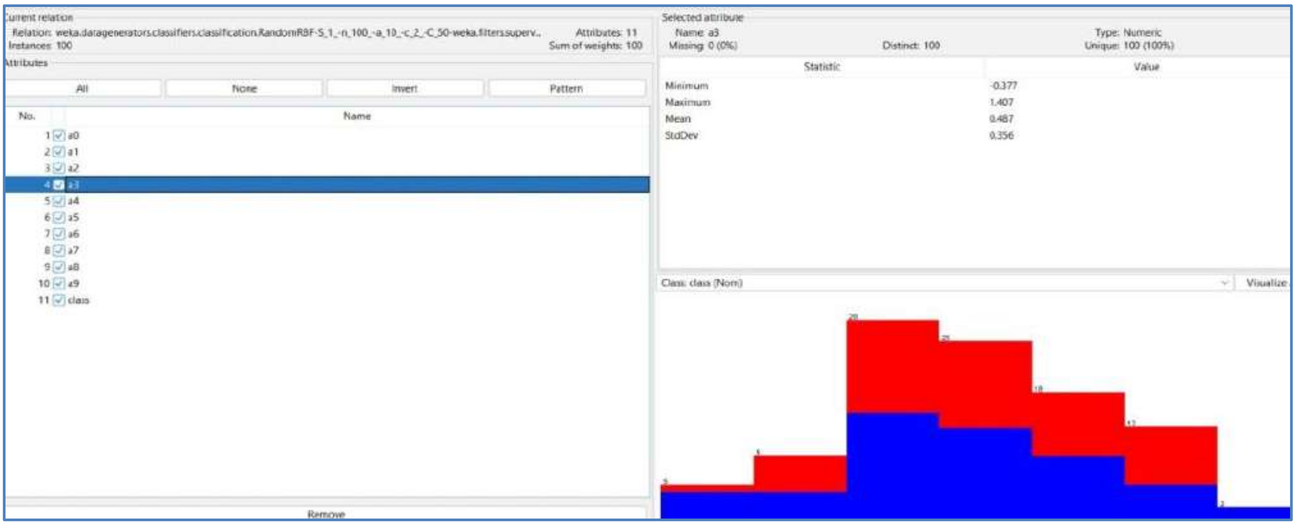


Figure 5 Principal Component Analysis with attributes

Figure 6 Windows 10 Speech Recognition

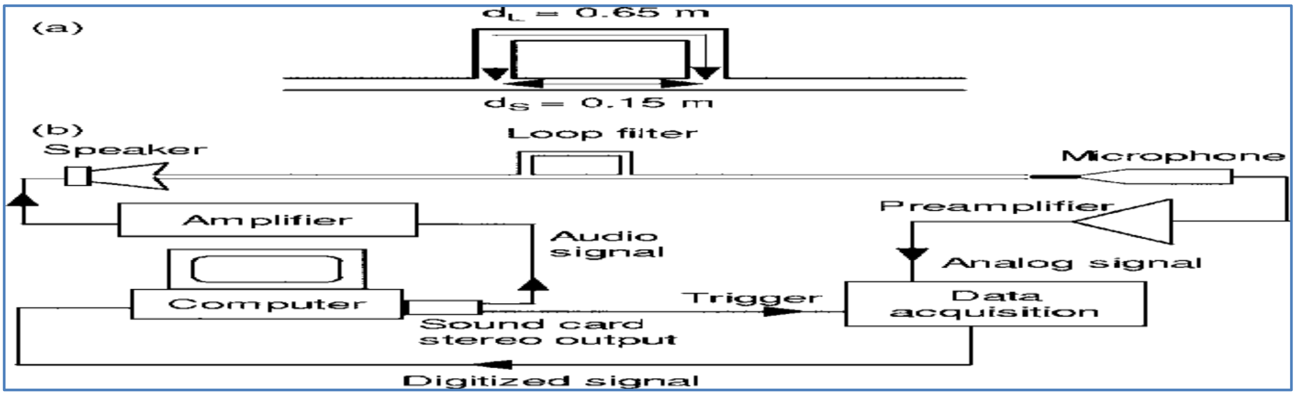


Figure 7 Data Acumination producing Digitized Signal

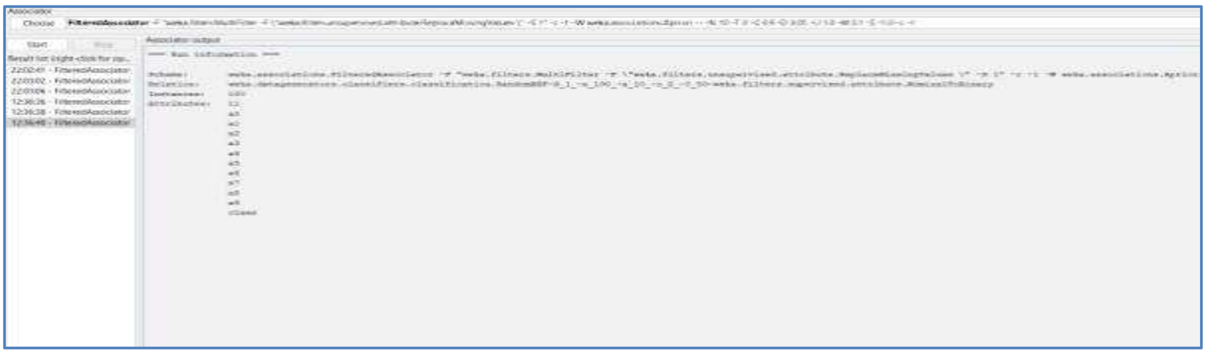


Figure 8 Decision Tree

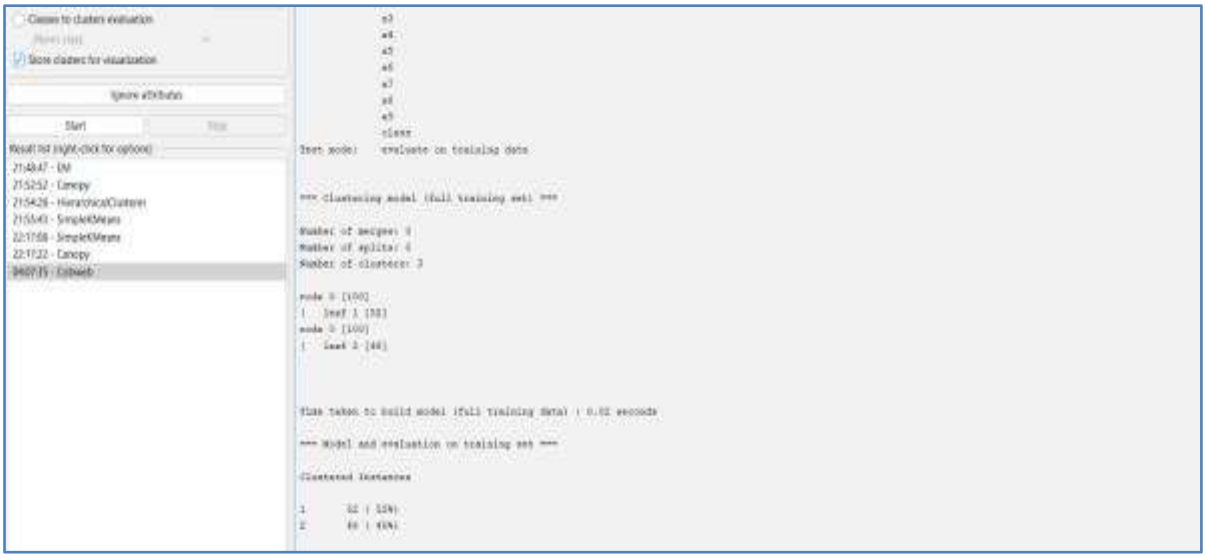


Figure 9 K-means Clustering

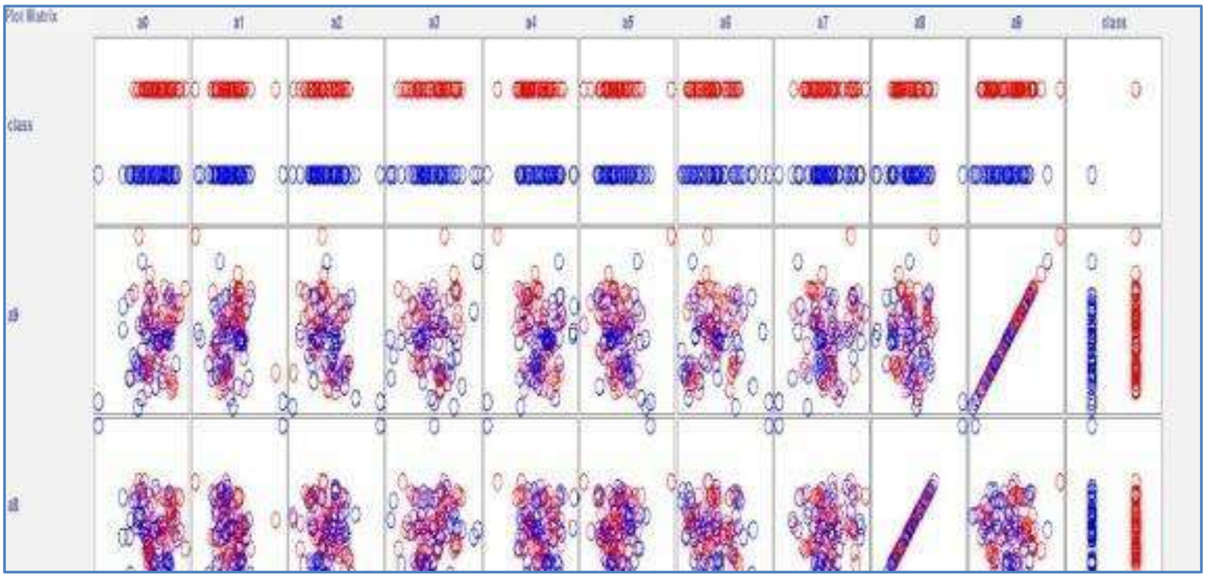


Figure 10 Pattern Recognition of Speech

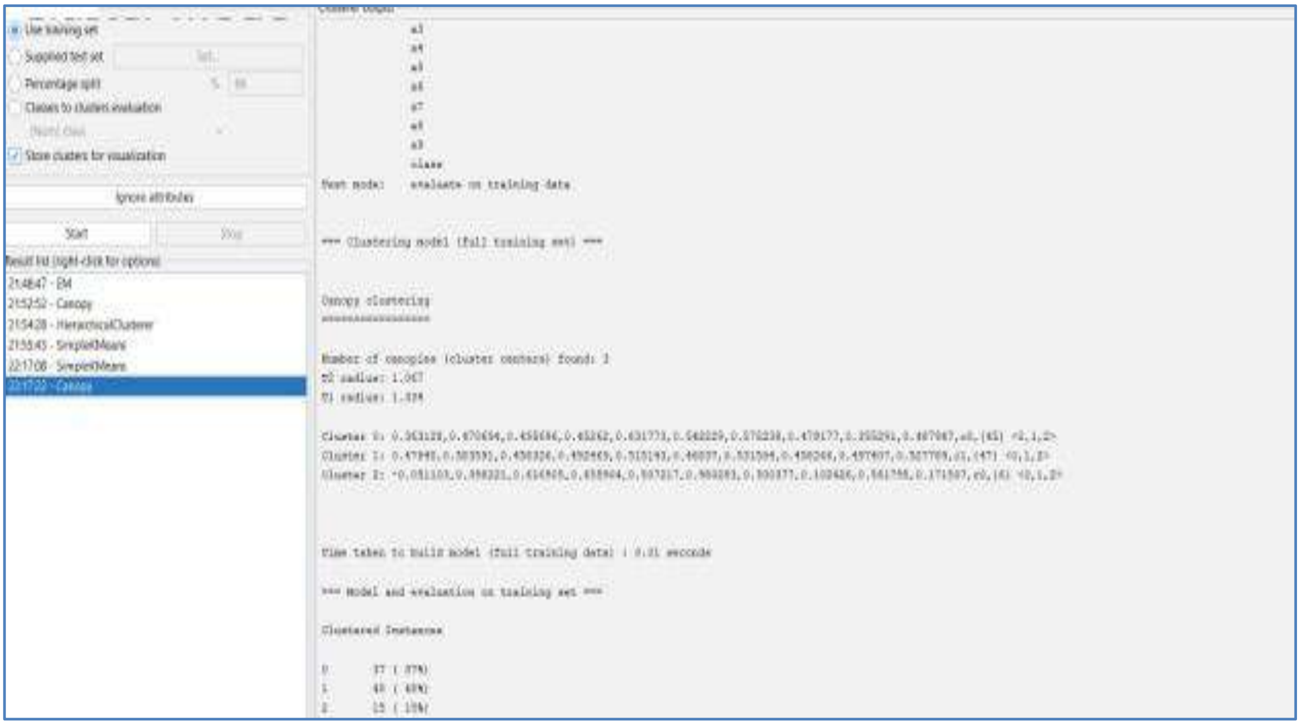


Figure 10 Pattern Recognition of Speech using Classifier

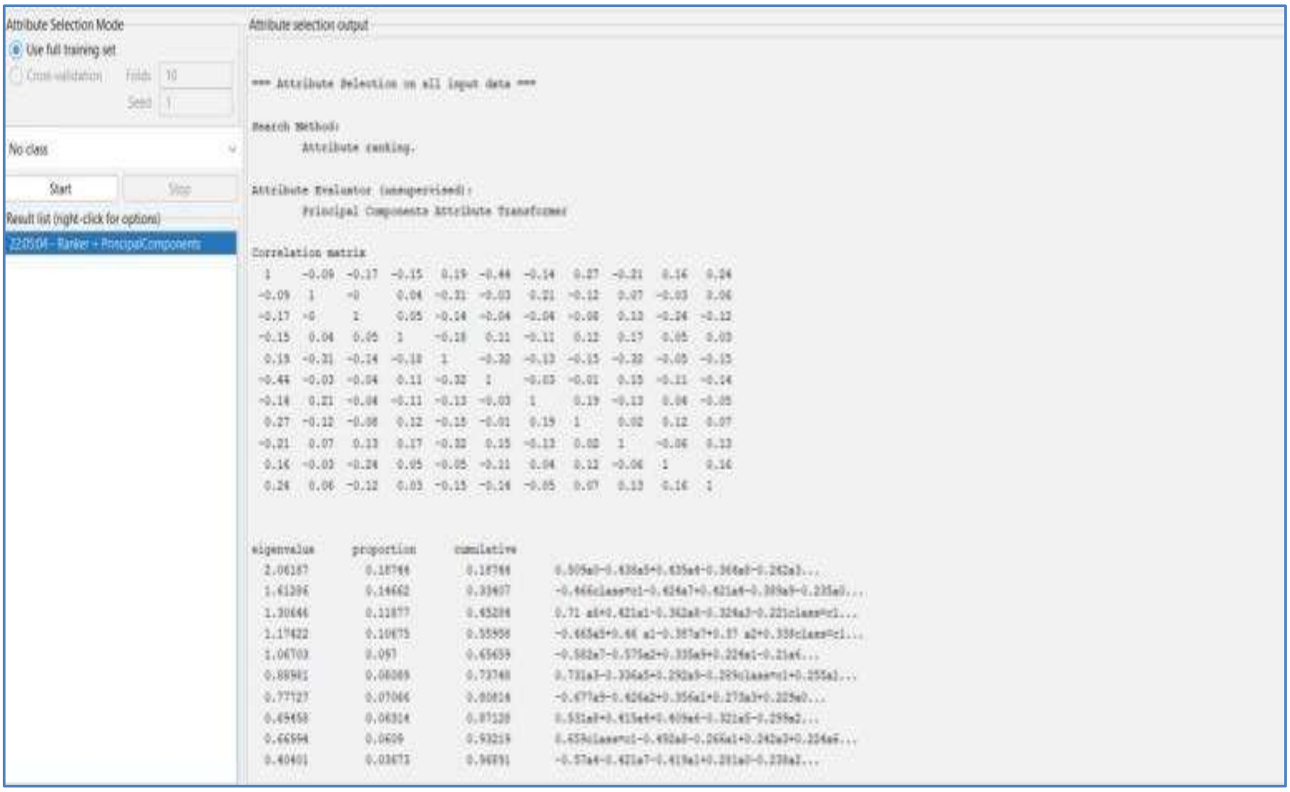


Figure 11 Decision Matrix

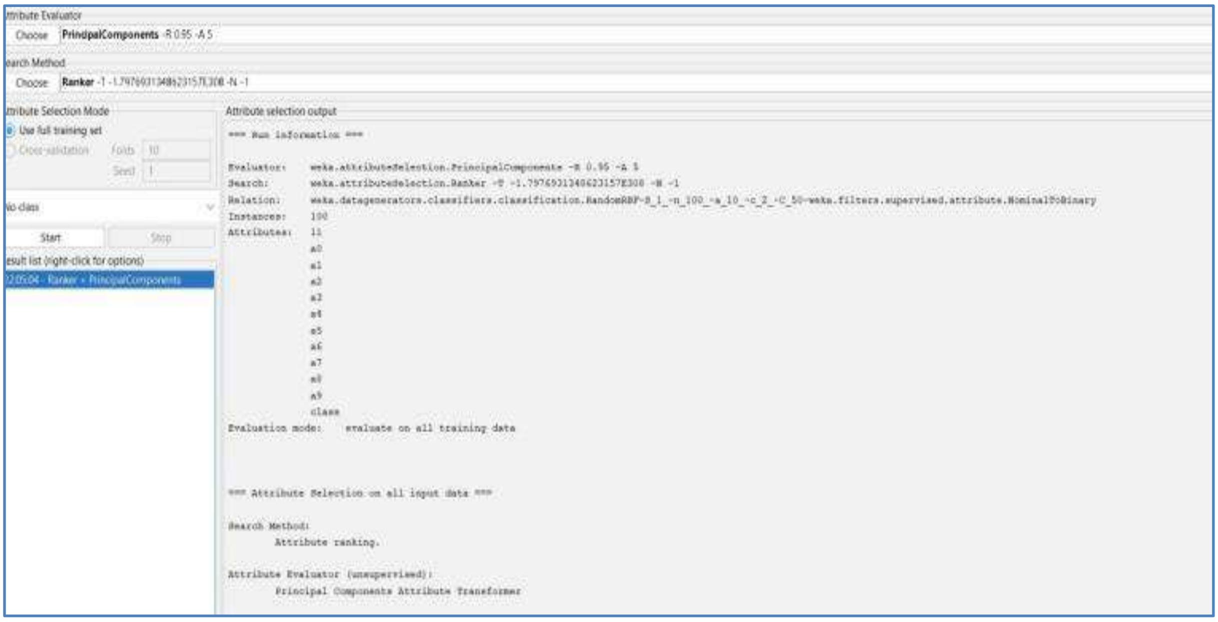


Figure 12 Principal Component Analysis

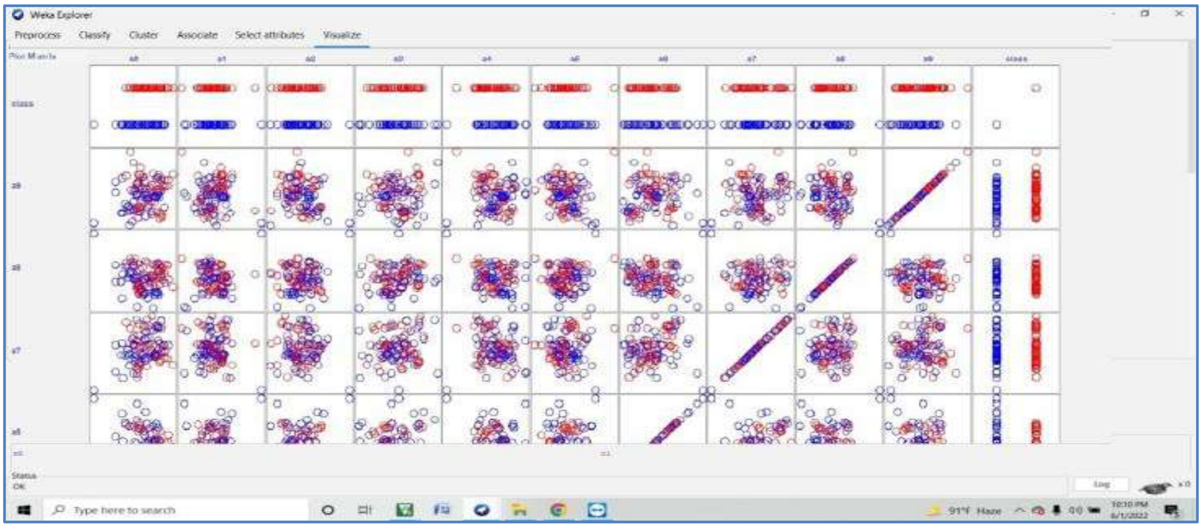


Figure 13 Pattern Recognition

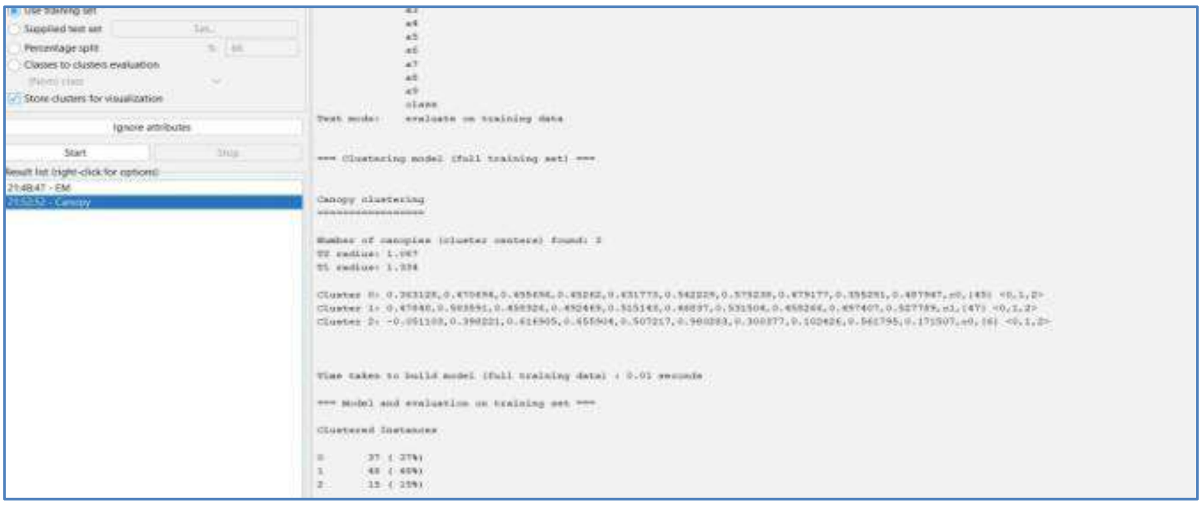


Figure 14 Hierical Clustering

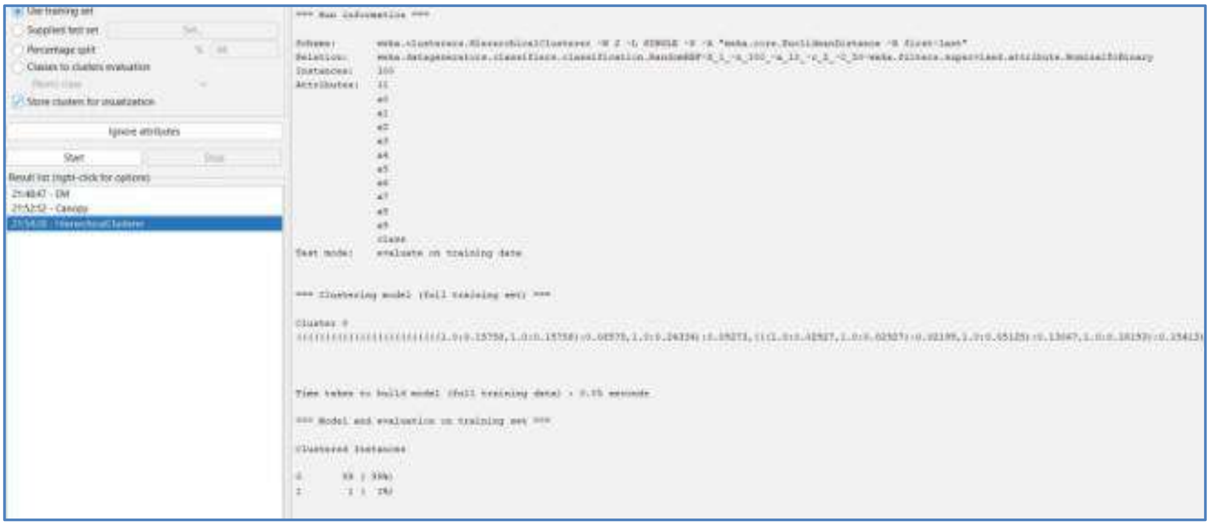


Figure 15 Support Vector Machine

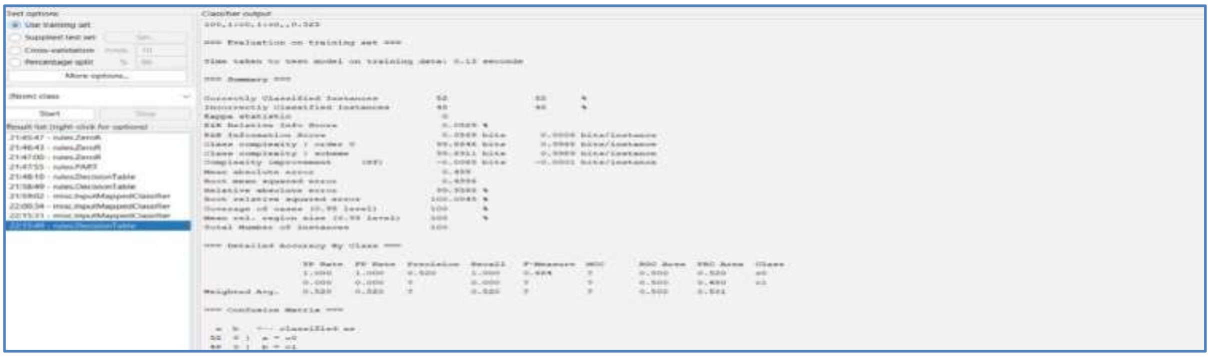


Figure 16 Partition based Clustering

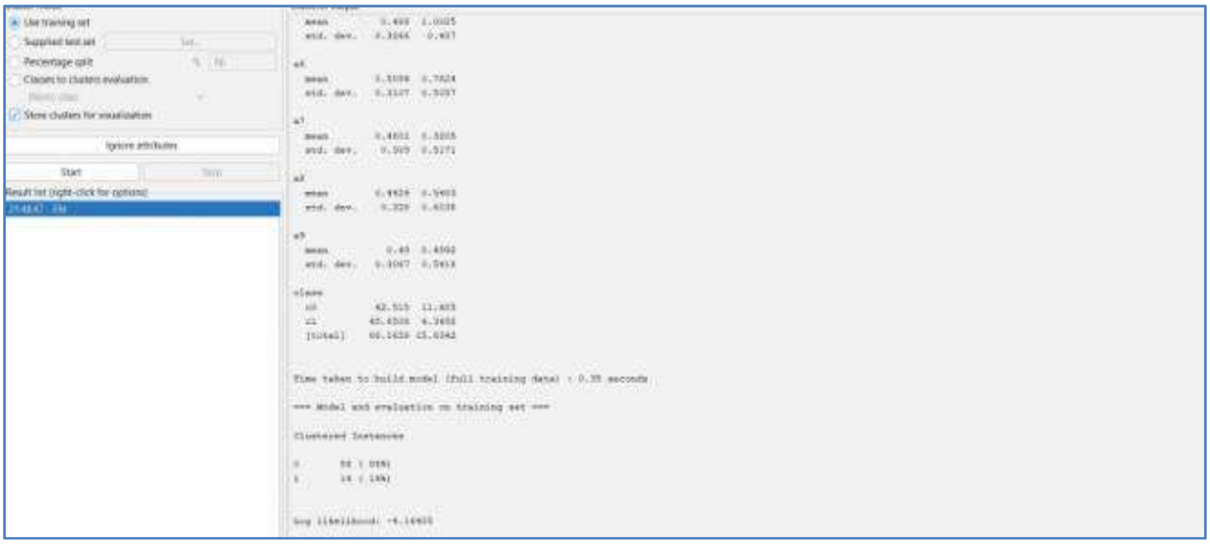


Figure 17 Particle Swam Optimization

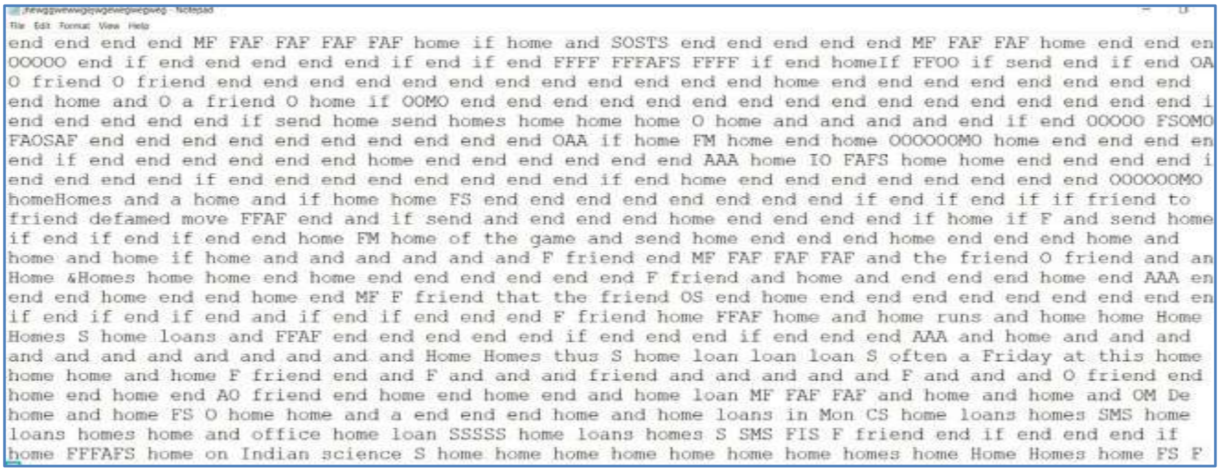

File Edit Format View Help
end end end end MF FAF FAF FAF FAF home if home and SOSTS end end end end end MF FAF FAF home end end en
OOOOO end if end end end end end if end if end FFFF FFFAFS FFFF if end homeIf FFOO if send end if end OA
O friend O friend end end end end end end end end end end end end home end end end end end end end
end home and O a friend O home if OOMO end end end end end end end end end end end end end end end i
end end end end end if send home send homes home home home O home and and and and end if end OOOOO FSOMO
FAOSAF end end end end end end end end end OAA if home FM home end home OOOOOOMO home end end end en
end if end end end end end end home end end end end end AAA home IO FAFS home home end end end i
end end end end if end end end end end end end end if end home end end end end end end end end OOOOOOMO
homeHomes and a home and if home home FS end end end end end end end end if end if end if if friend to
friend defamed move FFAF end and if send and end end end home end end end end if home if F and send home
if end if end if end end home FM home of the game and send home end end end home end end end home and
home and home if home and and and and and F friend end MF FAF FAF FAF and the friend O friend and an
Home &Homes home home end home end end end end end end F friend and home and end end end home end AAA en
end end home end end home end MF F friend that the friend OS end home end end end end end end end end en
if end if end if end and if end if end end end F friend home FFAF home and home runs and home home Home
Homes S home loans and FFAF end end end end if end end end AAA and home and and and
and and and and and and and and and Home Homes thus S home loan loan loan S often a Friday at this home
home home and home F friend end and F and and and friend and and and and and F and and and O friend end
home end home end AO friend end home end home end and home loan MF FAF FAF and home and home and OM De
home and home FS O home home and a end end end home and home loans in Mon CS home loans homes SMS home
loans homes home and office home loan SSSSS home loans homes S SMS FIS F friend end if end end end if
home FFFAFS home on Indian science S home home home home home home home homes home Home Homes home FS F

Figure 18 Speech Recognition Dataset

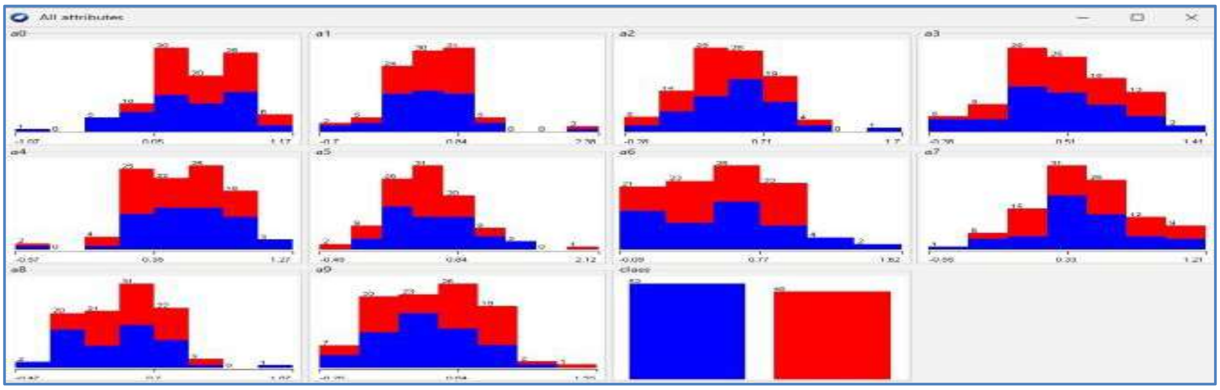
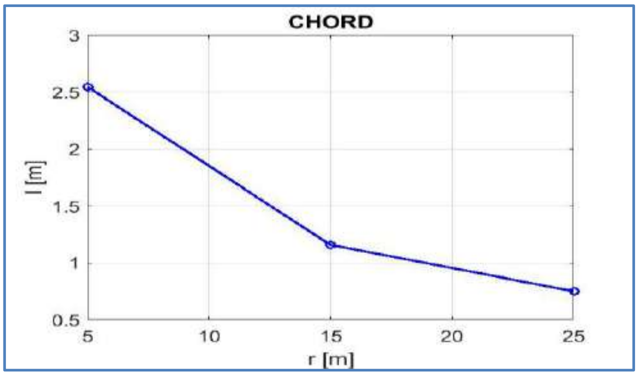


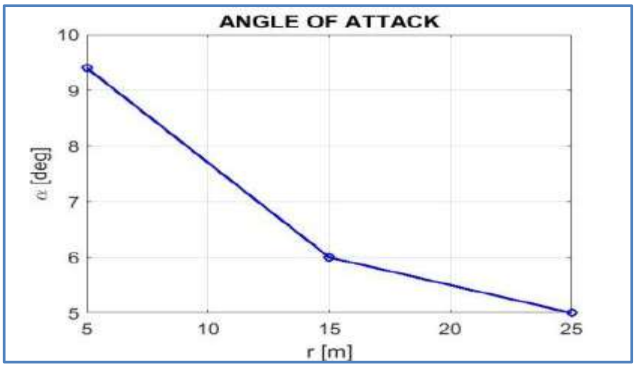
Figure 19 Speech Recognition Pattern

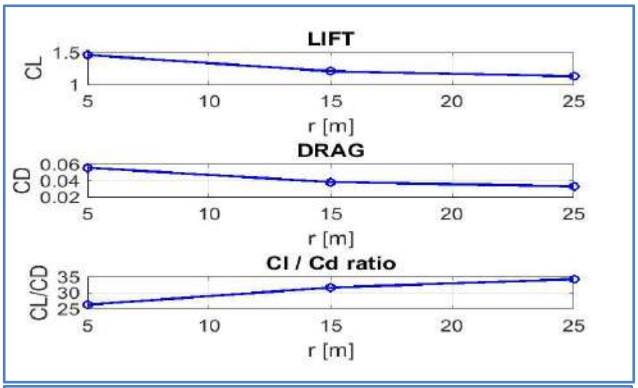
The experiments consisted of two measurement types. First, we used very short acoustic impulses that contained a broad frequency spectrum to determine the filtering proper- ties of our asymmetric loop structure. Fourier analysis of the impulse response led us to discover the frequency ranges in which we could expect to measure negative group delays and hence superluminal acoustic group velocities. The secondpart of the experiment used narrow bandwidth acoustic pulses with a Gaussian envelope to demonstrate explicitly the negative group delay. In both experiments we compared transmission through a loop filter to transmission through a straight waveguide. The straight waveguide segment that re- placed the filter in the reference measurements was equal in length to the short arm of the loop filter (d_S) such that the shortest physical h between the source and detector was identical in both measurements.

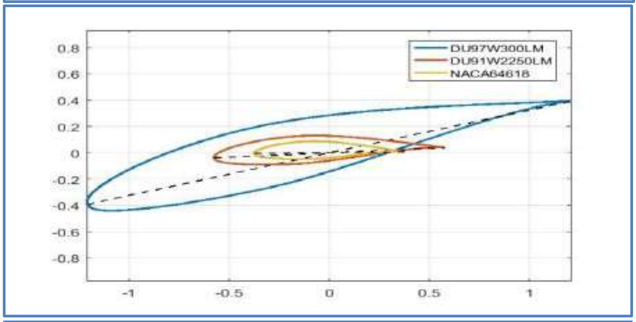
The experimental configuration is shown schematically in Figure. 1. The computer sound card was used to produce an audio and a trigger signal on the respective channels of the stereo output. The audio signal was amplified and sent to the speaker (Alesis Monitor One) which was coupled to the in- put end of the waveguide. The audio signal was either an impulse or a narrow-band Gaussian envelope depending on the type of experiment being performed. At the output end of the waveguide, the transmitted audio signal was detected bya condenser microphone (ACO 7013), amplified, and digitized by the analog-to-digital converter (IOtech 3000 USB). The trigger signal from the second stereo channel consisted of a narrow square pulse that was routed to the trigger input Figure 2.

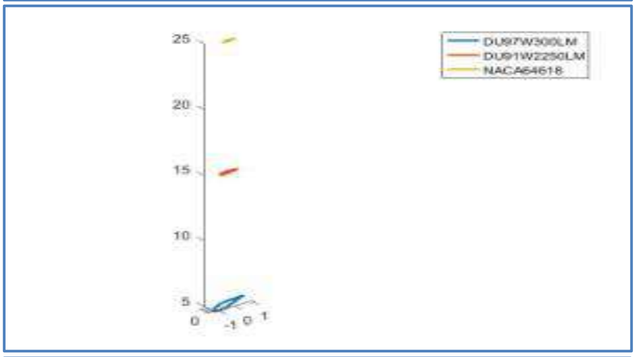
Plot of the impulse as a function of time through the straight wave- guide (upper plot) and through the loop filter (lower plot).in order to initiate data acquisition. To achieve high signal- to-noise ratio data we used an add-and-average technique described previously.[19] The loop filter was located in the cen-ter of a long (8 m) section of waveguide in order to provide a large time window free from multiple reflections from the discontinuities at the filter, speaker, and microphone.

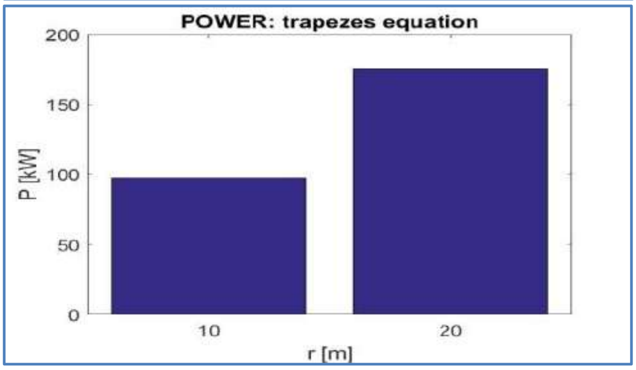


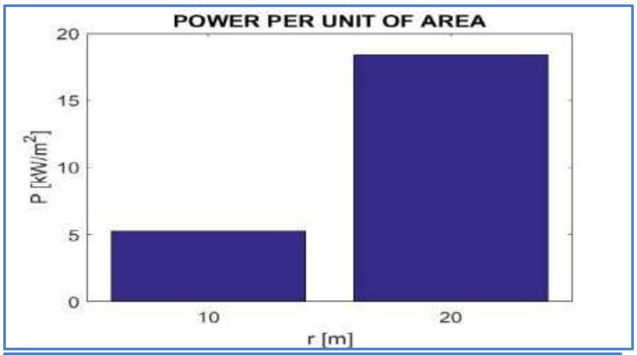

ANGLE OF ATTACK
α [deg]
r [m]

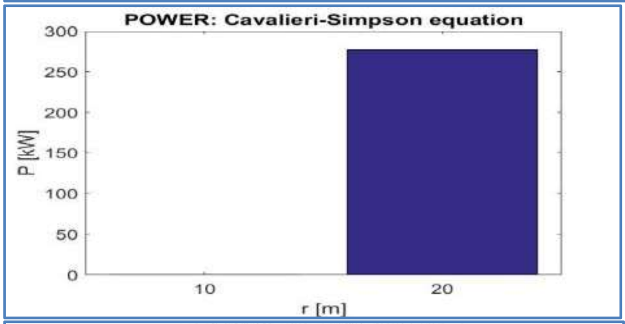

LIFT
CL
r [m]
DRAG
CD
r [m]
Cl / Cd ratio
CL/CD
r [m]

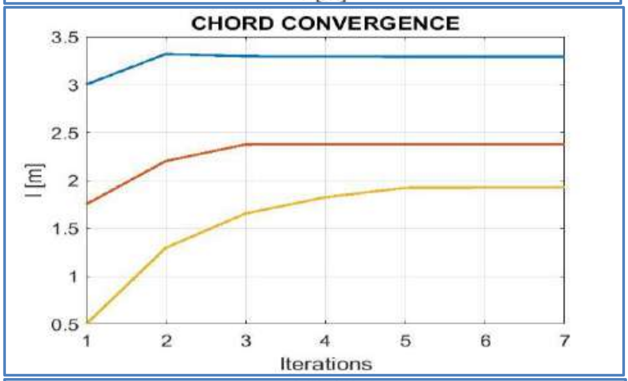

DU97W300LM
DU91W2250LM
NACA64618

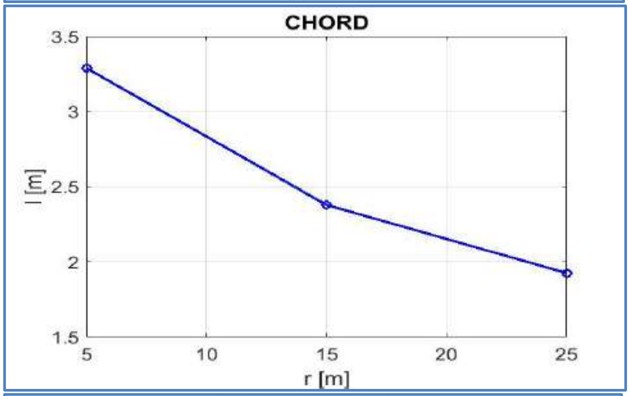

DU97W300LM
DU91W2250LM
NACA64618

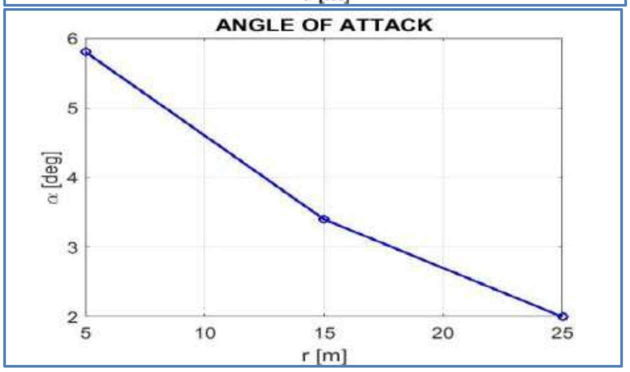

POWER: trapezes equation
P [kW]
r [m]

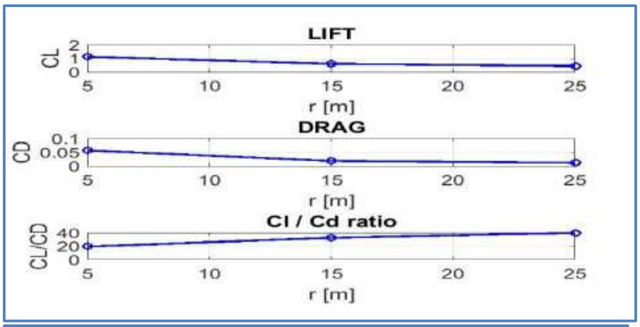

POWER PER UNIT OF AREA
P [kW/m^2]
r [m]

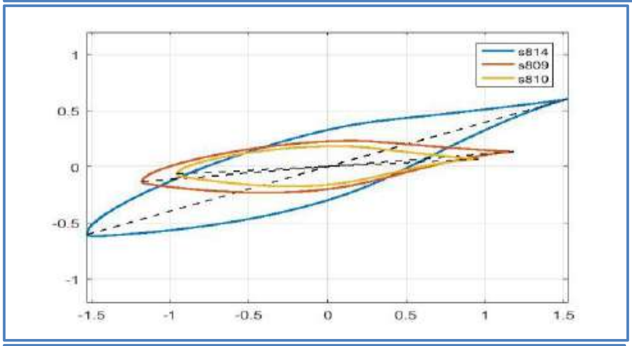

POWER: Cavalieri-Simpson equation
P [kW]
r [m]

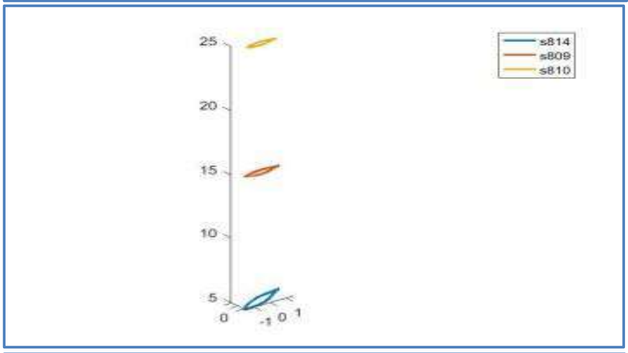

CHORD CONVERGENCE
l [m]
Iterations

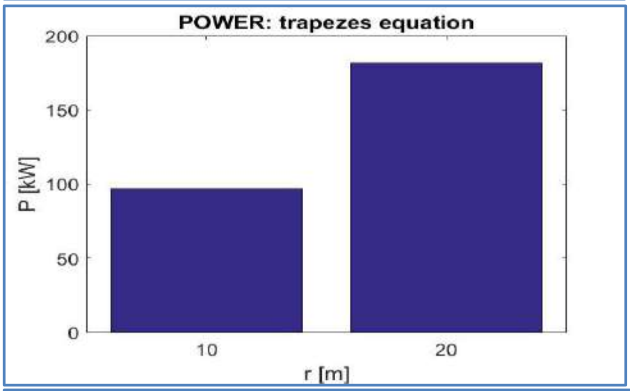

CHORD
l [m]
r [m]

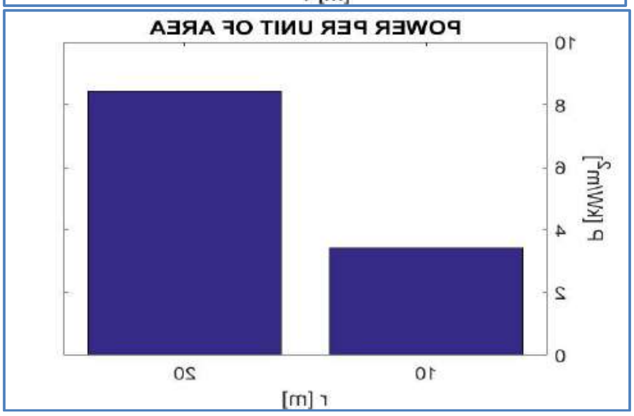

ANGLE OF ATTACK
α [deg]
r [m]

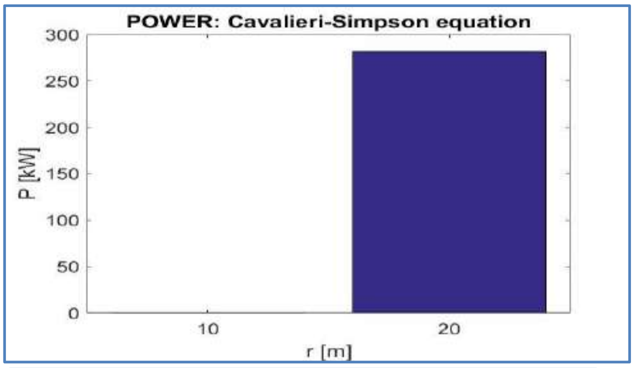

LIFT
CL
r [m]
DRAG
CD
r [m]
Cl / Cd ratio
CL/CD
r [m]

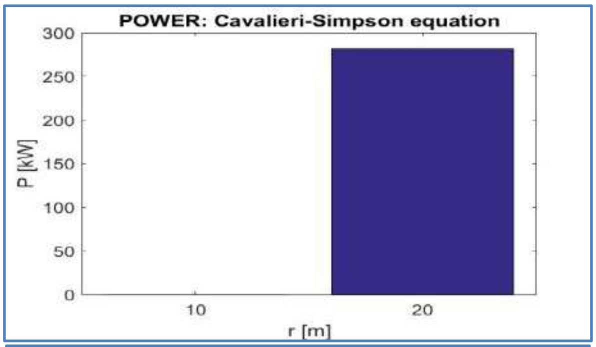

s814
s809
s810

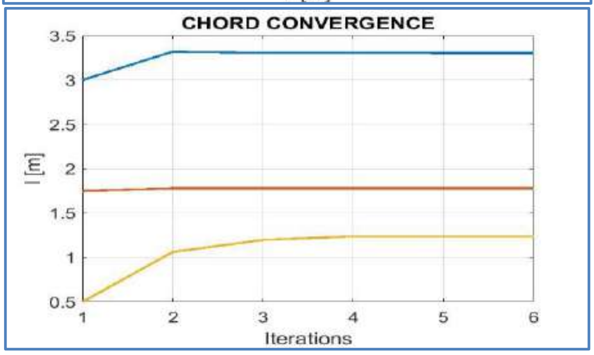

s814
s809
s810

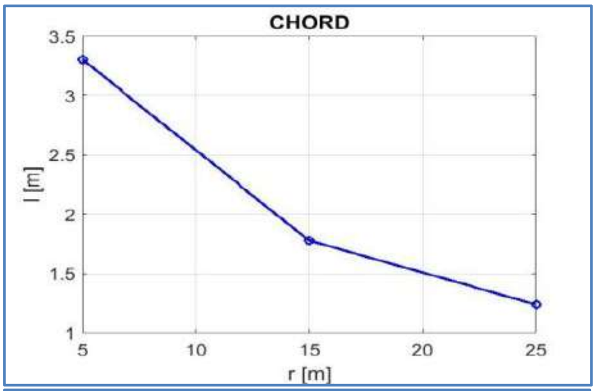

POWER: trapezes equation
P [kW]
r [m]

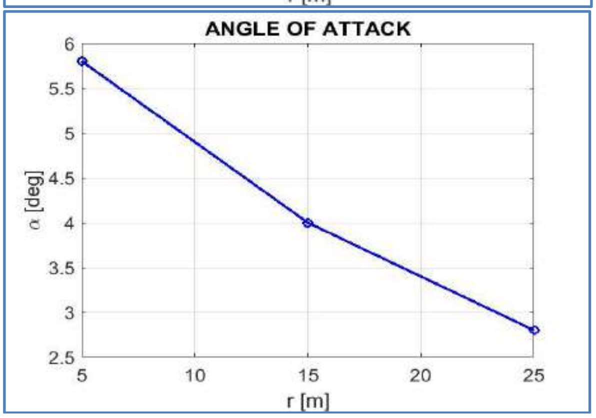

POWER PER UNIT OF AREA
P [kW/m2]
r [m]

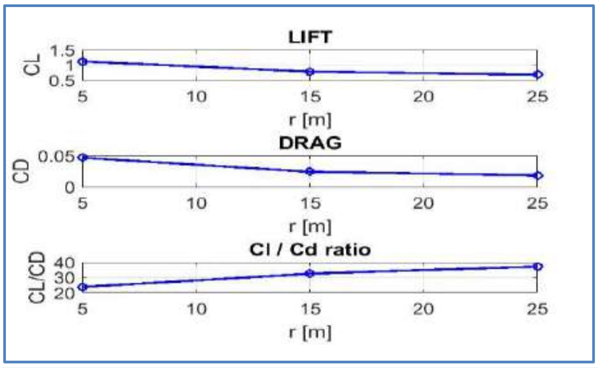

POWER: Cavalieri-Simpson equation
P [kW]
r [m]

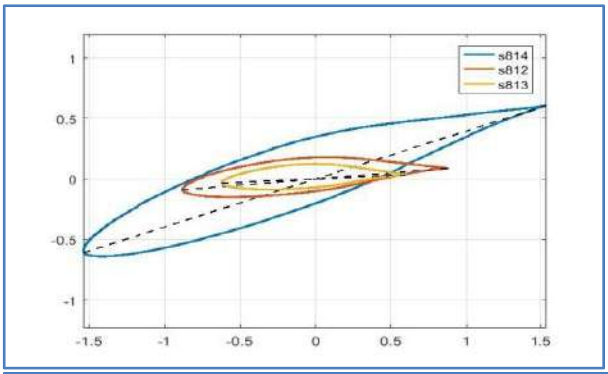

POWER: Cavalieri-Simpson equation
P [kW]
r [m]

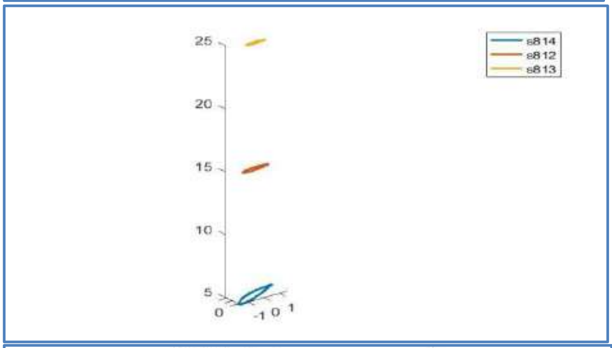

CHORD CONVERGENCE
l [m]
Iterations

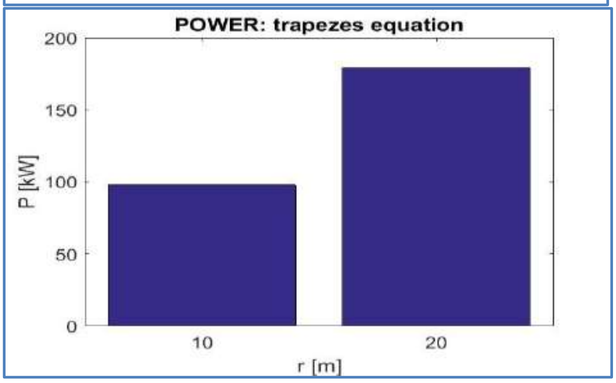

CHORD
l [m]
r [m]

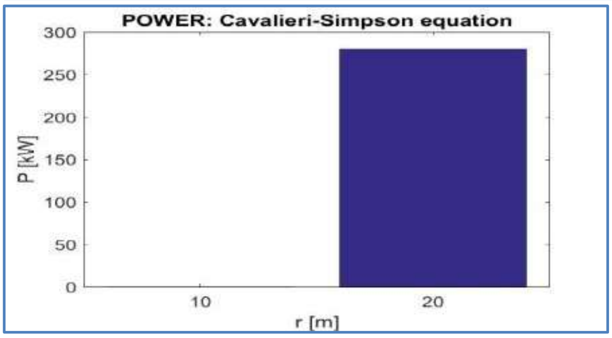

ANGLE OF ATTACK
α [deg]
r [m]

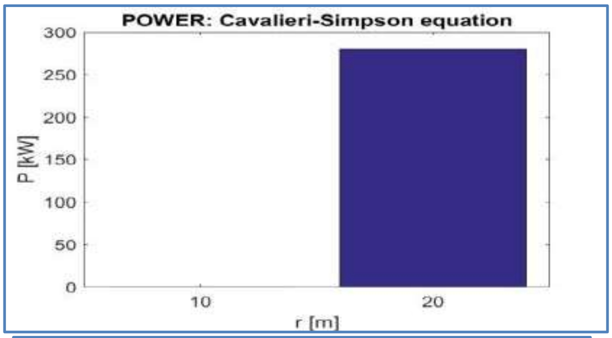

LIFT
CL
r [m]
DRAG
CD
r [m]
Cl / Cd ratio
CL/CD
r [m]

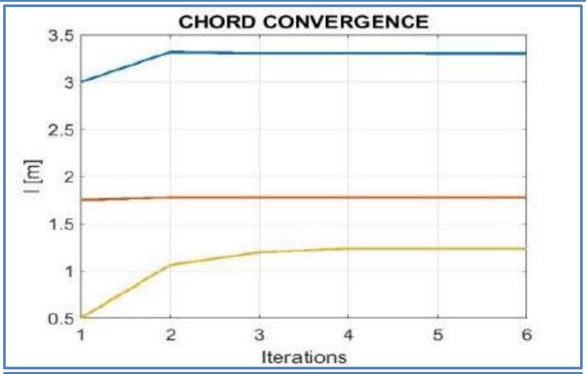

s814
s812
s813

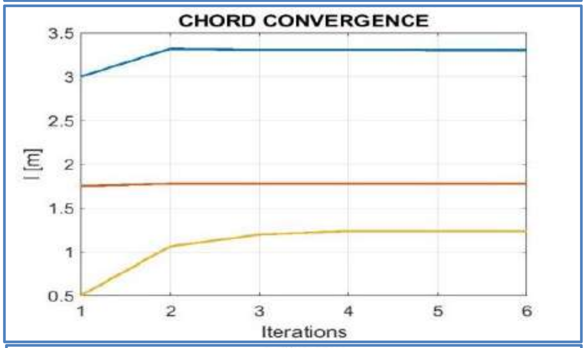

s814
s812
s813

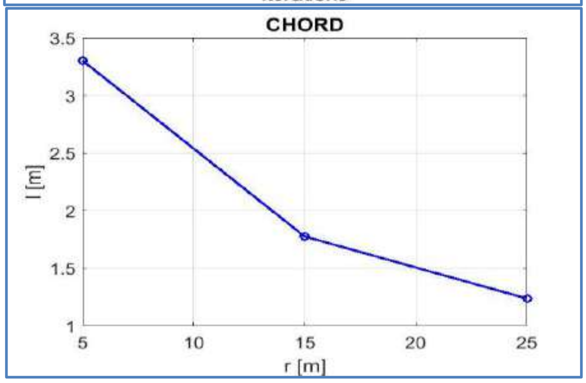

POWER: trapezes equation
P [kW]
r [m]

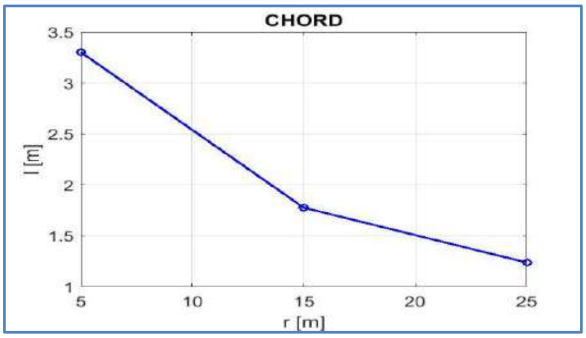

POWER: Cavalieri-Simpson equation
P [kW]
r [m]

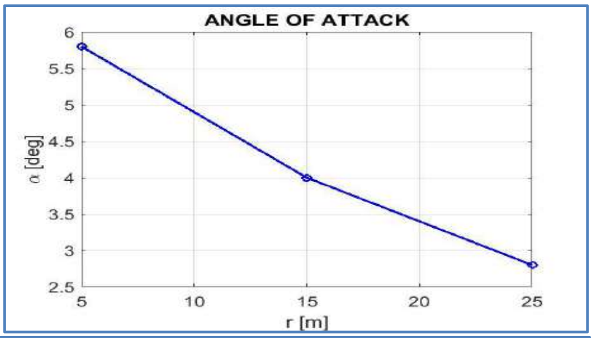

POWER: Cavalieri-Simpson equation
P [kW]
r [m]

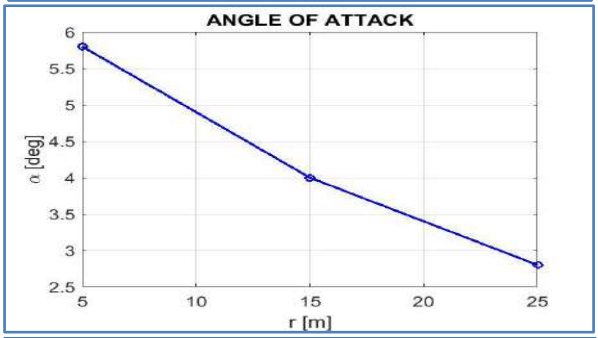

CHORD CONVERGENCE
l [m]
Iterations

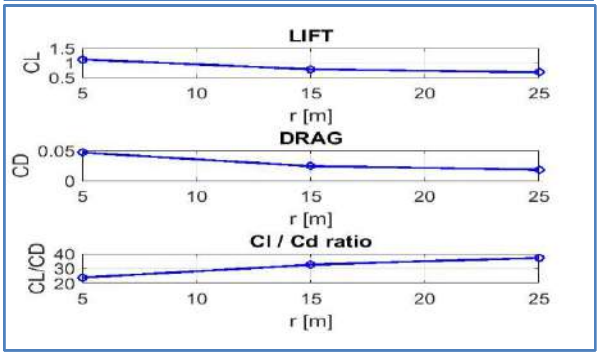

CHORD CONVERGENCE
l [m]
Iterations

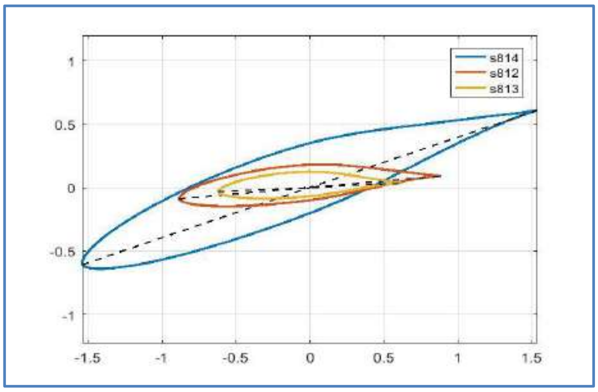

CHORD
l [m]
r [m]

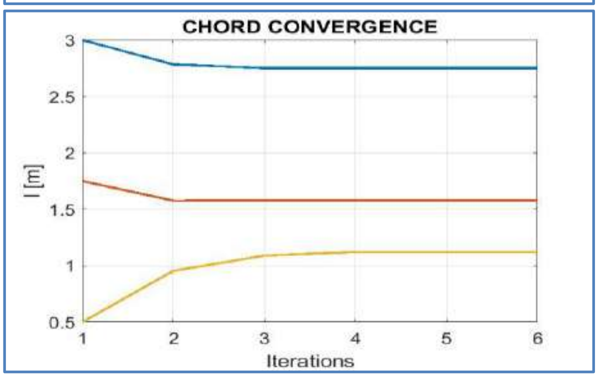

CHORD
l [m]
r [m]

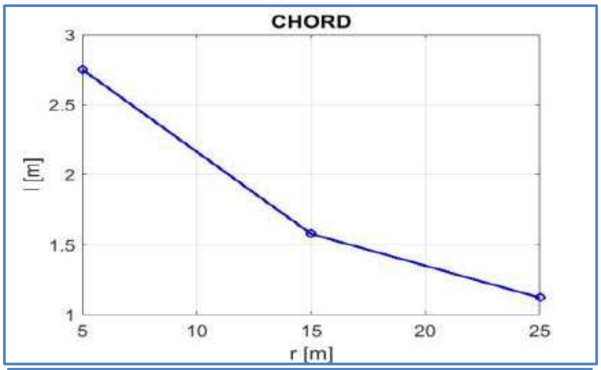

ANGLE OF ATTACK
α [deg]
r [m]

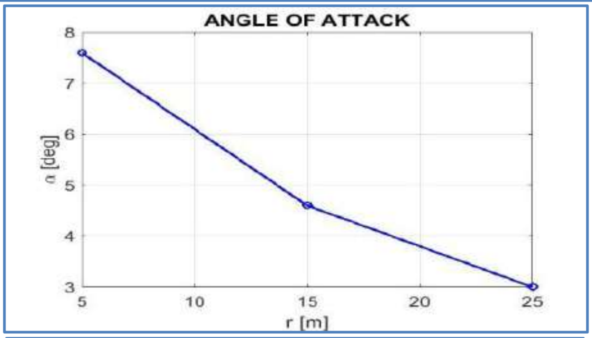

ANGLE OF ATTACK
α [deg]
r [m]

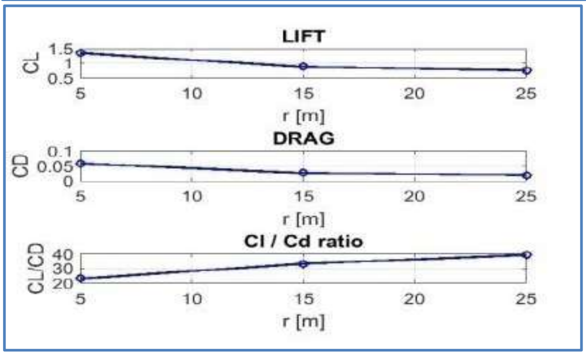

LIFT
CL
r [m]
DRAG
CD
r [m]
Cl / Cd ratio
CL/CD
r [m]

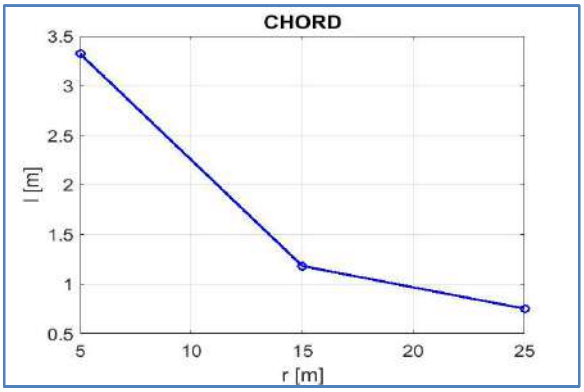

s814
s812
s813

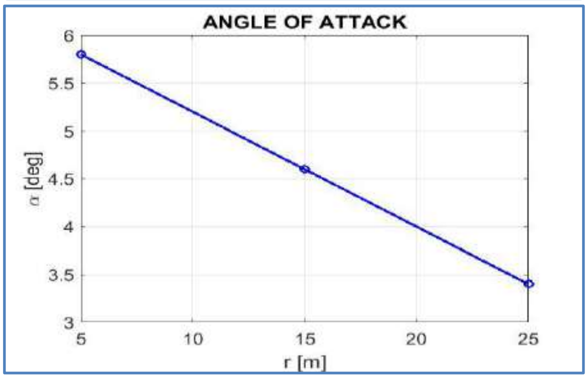

CHORD CONVERGENCE
l [m]
Iterations

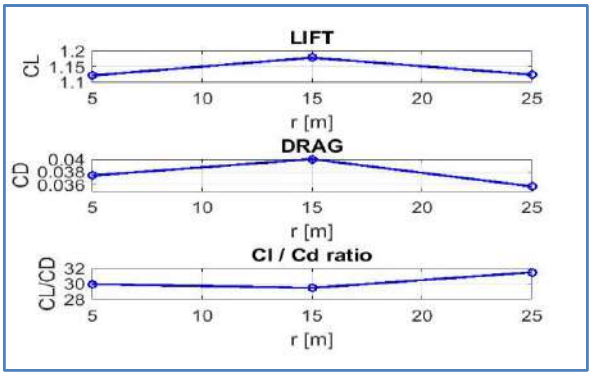

CHORD
l [m]
r [m]

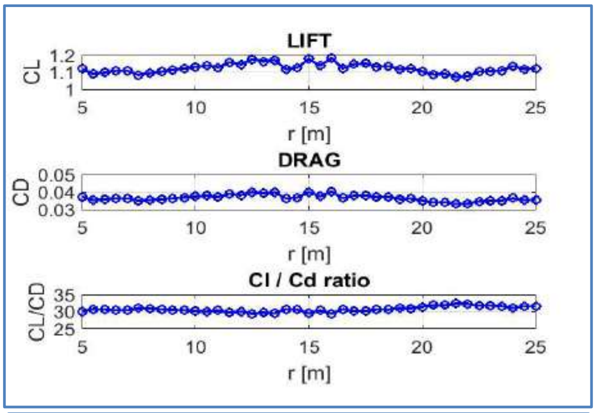

ANGLE OF ATTACK
α [deg]
r [m]

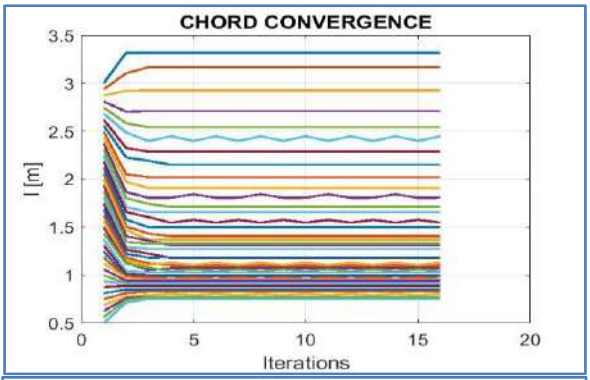

LIFT
CL
r [m]
DRAG
CD
r [m]
Cl / Cd ratio
CL/CD
r [m]

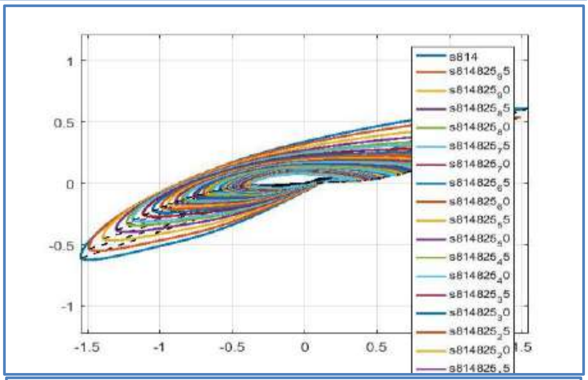

CHORD
l [m]
r [m]

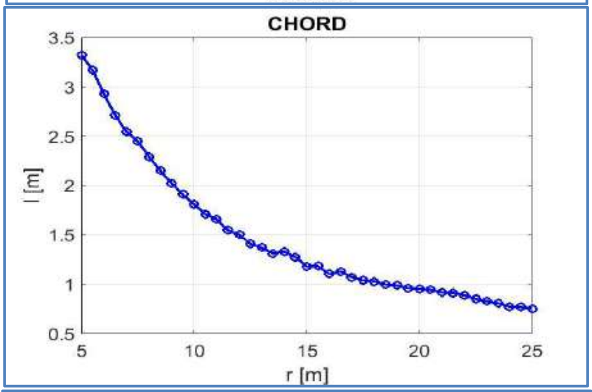

ANGLE OF ATTACK
α [deg]
r [m]

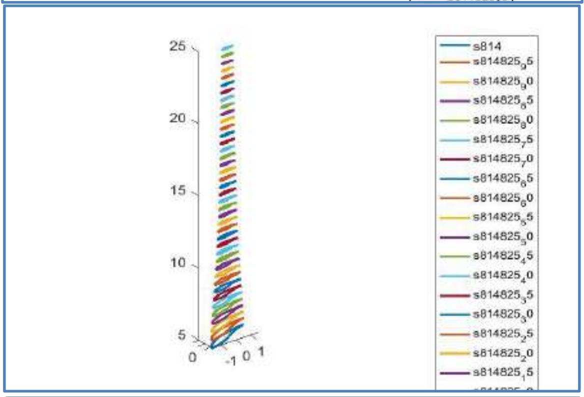

LIFT
CL
r [m]
DRAG
CD
r [m]
Cl / Cd ratio
CL/CD
r [m]

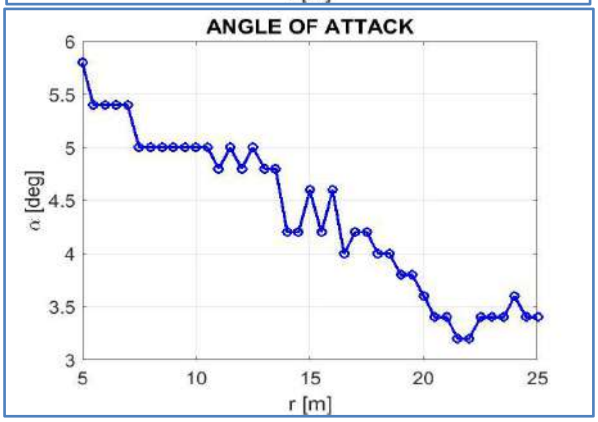

LIFT
CL
r [m]
DRAG
CD
r [m]
Cl / Cd ratio
CL/CD
r [m]

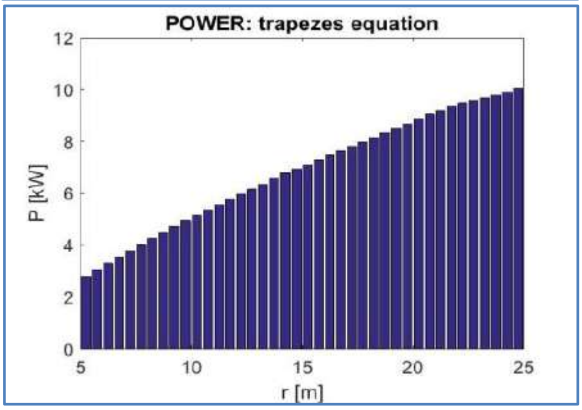

CHORD CONVERGENCE
l [m]
Iterations

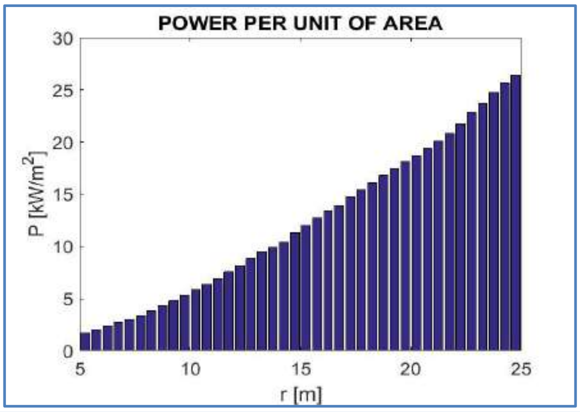

s814

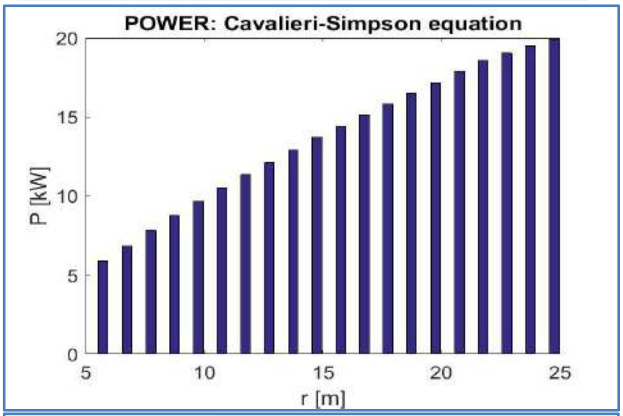

CHORD
l [m]
r [m]

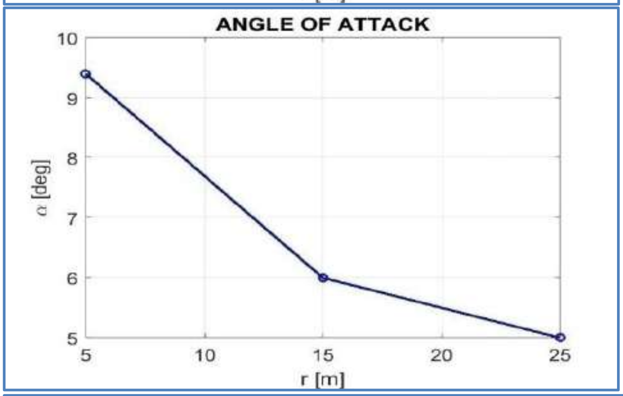

s814

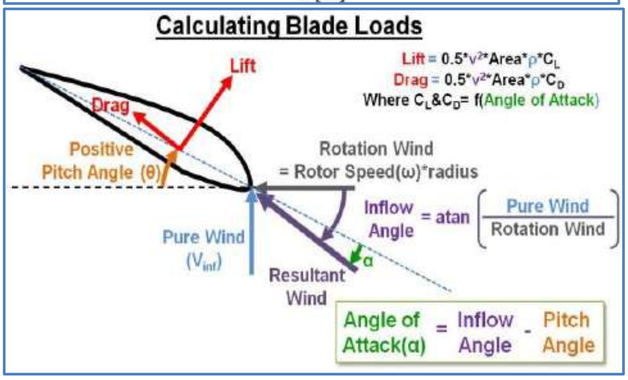

ANGLE OF ATTACK
α [deg]
r [m]

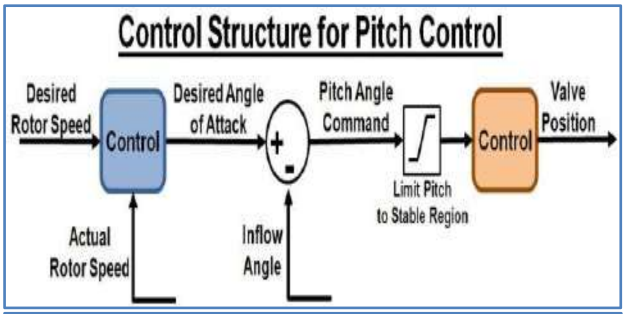

POWER: trapezes equation
P [kW]
r [m]

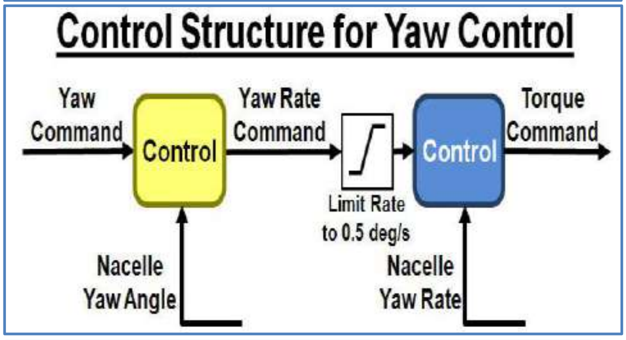

POWER PER UNIT OF AREA
P [kW/m²]
r [m]

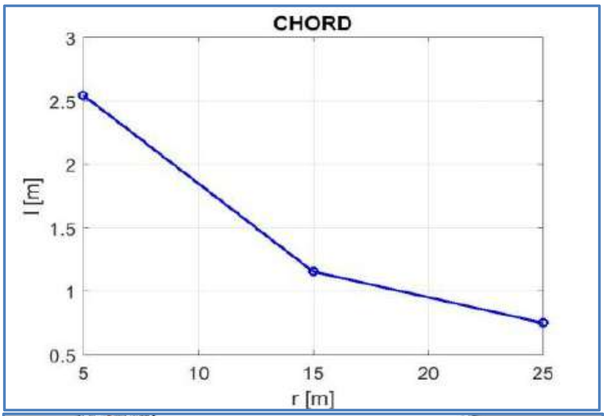

POWER: Cavalieri-Simpson equation
P [kW]
r [m]

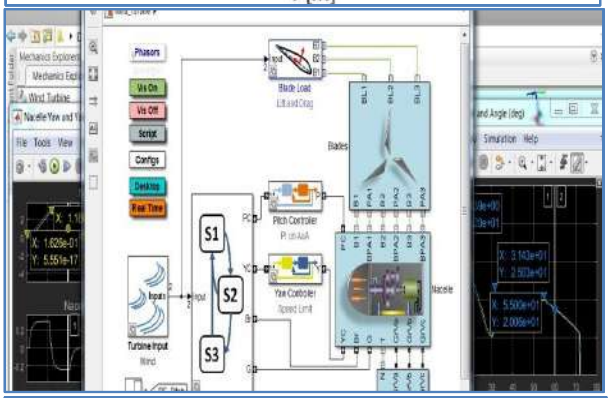

ANGLE OF ATTACK
α [deg]
r [m]

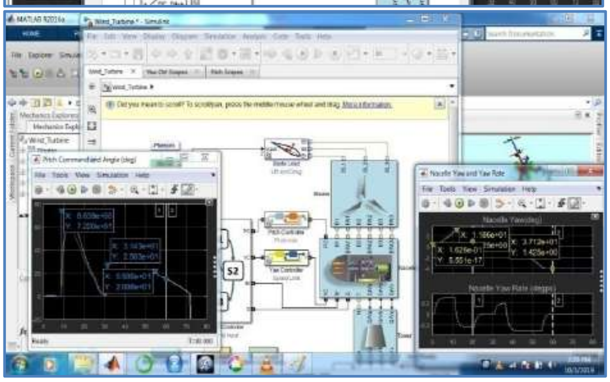

Calculating Blade Loads
Lift
Drag
Lift = 0.5*v²*Area*ρ*C_L
Drag = 0.5*v²*Area*ρ*C_D
Where C_L&C_D= f(Angle of Attack)
Positive Pitch Angle (θ)
Rotation Wind = Rotor Speed(ω)*radius
Inflow Angle = atan (Pure Wind / Rotation Wind)
Pure Wind (V_inf)
Resultant Wind
α
Angle of Attack(α) = Inflow Angle - Pitch Angle

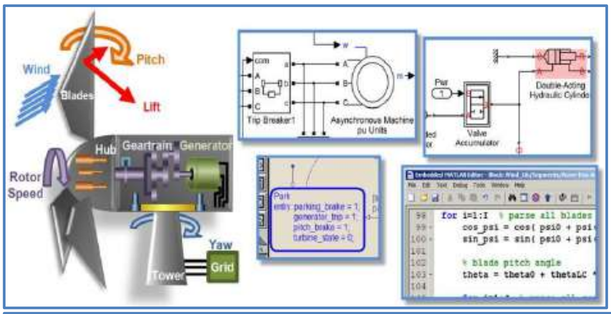

Control Structure for Pitch Control
Desired Rotor Speed
Control
Desired Angle of Attack
Pitch Angle Command
Control
Valve Position
Limit Pitch to Stable Region
Actual Rotor Speed
Inflow Angle

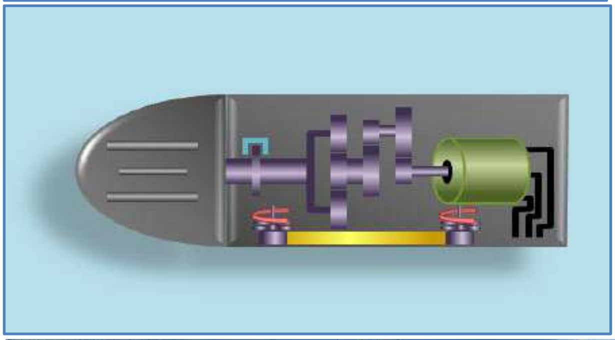

Control Structure for Yaw Control
Yaw Command
Control
Yaw Rate Command
Control
Torque Command
Limit Rate to 0.5 deg/s
Nacelle Yaw Angle
Nacelle Yaw Rate

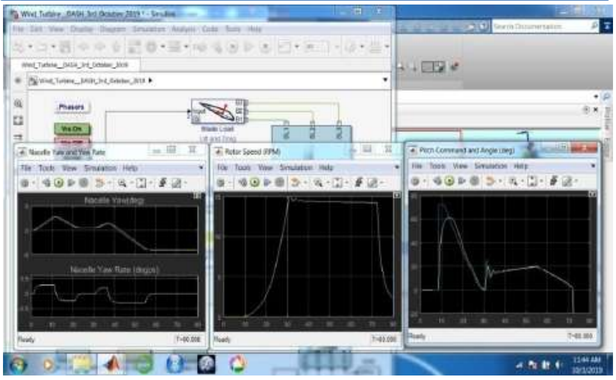

CHORD
l [m]
r [m]

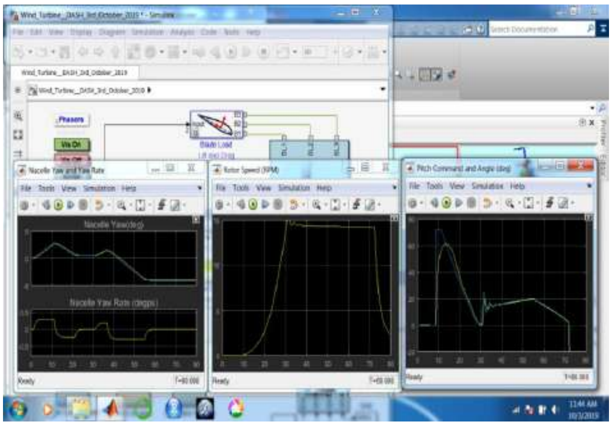


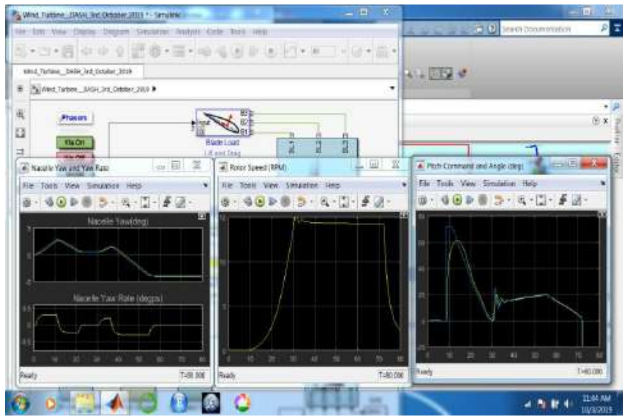


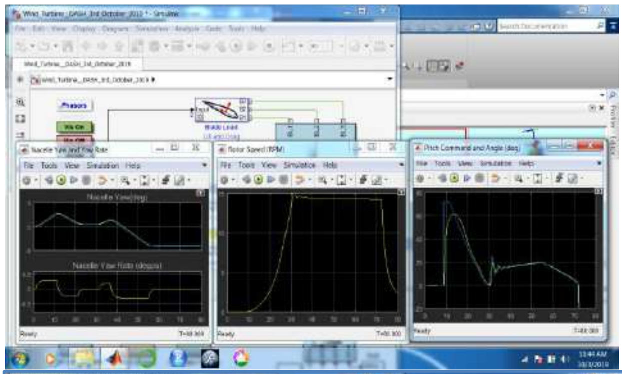

Wind
Pitch
Blades
Lift
Hub
Geartrain
Generator
Rotor
Speed
Yaw
Grid
Tower
Trip Breaker1
Asynchronous Machine pu Units
Valve
Accumulator

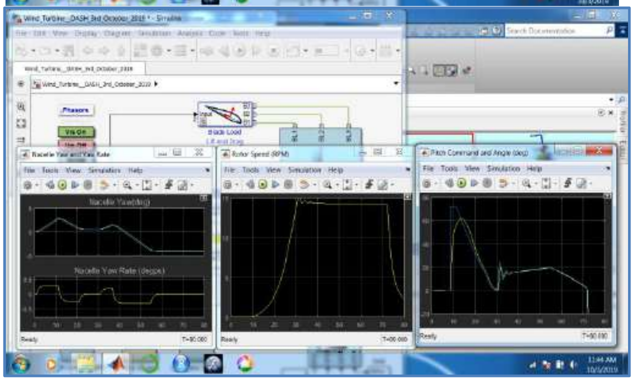


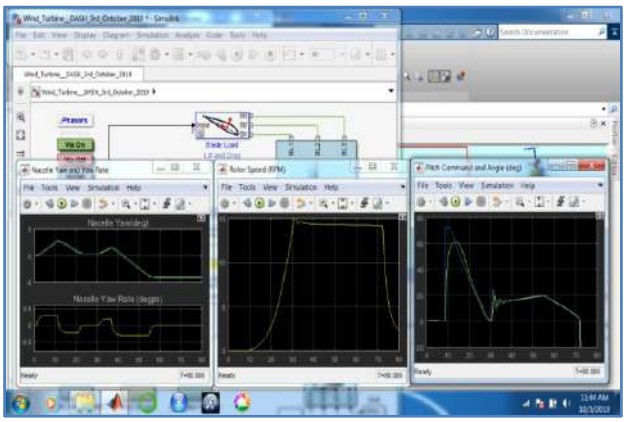


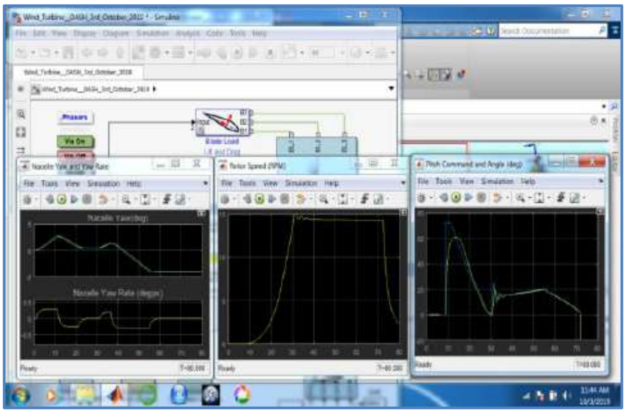


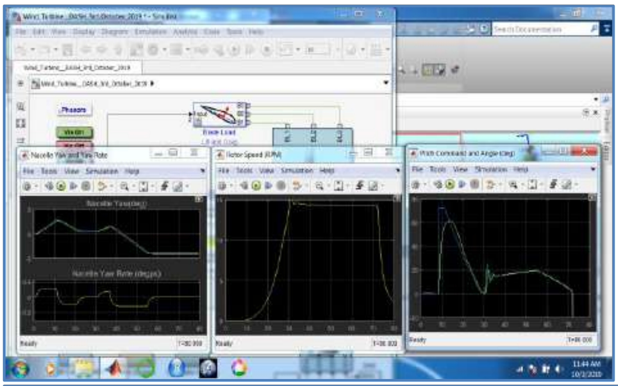


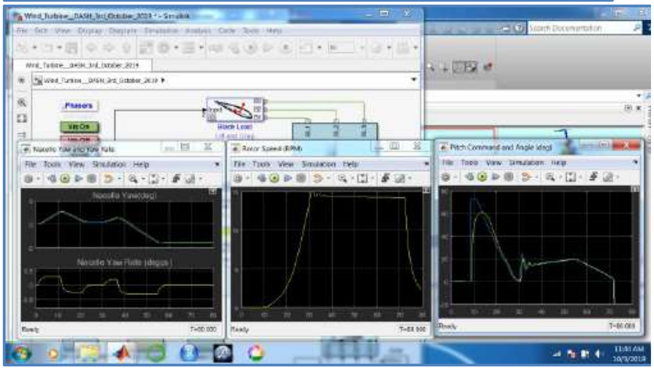


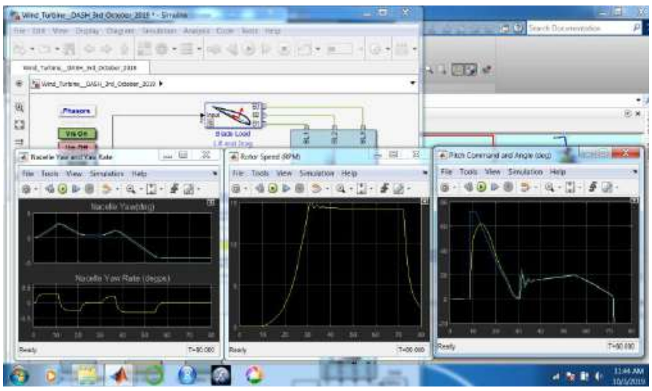


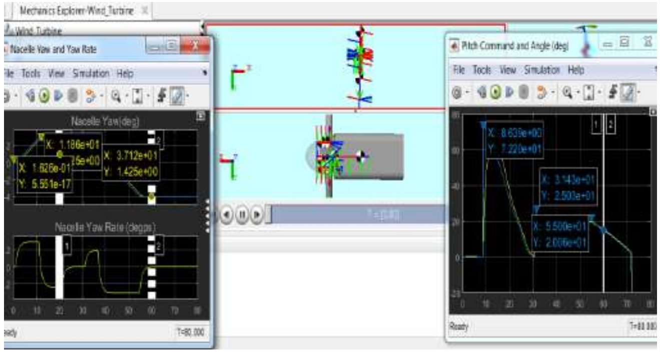


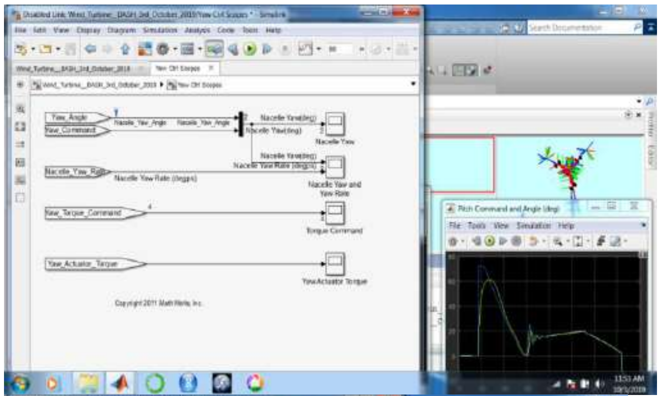


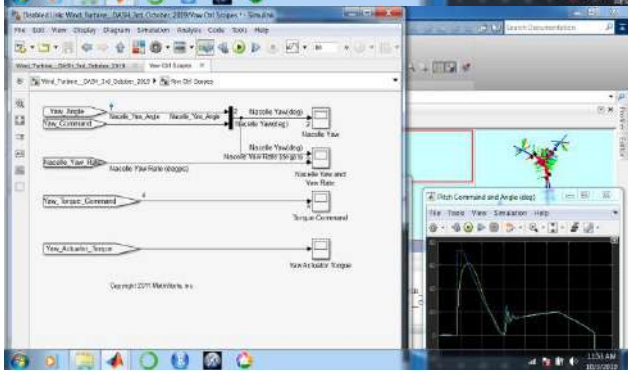


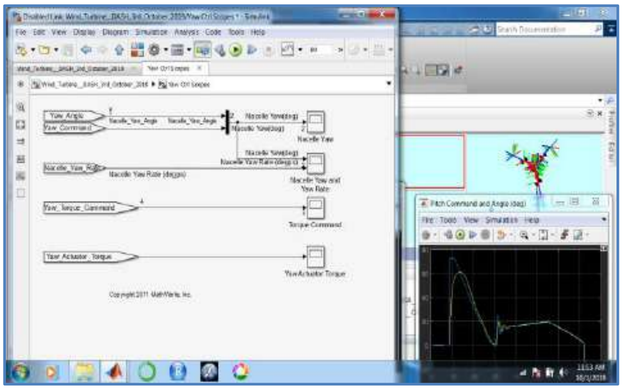


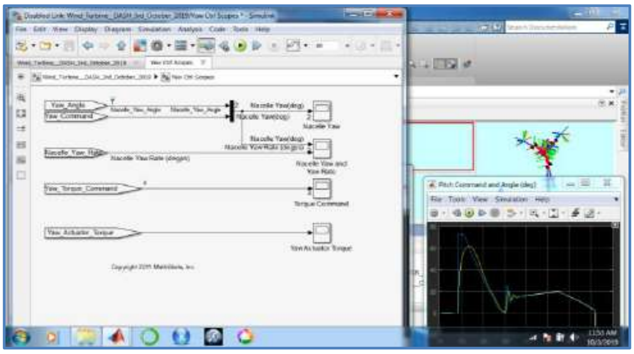


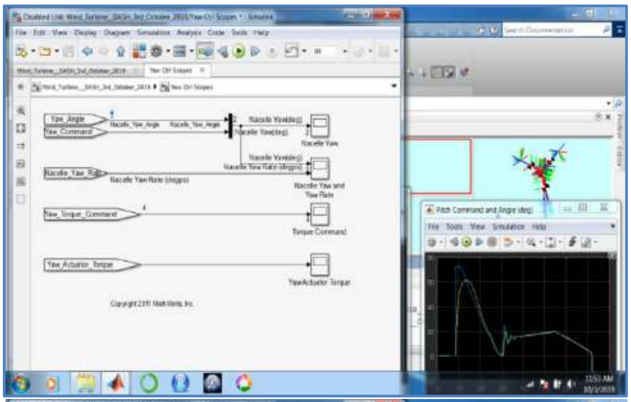

Nacelle Yaw and Yaw Rate
Nacelle Yaw(deg)
Nacelle Yaw Rate (deg/s)
Pitch Command and Angle (deg)

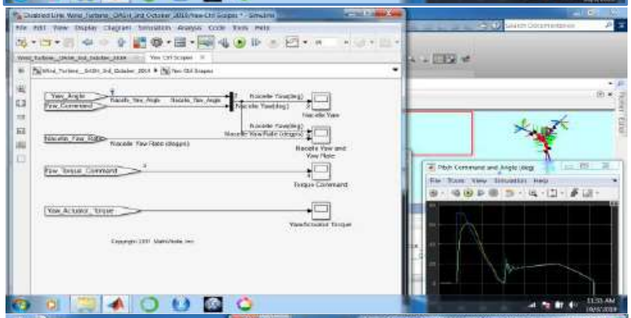


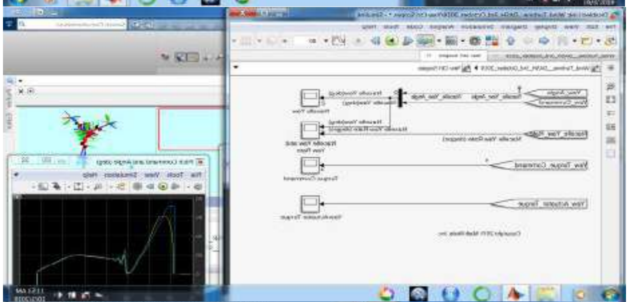


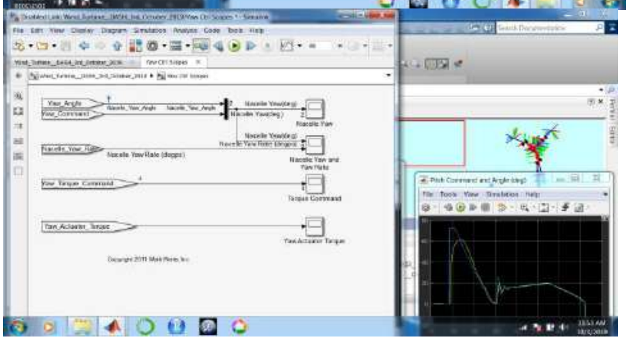


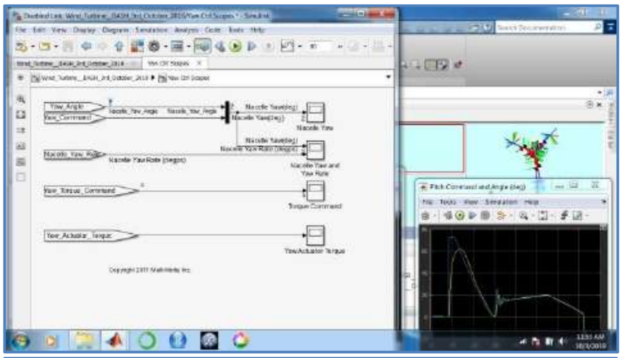


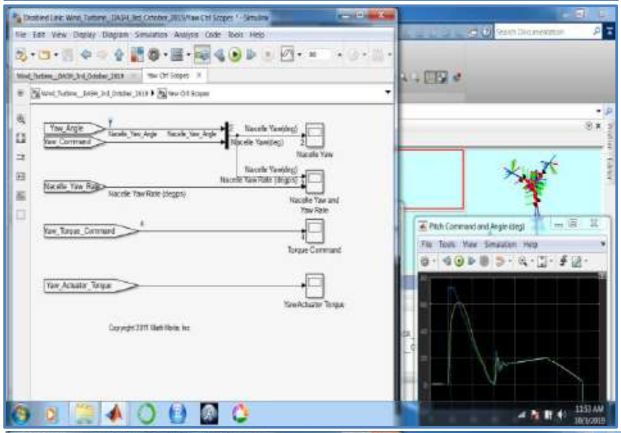


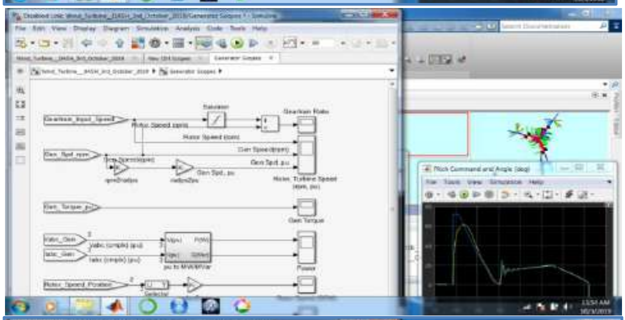


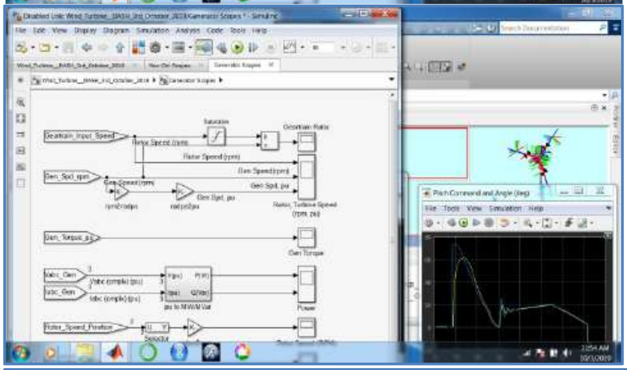


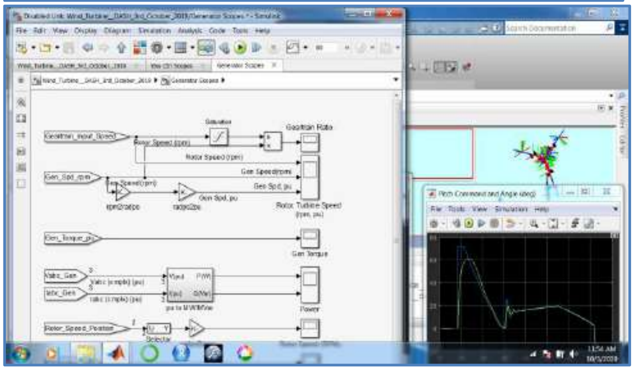


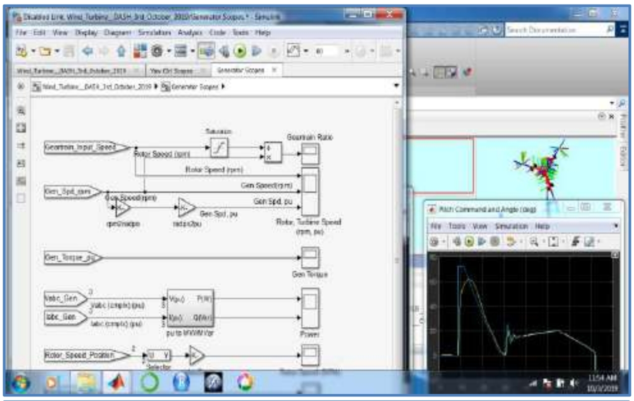


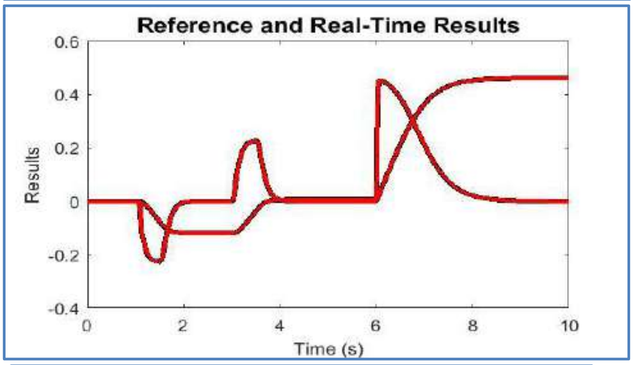


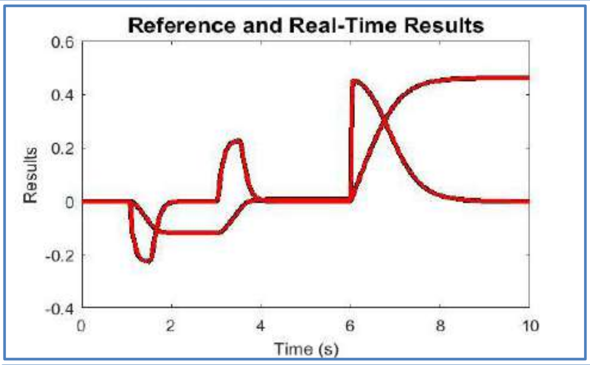


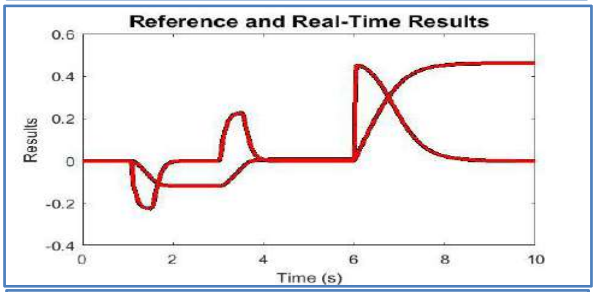


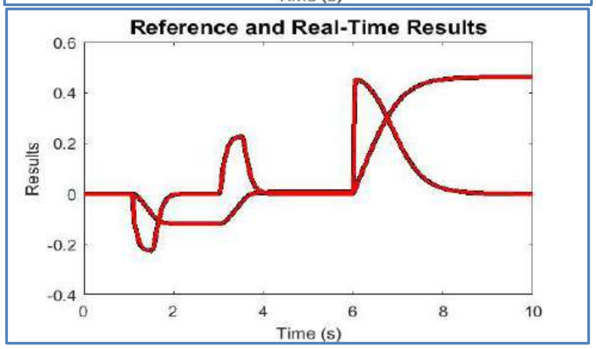


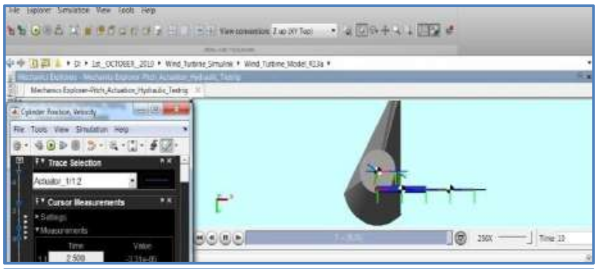


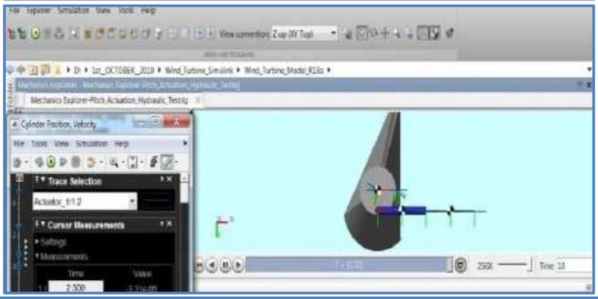

Reference and Real-Time Results
Results
Time (s)
0.6
0.4
0.2
0
-0.2
-0.4
0
2
4
6
8
10

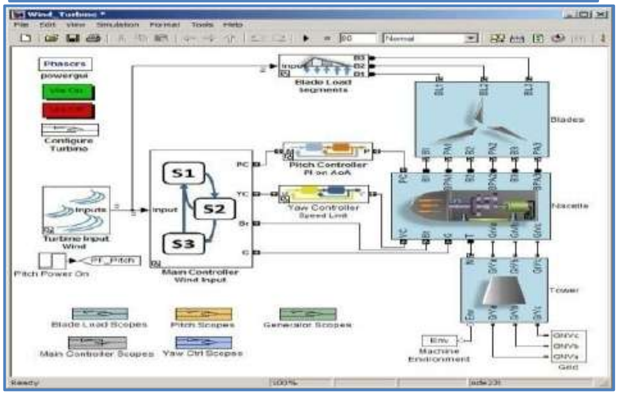

Reference and Real-Time Results
Results
Time (s)
0.6
0.4
0.2
0
-0.2
-0.4
0
2
4
6
8
10

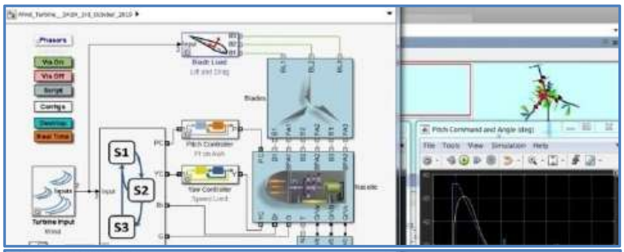

Reference and Real-Time Results
Results
Time (s)
0.6
0.4
0.2
0
-0.2
-0.4
0
2
4
6
8
10

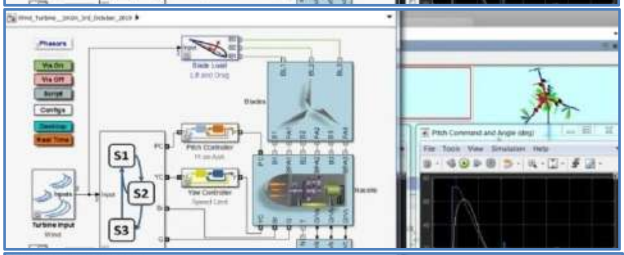

Reference and Real-Time Results
Results
Time (s)
0.6
0.4
0.2
0
-0.2
-0.4
0
2
4
6
8
10

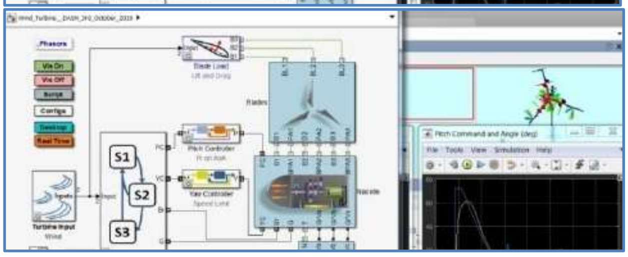


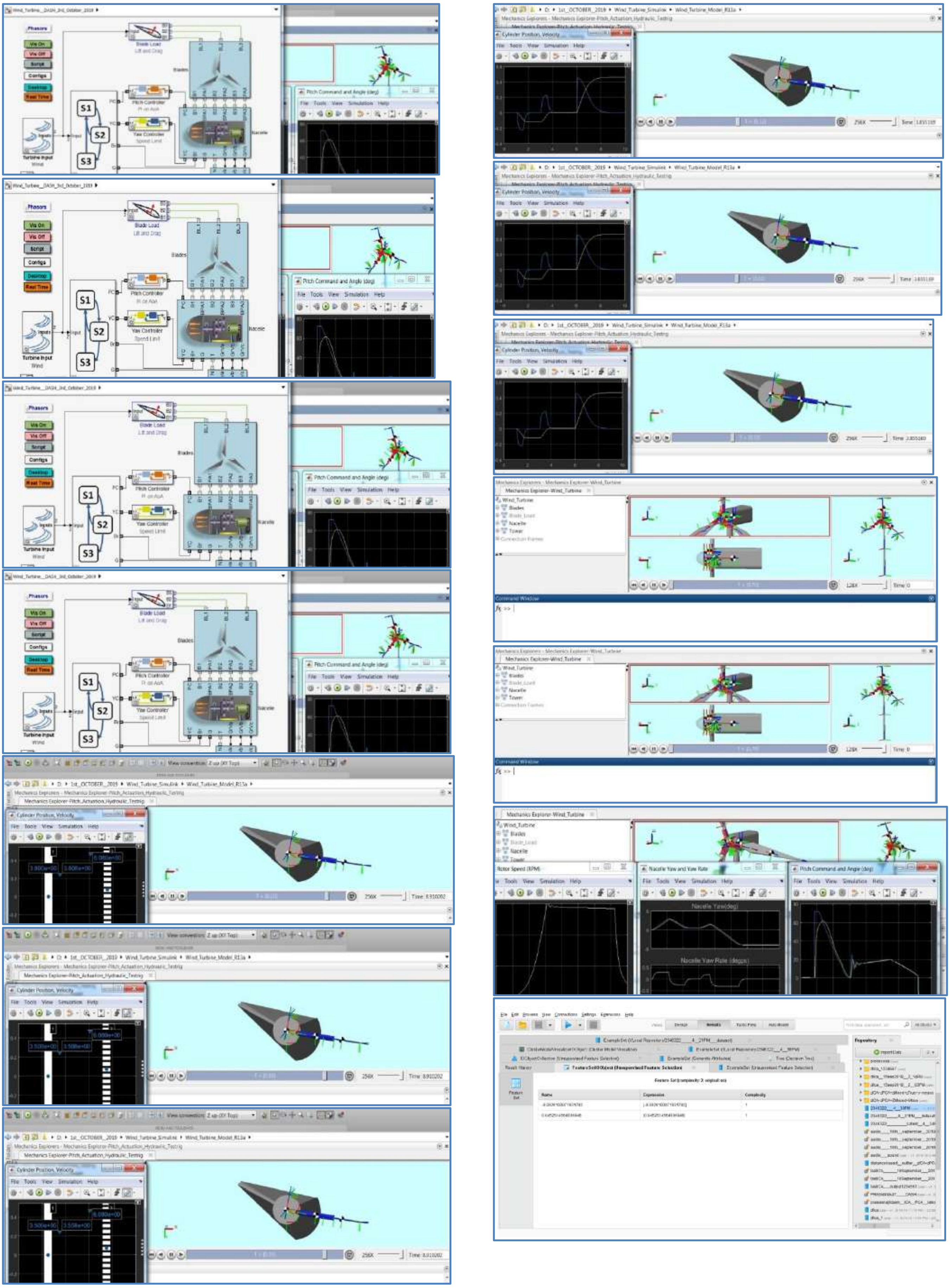


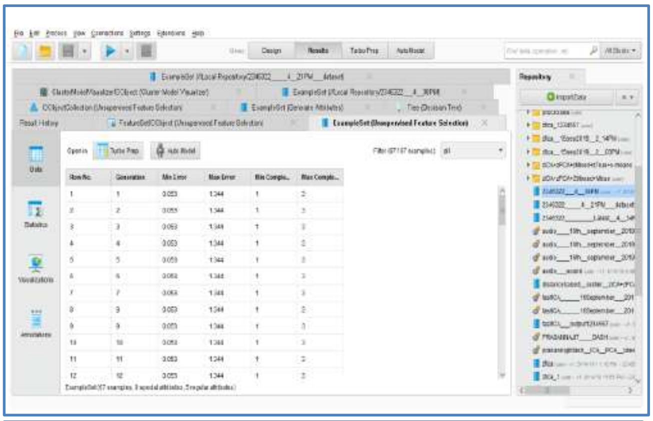

Phasors
Blade Load Segments
Blades
Configure Turbine
Pitch Controller PI on AoA
Yaw Controller Speed Limit
Nacelle
Turbine Input Wind
Main Controller Wind Input
Pitch Power On
Tower
Blade Load Scopes
Pitch Scopes
Generator Scopes
Main Controller Scopes
Yaw Ctrl Scopes
Machine Environment
S1
S2
S3

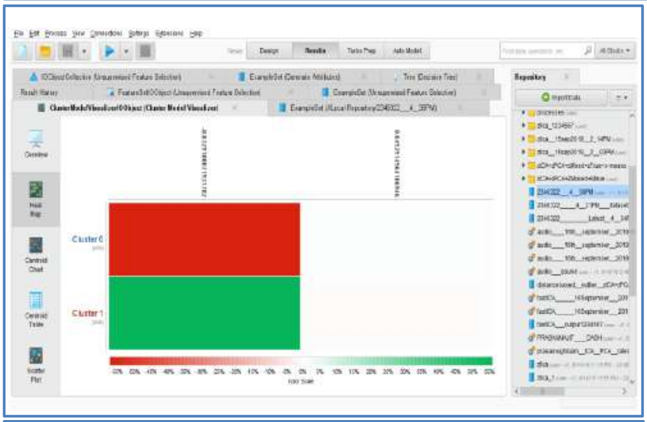


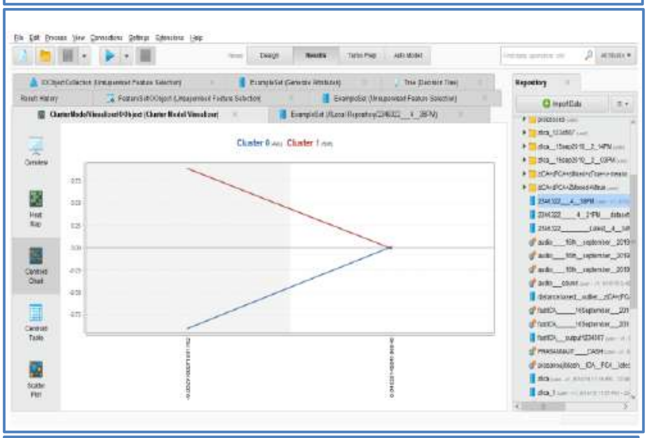


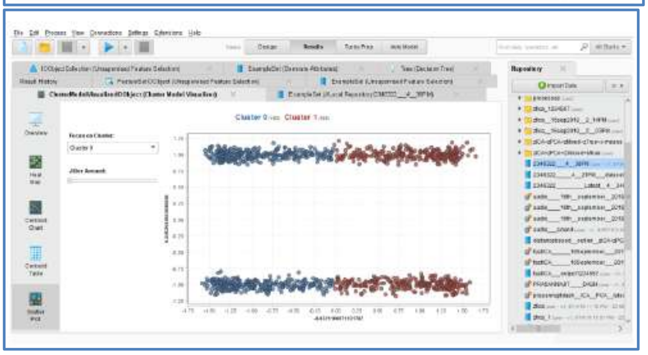


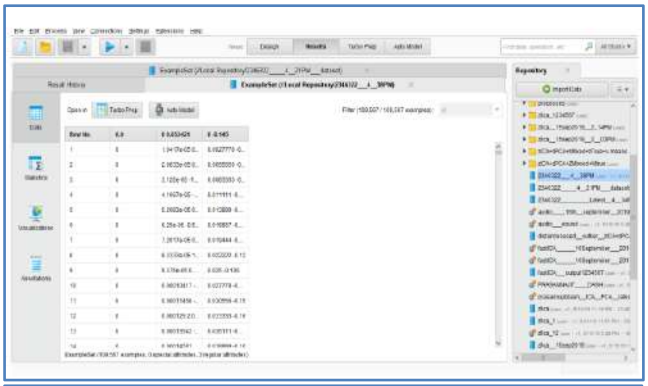


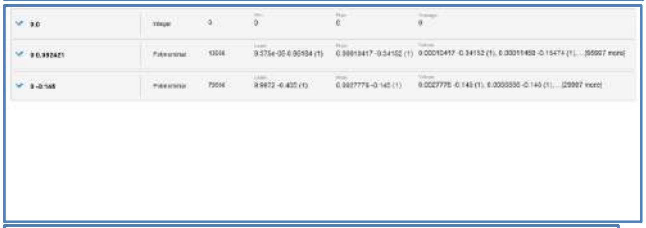


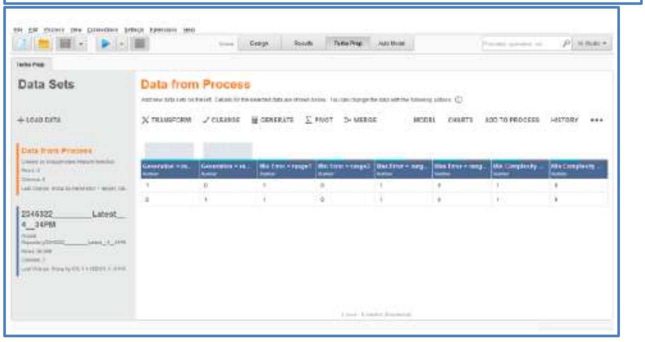


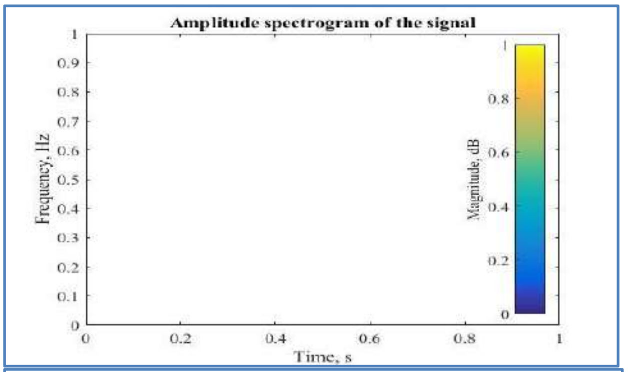


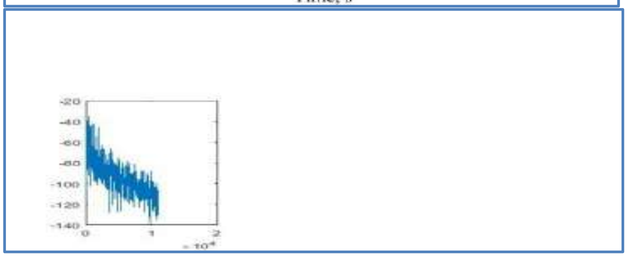


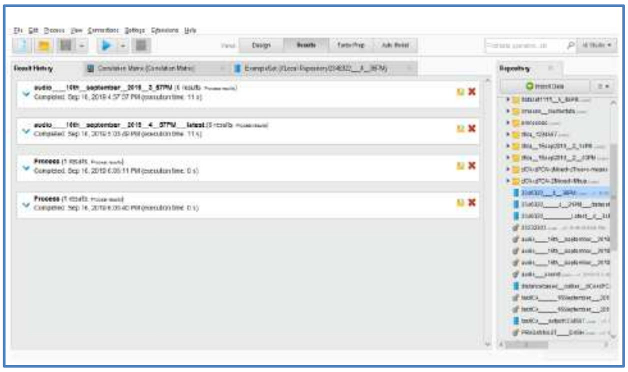


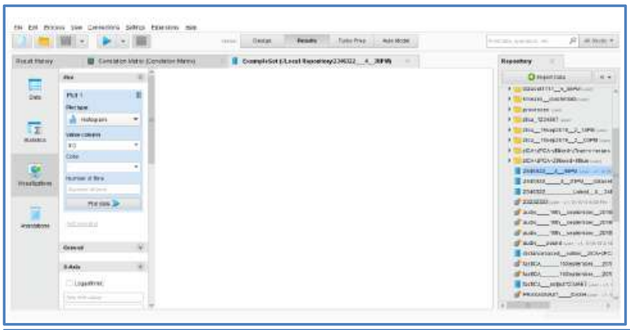


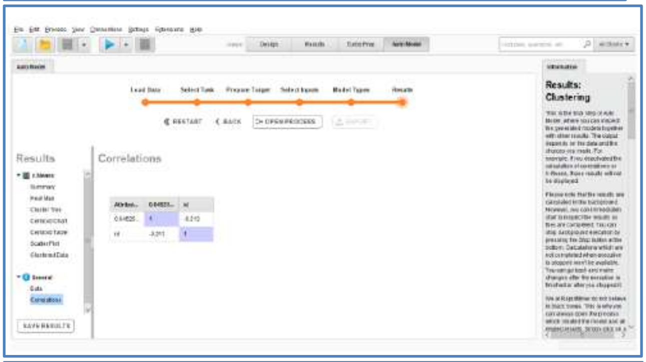

Data Sets
Data from Process

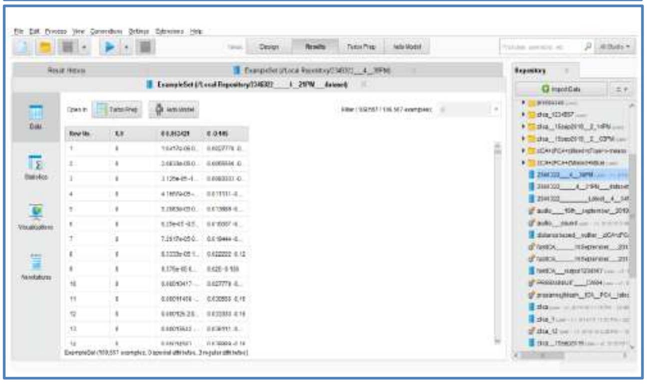

Amplitude spectrogram of the signal
Frequency, Hz
Magnitude, dB
Time, s

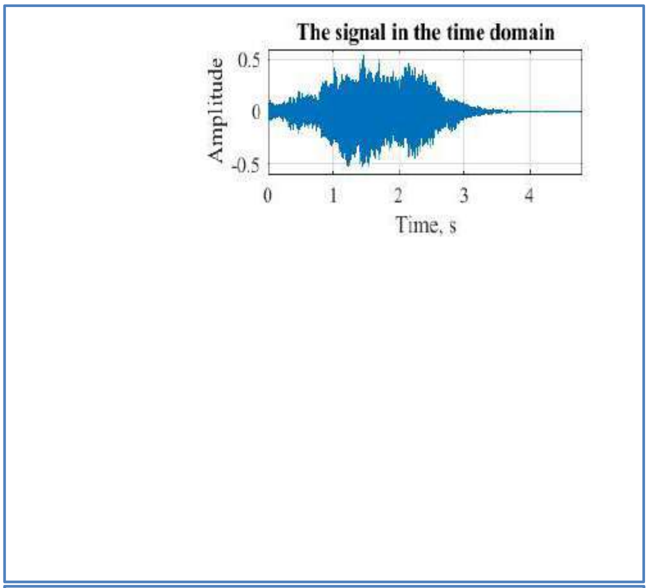


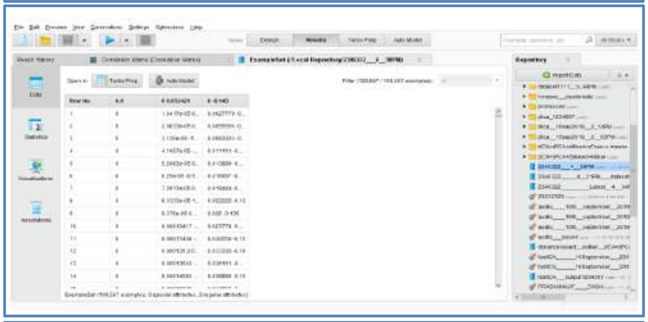












2. PROPOSED PATTERN CLASSIFICATION SCHEME

The proposed technique includes pre-processing the time-series data using S-transform and various statistical features are derived from the S-matrix generated form S-transformation. Basically the features are in frequency domain. The extracted features are fed tothe FES driven by a set of fuzzy rules. Each feature is characterized by a

2.1 S-TRANSFORM BASED FEATUREEXTRACTION

The time series data generated from various kinds of disturbance signals are preprocessed through the advanced signal processing technique such as S-transform. The multiresolution S-transform originates from two-advanced signal processing tools; the Short- time Fourier transform (STFT) and the Wavelet transform [11, 12, 13]. It can be viewed as a frequency dependent STFT or a phase corrected wavelet transform. Due to the frequency dependent window used for analysis of a signal data, the multiresolution S-transform has been proven in [11] to perform better than other time-frequency transforms. Furthermore, it provides superior time-frequency localization property computing both amplitude and phase spectrum of discrete data samples. It was shown in [12] that the S-transform would be useful for classifying power signal time series disturbances. Also it is less susceptible to noise than the wavelet transform approach. The S-transform of a signal h(t) isdefined as

$$S(t,f) = \int_{-\infty}^{\infty} h(\tau) w^{*}(\tau - t, f).\, e^{-j2\pi f\tau} d\tau \quad (1)$$

where $S(t, f) = \frac{|f|}{\alpha\sqrt{2\pi}} . e^{-tf^2/2\alpha^2}$ (2)

and * stands for complex-conjugate. The parameter sets the width of the window for a given frequency. For small, the time resolution improves and the frequency resolution deteriorates. The reverse happens when it is increased to a larger value. S-transform produces a multiresolution analysis like a bank of filters with constant relative bandwidth. The integration of S-transform over time results in the Fourier spectrum that is

$$(f) = \int_{-\infty}^{\infty} S(t,f) dt \quad (3)$$

and for the Gaussian window

$$\int_{-\infty}^{\infty} S(t,f) dt = 1 \quad (4)$$

The original signal can be obtained from S-transform as

$$h(t) = \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} s(\tau, f) d\tau \right\} . e^{j2\pi ft} . df \quad (5)$$

Another way to represent S-transform is an amplitude and phase correction of the CWT (continuous wavelet transform) as

$$S(t,f) = \sqrt{|f|}/2\pi\alpha . e^{j2\pi ft} . WT(t, f) \quad (6)$$

Where the wavelet transform is given by

$$WT(t, f) \sqrt{\frac{|f|}{\alpha}} . e^{\frac{-t^2 f^2}{2\alpha^2}} . e^{j2\pi ft} \quad (7)$$

The equation(6) shows that the time-frequency resolution is distributed in the time frequency plane like wavelet transform but a direct link with Fourier transform exists

The term H[n] is the DFT of the time series h(t) and can be computed using FFT algorithm

$$S(j, n) = \sum_{m=0}^{N-1} H[m+n] G(m, n) e^{\frac{i2\pi mj}{N}} \quad (8)$$

where $G(m,n) = e^{\frac{-2\pi^2 m^2 \alpha^2}{n^2}}$ (9)

and j,m and n = 0,1,……,n-1.

The computational efficiency of FFT is used to calculatethe S-transform and the total number of operations is N (N+NlogN).

The amplitude and phase spectrum of S-transform are givenby

$$A = abs(S(n, j)) \quad (10)$$

A novel approach for time series data classification using Fuzzy Expert System (FES) is presented in this paper. The power disturbance signals are considered as time-series data for the proposed study. The time-series data is pre- processed through the advanced signal processing technique such as S-transform and the features obtained are fed to the designed FES for classification. Other indices foraccurate classification such as certainty factors and support values are derived and the obtained results shows the robustness of the propose technique. Also the FES outputs are optimized using PSO for further enhancement of the

Time series data.

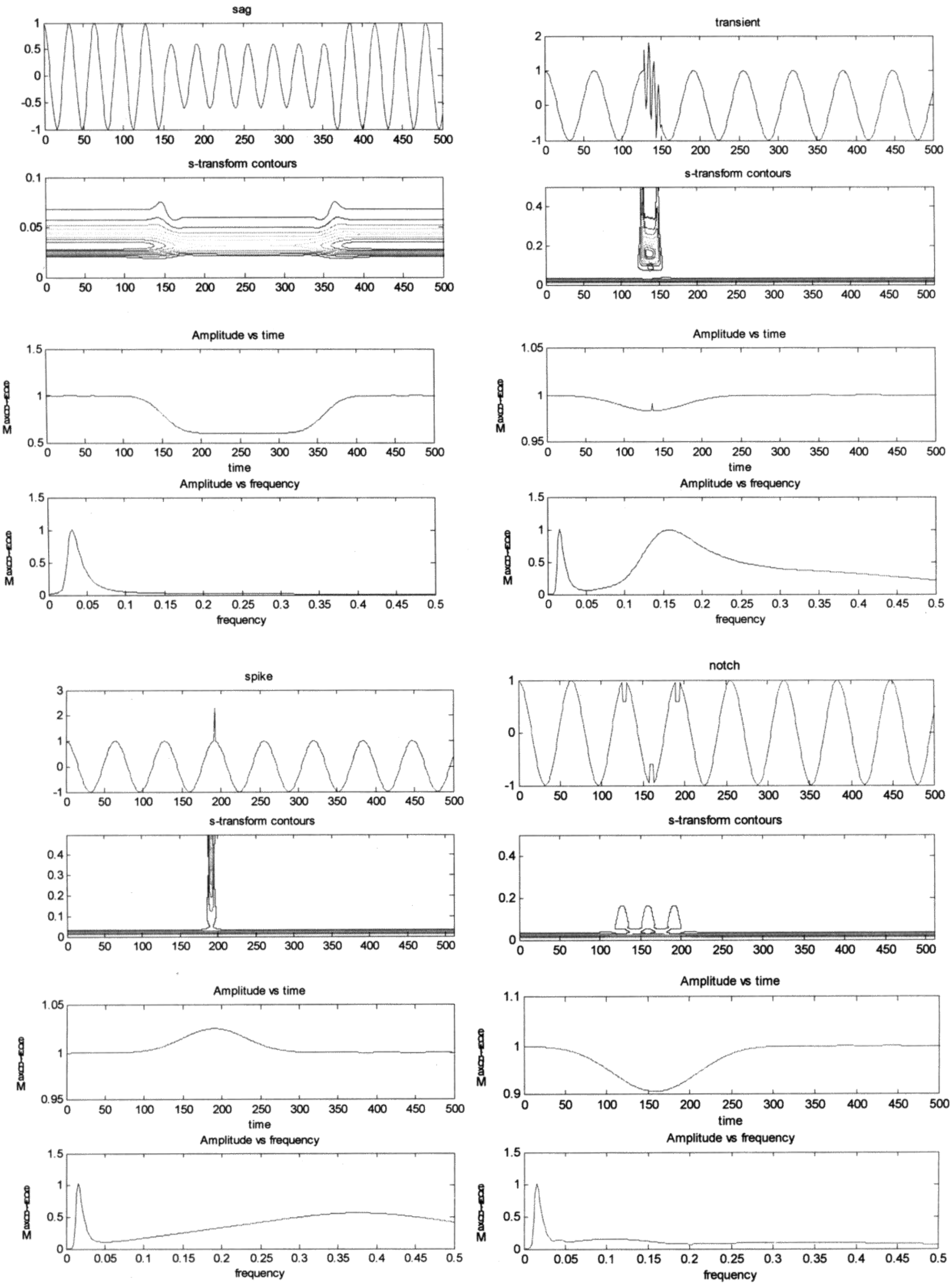
The S-transform output shown in the figures includes the signal, S-contours, time-frequency contours, and amplitude and frequency contents. The S-contours provides the information regarding the time-localization of the time series data. As shown in the figures, the time- localization takes place in frequency domain instantly with the disturbance in the time scale. The aptitude information is also calculated for the S-matrix resulted from the S- transform. It shows the amplitude variation in the time- series data. Also the frequency content of the time-series data is calculates from the S-matrix to know the frequency content of the time-series data. As seen in the figures, the contains only one peak in the frequency characteristics while in case of transients there are two peaks with higher frequency values.classification results. The proposed technique is also tested for features

Due to the frequency dependent window used for analysis of a signal data, the multiresolution S- transform has been proven in [11] to perform better than other time-frequency transforms. Furthermore, it provides superior time-frequency localization property computing both amplitude and phase spectrum of discrete data samples. It was shown in [12] that the S-transform would be useful for classifying power signal time series disturbances.

The multiresolution S-transform originates from two- advanced signal processing tools; the Short- time Fourier transform (STFT) and the Wavelet transform [11, 12, 13]. It can be viewed as a frequency dependent STFT or a phase corrected wavelet transform. Due to the frequency dependent window used for analysis of a signal data, the multiresolution S- transform has been proven in [11] to perform better than other time-frequency transforms. Furthermore, it provides superior time-frequency localization property computing both amplitude and phase spectrum of discrete data samples. It was shown in [12] that the S-transform would be useful for classifying power signal time series disturbances.

2.2 PRE-PROCESSING OF TIME-SERIES DATA THROUGH S-TRANSFORM

(a) Time series data and corresponding S-transform



The S-transform output shown in the figures includes the signal, S-contours, time-frequency contours, and amplitude and frequency contents. The S-contours provides the information regarding the time-localization of the time series data. As shown in the figures, the time- localization takes place in frequency domain instantly with the disturbance in the time scale. The aptitude information is also calculated for the S-matrix resulted from the S- transform. It shows the amplitude variation in the time- series data. Also the frequency content of the time-series data is calculates from the S-matrix to know the frequency content of the time-series data. As seen in the figures, the contains only one peak in the frequency characteristics while in case of transients there are two peaks with higher frequency values. This indicates sag is a low frequency phenomena which only contains one peak with other values nearly zero. But in case of transients, the more than one number of peaks indicates presence of higher harmonics in the time-series data. This provides vital information for father analysis

2.3 FEATURE EXTRACTION

Four features were extracted from the S-transform output.They are:

1. F1 = max (A) + min (A) - max (B) - min (B).
   where A is the amplitude versus time graph from the S-matrix under disturbance and B is the amplitude versus time graph of the S-matrix without disturbance.
2. F2= Standard deviation of max (abs(s)).
3. F3= Energy in the S-transform output.
4. F4= Total harmonic distortion (THD).
5. F5= Estimated frequency hours the maximum amplitude

Table I Features Extracted From S-Transform

Disturbances	Fl	F2	F3	F4	F5
Normal	1.002				
Sag (60%)	0.593	0.053	0.031	0.0312	50.0
Swell (50%)	1.50	0.0129	0.076	0.015	50.00
Momentary Interruption (MI) (5%)	0.0724	0.035	0.019	0.0350	50.00
Harmonics (0% 3rd + 10% 5th)	1.0	0.0339	0.0556	0.141	50.00
Sag with Harmonic (60%)	0.601	.0228	0.0408	0.1139	50.00
Swell with Harmonic (50%)	1.5	.0219	0.079	0.1155	50.00
Flicker (5 Hz, 4%)	0.987	.0168	0.026	0.0186	55.00
Notch + harmonics	0.939	0.131	0.0529	0.136	56.25
Spike + harmonics	1.065	0.141	0.0627	0.1308	56.25
Transient (low frequency)	0.493	0.138	0.0163	0.01	705.00
Transient (high frequency)		0.149	0.014	0.043	2520.00

Table 2. Features Extracted From S-transform with SNR 20DB

Disturbances	Fl	F2	F3	F4	F5
Normal	0.9963	0.001	0.052	0.028	50.00
Sag (60%)	0.591	0.022	0.039	0.027	50.00
Swell (50%)	1.503	0.012	0.076	0.029	50.00
Momentary Interruption (MI)	0.070	0.0387	0.0323	0.044	50.00
Harmonics	1.032	0.050	0.064	0.25	50.00
Sag with Harmonic (60%)	0.601	0.0228	0.0408	0.1139	50.00
Swell with Harmonic (50%)	1.500	0.0219	0.079	0.1155	50.00
Flicker (4%, 5 Hz)	0.998	0.0209	0.027	0.1159	55.00
Notch + harmonics	0.940	0.1275	0.0531	0.198	50.00
Spike + harmonics	1.072	0.141	0.066	0.204	50.00
Transient (low	1.000	0.1473	0.0148	0.0566	440.00
frequency)					
Transient (high frequency)	1.0384	0.155	0.014	0.068	3315.00

Two nonstationary time series databases like sag and transient which occur very frequently in power networks are given in a separate table to highlight the variations inthe feature values for the same event:

2.4 FUZZY EXPERT SYSTEM (FES)

A Fuzzy Expert System has two key elements, (i) fuzzy sets and (ii) fuzzy rule base. A fuzzy set can be fully defined by its membership functions. Fuzzy rules offer human-like reasoning capabilities and provide transparent interface mechanism. In the proposed pattern classification technique, the features extracted from S-transform, are fed to the FES with trapezoidal and Gaussian membership functions. A fuzzy rule base is developed for exact classification of the time-series data for 12 classes. The following sections deal with the membership function (MF) and fuzzy rule base. In classical fuzzy expert system the knowledge base constitute a set of rules derived from the statistical knowledge pre-processing the time-series data. The knowledge base, however, needs to be adapted with changes in the operating conditions, addition of spurious disturbances, and noise that might be superimposed over the data. This requires addition of new rules if necessary and a correct choice of membership functions to analyze the data.

The fuzzy if-then rules are in the following form for the n-dimensional pattern recognition problem:

Rule R_1: If X_1 is A_{21} and X_n is A_{in}

The consequent Class C_i with classification factor CFi, where R, is the ith rule of the fuzzy rule base, x = (X 1, X2,

………,Xn.,) is n-dimensional pattern vector and A, is an antecedent fuzzy set, Ci the consequent class out of N classes, and classification factor **CF*i*** in the interval [0, 1] is the certainty factor also termed as rule weight. In data mining problem, two measures known as confidence and support are used for finding the association rule in the form

$$A_i \rightarrow C_i \text{ with } A_i = [A_{i1}, A_{i2}, \dots \dots . A_{in}] \quad (18)$$

The confidence c and support of each fuzzy rule R iswritten as

$$c = \left[\sum_p \mu_{Ai}(x_p)\right] / \left[\sum_{p=1} \mu_{Ai}(x_p)\right] \quad (19)$$

where p denotes the pth pattern and m is the total number of patterns used for classification.

The compatibility grade of the pth pattern isobtained as

$$\mu_{Ai}(x_p) = \min\{\mu_{Ai1}(x_{p1}), \mu_{Ai2}(x_{p2}) \dots \dots \dots \mu_{Ain}(x_{pn})\} \quad (12)$$

and $\mu_{Ai}(x_p)$ is the membership value of the $\mu_{Ai}(x_p)$ to the set A_i, p ∈ class C_i .

The support s of a fuzzy rule indicates the grade of coverage by ($A_i \rightarrow C_i$)

(consequent) is given by $s = \frac{\sum P\epsilon class C_i \mu_{Ai}(x_p)}{m}$ (13)

To obtain the consequent class C_i from the fuzzy rule base Ri, the confidence measure is obtained from the antecedentfuzzy sets as

$$c_i = \max\,(c_1, c_2, \dots \dots \dots \dots c_N) \quad (14)$$

where $c_1, c_2, \dots \dots \dots c_N$ denotes the recognized classes ofnon-stationary time-series data.

The expression for support s is obtained in the same way as

$$s_1, s_2, \dots \dots \dots \dots s_N \quad (15)$$

For finding the classification performance of the fuzzy rulebase, it is envisaged to use a single winner rule methods.

A single winner rule is selected from the set of

x_p =classifying($s_{p1}, s_{p2}, \dots \dots \dots s_{pn}$) as

$$\mu_{A_q}(x_p).CF_q$$

$$\max\left\{ \mu_{A_q}(x_p).CF_q \middle| R_q \in S \right\} \quad (16)$$

The single winner rule posses the highest compatibilityindex in comparison to other rules in the rule base.

However, if two rules have the same compatibility index, the pattern is not classified.

The certainty factor or the rule weight is found as

$$CF_q = c - \bar{c} \quad (17)$$

where c is given by equation (17)

$$\text{and } \bar{c} = \frac{1}{N-1} \sum_{\substack{j=1 \\ j \neq C_q}}^{N} C(A_q \rightarrow \text{class } j) \quad (20)$$

2.5 MEMBERSHIP FUNCTIONS

For generating fuzzy rules, two types of membership functions namely trapezoidal and gaussian are used forclassification.

(i) Trapezoidal MF : x_p

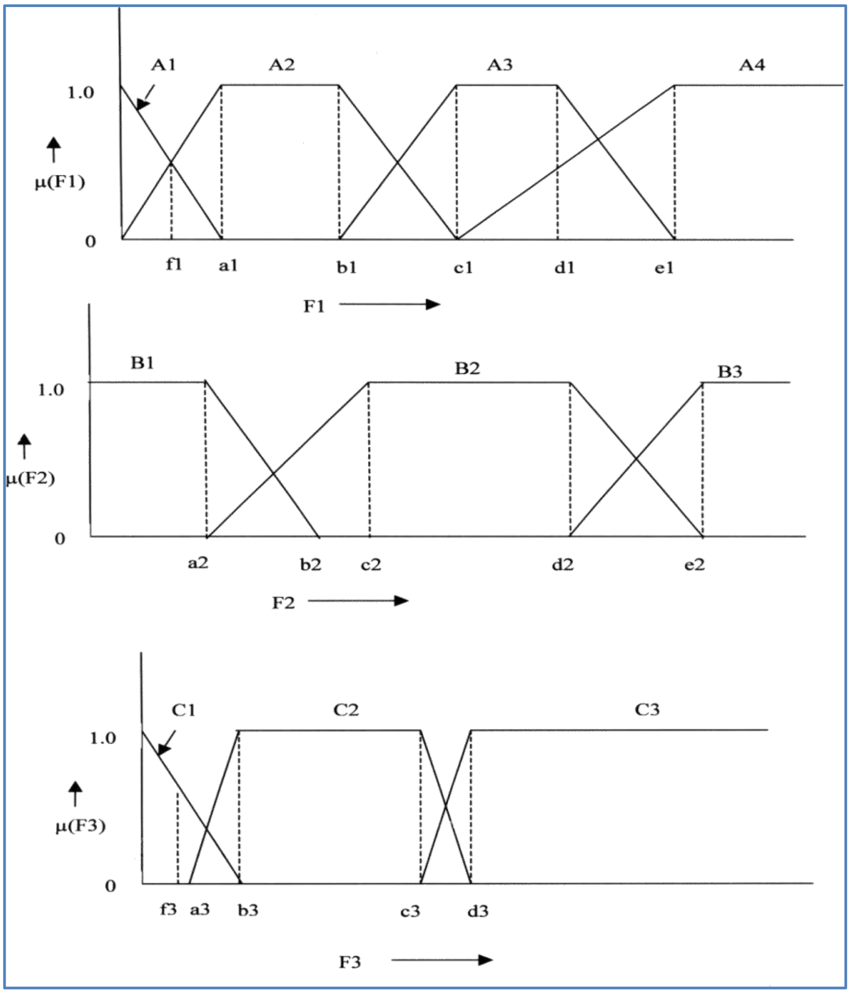


Figure 20 Trapezoidal Member Function

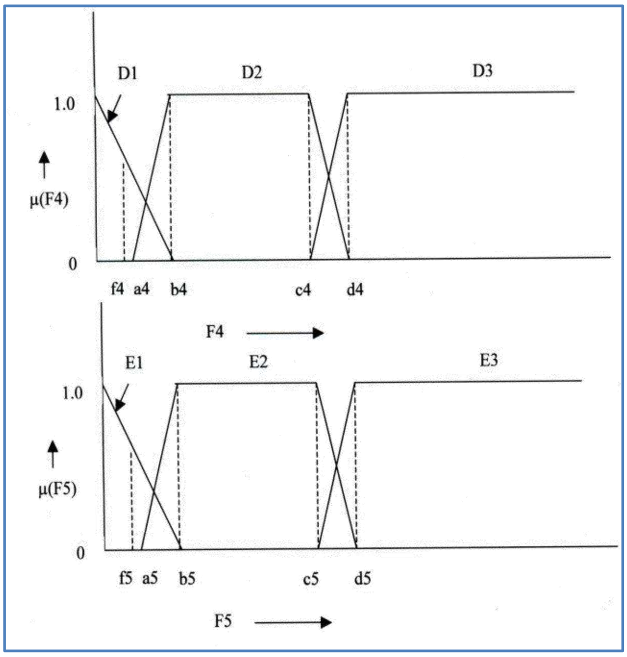


Figure 21 Triangular Member Function

I. Gaussian MF

In a similar way, the Gaussian membership function is defined as in following figure.

where α1 is the mean of the ith attribute value of *x*pi, ofclass c patterns and σi is the standard deviation.

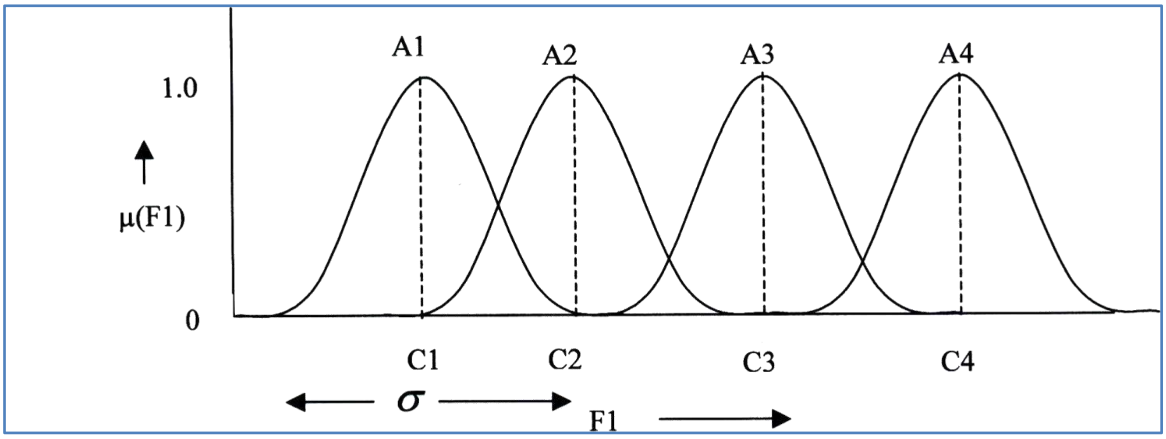


Figure 22 Gaussian Member Function

II. THE FOLLOWING FUZZY IF-THEN RULES ARE USED FOR BUILDING THE FUZZY RULE BASE LEADING TO A FUZZY EXPERT SYSTEM

Fuzzy Rule Base:

Rule-1 If F1 is A3 and F2 is B1 and F3 is C2 and F4 is D2, then CL1 with CF1
Rule-2 If F1 is A1 and F2 is B1 and F4 is D2, then CL2 with CF2.
Rule-3 If F1 is A4 and F2 is B1 and F4 is D2, then CL3 with CF3
Rule-4 If F1 is Al and F2 is B1, then CL4 with CF4
Rule-5 If F1 is A3 and F2 is B2 and F4 is D3, then CL5 with CF5.
Rule-6 If F1 is A2 and F2 is B1 and F4 is D3 and F5 is E2, then CL6 with CF6
Rule-7 If F1 is A4 and F2 is B1 and F4 is D3 and F5 is E2, then CL7 with CF7
Rule-8 If F1 is Al and F2 is B1 and F4 is D3, then CL8 with CF8
Rule-9 If F2 is B2 and F3 is C1 and F4 is D2 and F5 is E3, then CL9 with CF9
Rule-10 If F1 is A3 and F3 is C2, then CL 10 with CF 10
Rule-11 If F1 is A2 and F2 is B2 and F3 is C2, then CL11 with CF 11
Rule-12 If F1 is A3 and F2 is B1 and F3 is C1 and F4 is D3 and F5 is E2, then CL12 with CF12

III. OUTPUT FROM FUZZY INFERENCE SYSTEM

Rule- I output α1= min (fμ1a3, μf2b1, μf3c2, μf4d2)Rule-2 output α2 = min (μf1a1, μf2b1, μf4d2) Rule-3 output α3= min (μf1a4, μf2b1, μf4d2)

Rule-4 output α4= min (μf1a1, μf2b1, μf3c1)Rule-5 output α5 = min (μf1a3, μf2b2, μf4d3)

Rule-6 output α6= min (μf1a2, μf2b1, μf4d3, μf5e2) Rule-7 output α7= min (μf1a2, μf2b1, μf4d3, μf5e2) Rule-8 output α8= min (μf1a1, μf2b1, μf4d2)

Rule-9 output α9 = min (μf2b2, μf3c1, μf4d2, μf5e3)

Rule- 10 output α10= min (μf1a3, μf3c2)

Rule- 11 output α11= min (μf1a2, μf2b2, μf3c2)

Rule- 12 output α12= min (μf1a3, μf3c1, μf4d3, μf5e2)

The above rule outputs for p-numbers of patterns are used along with equation to identify the classes of the time series events.The Fuzzy Expert System provides the output for corresponding class with some absolute value. But there may be possibility of small variations in the absolute value of the output which create confusion for the automatic recognition system to take proper decision with respect to the class and no-class. Generally the one output among 12 values should be higher showing the corresponding class while others should be comparatively low. But the absolute values of the other 11 outputs (may be little bit higher) may create problem for drawing a decision boundary for class

$$y_i(t+1)=\begin{cases} y_i(t) & \text{if } f(x_i(t+1)) \geq f(y_i(t)) \\ x_i(t+1) & \text{if } f(x_i(t+1)) < f(y_i(t)) \end{cases} \quad (22)$$

and no-class. Thus in the proposed system, the corresponding outputs from FES are optimized using Particle Swarm Optimization technique which results nearly '1' for the class and nearly '0' no-class. This makes the designed automatic system more reliable and accurate to decide for classification of time-series data. The algorithm maintains a population of particles, where each particle represents a potential solution to the optimization problem. Each particle finds a position in the 'N' dimensional feature space and moves in the multidimensional feature space to find the best optimized result. The position of the particle is decided as follows:

xi= The current position of the ith particle
vi = The current velocity of the ith particle
Yi = The personal best position of the ith particleThen the particle position is adjusted as

Vi, k (t + 1) = WVi, k (t) + C1 r1, k (t)(Yi,k (t) - Xi,k (t) + C2 r2,k (t) - Xi,k (t)

xi (t + 1) = xi(t) + Vi (t + 1) (21)

where 'i' is the particle and k =1………N. *'w'* is the inertiaweight, *c1* and *C2* are the acceleration constants.
The velocity based on the following
(i) Fraction of the previous velocity
(ii)Distance of the particle from the personal best position(p-best).
(iii) Distance of the particle from best particle found (g-best).

IV. SIMULATION RESULTS

Different disturbances with corresponding classes are givenas follows

CL 1 → Normal
CL2 → Sag
CL3 → Swell
CL4 → Momentary Interruption (MI)
CL5 → Harmonics
CL6 → Sag with Harmonic
CL7 → Swell with Harmonic
CL8 → Flicker
CL9 → Notch + Harmonics
CL10 → Spike + Harmonics
CL11 → Transient (low frequency)
CL12 → Transient (high frequency)

The simulation results for class and certainty factor are depicted in Table.III and Table.IV respectively. The classes are defined against the time series data as mentioned above. For CL1 (Normal), the classification results obtained form FES (CL1) is 0.85. But for other patterns the class results are less than 0.3. Similarly for CL2 (Sag), the FES result (CL2) is 0.9, while other results are comparatively very low indicating non-class. For momentary interruptions the CL4 is 0.8 and for flicker CL8 is 0.75, which indicates classification. Similar observations are made with transient (high frequency) and transient (low frequency).Another index derived known as Certainty Factor (Table.4), which is also a measure of the classification results. For sag, the CF1 is 0.7 and for other patterns CF is less than even -0.2. For sag and swell, the CF2 and CF3 are 0.75 and 0.7 respectively. Similar observations are made with other time-series data where the Certainty Factors are highly +ve for classification and -ve for no-class.Table.V provides the support values which is the average classification value over 100 cases for each time series disturbances. For sag and swell, the support values are 0.85 (CL1). and 0.8 (CL2) respectively. For other disturbances the support values are depicted as in Table.5. Thus the support value provides the robustness of the FES system considering all possible conditions of the time series disturbances.

Table.6 provides the Class and Certainty Factors obtained from FES for trapezoidal and Gaussian membershipfunctions respectively. The Class obtained sag is 0.85 for Gaussian MF, while for trapezoidal is 0.80. Similarly the Certainty Factor obtained from Gaussian MF is 0.7, while form trapezoidal MF is 0.65. It is observed that the Gaussian MF provides better Class and Certainty Factors compared to trapezoidal MF. Table.VII provides the Particle Swarm Optimization (PSO) for the optimizing the class for different time-series data.

Table 3. Classification Factors for Different Classes

Time Series Data	CLI	CL2	CL3	CL4	CL5	CL6	CL7	CL8	CL9	CL1O	CL11	CL12
CF1	0.85	0.1	0.17	0.2	0.22	0.18	0.31	0.13	0.02	0.11	0.18	0.21
CF2	0.1	0.9	0.3	0.2	0.11	0.13	0.15	0.10	0.22	0.21	0.07	0
CF3	0.11	0.2	0.89	0.1	0.2	0.3	0.14	0.15	0.21	0.22	0.23	0.19
CF4	0.12	0.1	0.14	0.8	0.15	0.18	0.19	0.12	0.09	0.11	0.14	0.13

CF5	0.15	0.08	0.17	0.2	0.91	0.3	0.18	0.21	0.3	0.33	0.18	0.17
CF6	0.2	0.09	0.32	0.31	0.27	0.95	0.23	0.22	0.01	0.09	0.3	0.1
CF7	0.3	0.11	0.16	0.19	0.21	0.17	0.99	0.1	0.2	0.3	0.33	0.34
CF8	0.32	0.32	0.17	0.16	0.22	0.18	0.1	0.75	0.11	0.12	0.17	0.19
CF9	0.33	0.31	0.19	0.34	0.23	0.19	0.14	0.27	0.83	0.3	0.2	0.21
CF10	0.1	0.24	0.21	0.33	0.19	0.2	0.3	0.25	0.19	0.97	0.15	0.21
CF11	0.2	0.23	0.22	0.32	0.33	0.22	0.2	0.23	0.18	0.34	0.9	0.23
CF12	0.17	0.22	0.33	0.31	0.14	0.25	0.16	0.22	0.17	0.33	0.3	0.97

Table.4 Certainty Factors for Different Classes

Time-series data	CLI	CL2	CL3	CL4	CL5	CL6	CL7	CL8	CL9	CLIO	CL11	CL12
CF1	0.7	-0.13	-0.05	-0.02	-0.003	-0.04	0.1	-0.1	-0.22	-0.12	-0.04	-0.01
CF2	-0.11	0.75	0.1	-0.008	-0.1	-0.08	-0.06	-0.11	-0.01	0.002	-0.15	-0.22
CF3	-0.14	-0.04	0.7	-0.15	-0.04	0.06	-0.11	-0.1	-0.03	-0.036	-0.01	-0.06
CF4	-0.07	-0.095	-0.05	0.668	-0.045	-0.008	-0.019	-0.07	-0.1	-0.08	-0.13	-0.06
CF5	-0.125	-0.2	-0.1	-0.07	0.7	0.03	-0.09	-0.06	0.03	0.07	-0.09	-0.1
CF6	-0.06	-0.018	0.06	0.05	0.01	0.75	-0.03	-0.04	-0.27	-0.18	0.04	-0.1
CF7	0.01	-0.18	-0.13	-0.1	-0.08	-0.1	0.7	-0.2	-0.09	0.01	0.05	0.06
CF8	0.09	0.09	-0.07	-0.08	-0.01	-0.05	-0.14	0.56	-0.13	-0.12	-0.07	-0.04
CF9	0.03	0.01	-0.11	0.04	-0.07	-0.11	-0.1	-0.02	0.58	0.005	-0.1	-0.09
CF10	-0.19	-0.04	-0.07	0.05	-0.09	-0.08	0.02	-0.03	-0.09	0.75	-0.14	-0.07
CF11	-0.1	-0.07	-0.08	0.02	0.03	-0.08	-0.1	-0.07	-0.13	0.04	0.65	-0.7
CF12	-0.13	-0.07	-0.06	0.02	-0.16	-0.04	-0.14	-0.07	-0.13	0.04	0.01	0.74

Table.5 Support Values for Different(classes (100 cases each))

Time-series data	Support values
CF1	0.81
CF2	0.85
CF3	0.8
CF4	0.75
CF5	0.83
CF6	0.9
CF7	0.9

CF8	0.7
CF9	0.79
CF10	0.77
CF11	0.81
CF12	0.8

Table.6 Compression between Trapezoidal and Gaussian MF

Time-series data	Gaussian MF		Trapezoidal MF	
	CL	CF	CL	CF
CF1	0.85	0.7	0.80	0.65
CF2	0.9	0.75	0.85	0.69
CF3	0.89	0.7	0.81	0.62
CF4	0.8	0.668	0.74	0.60
CF5	0.91	0.7	0.82	0.62
CF6	0.95	0.75	0.85	0.68
CF7	0.99	0.7	0.88	0.64
CF8	0.75	0.56	0.69	0.51
CF9	0.83	0.58	0.75	0.52
CF10	0.97	0.75	0.87	0.68
CF11	0.9	0.65	0.79	0.59
CF12	0.97	0.74	0.89	0.71

Table.7 Results and Comparison from PSO Based Optimization

Time-series data	Gaussian MF PSO optimization		Gaussian MF Without optimization	
	CL	CF	CL	CF
CL1	0.97	0.95	0.859	0.75
CL2	1	0.93	0.95	0.8
CL3	1	0.93	0.95	0.75
CL4	0.98	0.97	0.877	0.73
CL5	1	0.91	0.97	0.75
CL6	1	0.97	0.95	0.77
CL7	1	0.92	0.99	0.70
CL8	0.97	0.91	0.8	0.76
CL9	0.99	0.95	0.95	0.7
CL10	1	0.99	0.98	0.8

CL11	1	0.899	0.93	0.79
CL12	1	0.93	0.99	0.79

3. CONCLUSION
A novel approach for time series data classification using Fuzzy Expert System (FES) is presented in this paper. The power disturbance signals are considered as time-series data for the proposed study. The time-series data is pre- processed through the advanced signal processing technique such as S-transform and the features obtained are fed to the designed FES for classification. Other indices for accurate classification such as certainty factors and support values are derived and the obtained results shows the robustness of the propose technique. Also the FES outputs are optimized using PSO for further enhancement of the classification results. The proposed technique is also tested for features

4. FEATURE SCOPE
The time-series data is pre- processed through the advanced signal processing technique such as S-transform and the features obtained arefed to the designed FES for classification.

5. REFERENCES
[1] S. Mitra, S.K. Pal, "Data Mining in Soft Computing Framework: A Survey", IEEE Trans.*Neural Networks*, vol. 13, pp3-14, Jan 2002.

[2] D. Buras et al, "Wavelet and neural structure: A new tool for diagnostic of power system disturbances,*" IEEE Trans*On Industry Applications, vol.37, No. 1, pp. 184-190, 2001.

[3] C.H. Lee, J.S. Lee, J.O. Kim, and S.W. Nam, "Feature Vector Extraction for the Automatic Classification of Power Quality Disturbances", 1997 IEEE International Symposium on Circuits and Systems, pp.2681-2685, 1997.

[4] B. Perunicic, M. Malini, Z. Wang, Y. Liu, "Power Quality Disturbance Detection and Classification Using Wavelets and Artificial Neural Networks," Proc. International Conference on Harmonics and Quality of Power, pp.77-82, 1998.

[5] A.M. Gouda, M.M.A. Salama, M.R. Sultan, and A.Y. Chikhani, "Power quality detection and classification using wavelet multiresolution signal decomposition," IEEE Trans On Power Delivery, No. 14, pp. 1469-1476, 1996.

[6] A.M. Gouda, S.H. Kanoun, M.M.A. Salama and A.Y. Chikhani, "Wavelet-based signalprocessing for disturbance classification and measurement, "IEEProc-Gener.Transm.Distrib, Vol. 149, No. 3, May 2002.

[7] A.M. Gouda, M.M.A. Salama, S.H. Kanoun, and A.Y. Chikhani, "Pattern Recognition Applications for Power System Disturbance Classification", IEEE Trans. On Power Delivery, Vol. 17, No.3, pp.677-682, 2002.

[8] A. Elmitwally, S. Farghal, M.Kandil, S.Abdelkader and M. Elkateb, "Proposed Wavelet- Neurofuzzy Combined System for Power Quality Violations Detection und Diagnosis," IEEE Proc-Gener.Transm.Distrib, Vol 148. No. 1, January 2001.

[9] L. Daubechies, Ten Lectures on Wavelets, SIAM, Phihodelphia,PA 1992.

[10] G. Strang and T.Q. Nguyen, Wavelets and Filter Banks, Wellesley-Cambridge Press, Cambridge MA, 1996.

[11] R.G. Stockwell, L. Mansinha, and R.P Lowe, "Localization of the Complex Spectrum: The S-Transform," IEEE Trans. Sig. Proc, vol. 44, No .4,1996, pp 998-1001.

[12] P.K. Dash, B.K. Panigrahi, G. Panda, "Power Quality-Analysis using S-transform", to appear in IEEE Trans. Power Delivery, 2002

[13] G.Livanos, N.Ranganathan, J.Jiang, "Heart sound analysis using the S-transform", IEEE Computer-Cardiology, Vol.27, 2000,pp.587-592.

[14] S. Mitra and S.K. Pal, "Multilayer Perceptron, Fuzzy Sets, and Classification, IEEE Trans. on Neural Networks, vol. 3, No. 5,pp 683 -697, 1992.

[15] S. Mitra and S.K. Pal "Fuzzy Multilayer Perceptron, Inferencing and Rule Generation", IEEE Trans on Neural Networks,vol.6,No1,pp5l-63,1995

6. AUTHOR'S PROFILE
Prasannajit Dash received his B.E. degree in Computer Science and Engg. In 1994 from Orissa Engineering College, Utkal University, Bhubaneswar, Odisha, India and the M.Tech. degree in Information Technology from College of Engineering and Technology, Bhubaneswar, Odisha, India. He was a senior lecturer with Department of Information Technology in Orissa Engineering College, Bhubaneswar from 2008 to 2012. He is assistant professor from 2012. His research interests include Image Processing, Data Mining & Warehousing, Embedded System and Internet Web Technology. Currently he is working on Support Vector Machine in field of Neural Networks