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INTELLIGENT FAULT DIAGNOSIS FOR BROKEN ROTOR BAR USING WAVELET PACKET SIGNATURE ANALYSIS

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By

SAHAR ZOLFAGHARI

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Master of Science

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DEDICATIONS

This thesis is dedicated to my husband, Arash Fattahi, who has been a constant source of support and encouragement during the challenges of graduate school and life. I am truly thankful for having you in my life.

This work is also dedicated to my parents, Akbar and Ferdoos Zolfaghari, who have always loved me unconditionally.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the Degree of Master of Science

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June 2016

Chairman : Associate Professor. Samsul Bahari Mohd Noor, PhD
Faculty : Engineering

Induction motors are one of the extensively used machines in many industries due to their high reliability and simple structure. However, owing to the high stresses that happen during operation, induction motors are subjected to unavoidable failures. Among numerous inevitable burdens happening in different part of induction machines, rotor faults are considerable priority as they cause precipitate deterioration and, secondary failures that lead to an unexpected shutdown and result in time-consuming and expensive maintenance. Therefore, intelligent fault diagnosis of induction machines is an ongoing research topic because of the complexity of the issue as well as progress in signal processing. As a sensitive signal processing wavelet-based analysis is implemented and some difficulties like, lack of frequency localization, selection of best basis, and fault index are addressed in this study.

Intelligent methods have concerted on sensing precise failure modes and recommending intelligent maintenance decisions based on the signatures collected through signal processing. Therefore, an advanced signal processing must be considered to derive the fault signature accomplish with a powerful decision-making technique. In this thesis, intelligent fault detection and severity classification of broken rotor bars in induction motor is carried out using the secondary data of stator current. The stator current was decomposed using wavelet packet decomposition. Then, the most precious faulty sub bands were identified after spectrum analysis. Next step to assist the most relevant feature extraction was the definition of mother wavelet function. In order to alleviate the time-variant characteristics of the wavelet packet transform coefficients, statistical parameters of wavelet packet coefficients are calculated. Some combinations of features extracted from wavelet packet signature analysis could design neural network trained, cross validated and tested input vector to not only elucidate the faultless from faulty condition, but also classify the number of broken rotor bars.

As an effective signal processing, the time-scale characteristic of wavelet packet transform fused with the frequency resolution of Fast Fourier Transform named as wavelet packet signature analysis. This transformation technique is suitable for locating

certain frequency components of a signal superimposed to fundamental frequency and associated with broken rotor bars. Then, the practically identical mother wavelet, db44, was selected based on standard deviation of wavelet packet coefficients. To make an intelligent decision without the presence of expert, in this research simple multi-layer perceptron NN-based fault classifier is proposed for fault diagnosis which is inexpensive, reliable, and non-invasive by employing best combination of wavelet statistical parameter after a simple feature selection technique as the input vector. The fault detection and classification algorithm is carried out under the unknown dataset and the off-line testing results with 98.8% classification accuracy indicate good reliability of the proposed method in identifying broken rotor bars severity.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk Ijazah Master Sains

INTELLIGENT DIAGNOSIS KEROSAKAN UNTUK BAR ROTOR BROKEN MENGGUNAKAN OMBAK PACKET SIGNATURE ANALISIS MENGGUNAKAN

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SAHAR ZOLFAGHARI

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Pengerusi : Profesor Madya Samsul Bahari Bin Mohd Noor, PhD
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Motor aruhan adalah salah satu mesin yang digunakan secara meluas dalam pelbagai industri kerana kebolehpercayaan yang tinggi dan strukturnya yang mudah. Walau bagaimanapun, oleh kerana tekanan yang tinggi yang berlaku semasa operasi, motor induksi mudah terdedah kepada kegagalan yang tidak dapat dielakkan. Dalam banyak kegagalan yang sering berlaku di bahagian yang berbeza dari mesin induksi, kerosakan pada pemutar adalah jenis kerosakan yang paling kritikal kerana ia menyebabkan mendakan kemerosotan dan kegagalan kedua yang boleh membawa kepada penutupan yang tidak dijangka dan kesannya memakan masa yang panjang untuk pembaikan pada masa sama kos penyelenggaraan yang tinggi. Oleh itu, 'intelligent fault' diagnosis mesin induksi adalah satu topik penyelidikan yang masih aktif kerana kerumitan kerosakan tersebut di samping kemajuan dalam pemprosesan isyarat. Isyarat sensitif berasaskan wavelet pemprosesan analisis dilaksanakan dan beberapa masalah seperti kekurangan kekerapan penyetempatan, pemilihan terbaik asas, dan indeks kesalahan ditangani dalam kajian ini. Kaedah Pintar telah bersepadu terhadap penderiaan mod kegagalan tepat dan mencadangkankeputusan penyelenggaraan pintar berdasarkan tandatangan yang dikumpulkan melalui pemprosesan isyarat.

Oleh itu, kemajuan pada pemprosesan isyarat perlu dipertimbangkan agar dapat mengenalpasti kesalahan-kesalahan dengan menggunakan teknik khas dan terbaik.Di dalam tesis ini, kesalahan pintar pengesanan dan klasifikasi tahap kerosakan bar pemutar di dalam motor induksi dijalankan menggunakan data sekunder pemegun semasa. Pemegun semasa diekstrak menggunakan paket ombak penguraian. Seterusnya sub band rosak telah dikenal pasti selepas melalui analisis spektrum. Langkah seterusnya untuk membantu pengekstrakan ciri yang paling relevan ialah definisi ombak ibu fungsi. Dalam usaha untuk mengurangkan ciri-ciri masa-varian paket ombak mengubah pekali, parameter statistik pekali paket ombak dikira. Diantara gabungan ciri yang diekstrak daripada ombak analisis tandatangan paket ialah kebolehan mereka bentuk neural rangkaian yang terlatih, pengesahan dan vektor input diuji untuk bukan sahaja menjelaskan tahap kritikal kerosakan daripada keadaan rosak, tetapi juga

mengklasifikasikan bilangan bar pemutar yang patah.

Sebagai pemprosesan isyarat yang berkesan, ciri-ciri masa skala paket ubahan wavelet disatukan dengan dengan resolusi frekuensi Fourier Transform Fast dinamakan sebagai tandatangan paket ombak analisis. Teknik transformasi ini sesuai bagi mengesan komponen frekuensi tertentu isyarat yang ditekankan kepada frekuensi asas dan yang berkaitan dengan bar pemutar patah. Kemudian, ombak ibu, db44, telah dipilih berdasarkan sisihan piawai ombak pekali paket. Untuk membuat keputusan yang bijak tanpa kehadiran pakar , kesalahan pengelas berasaskan NN yang mudah adalah dicadangkan untuk diagnosis kerosakan yang dapat dilakukan dengan murah,kebolehpercayaan yang tinggi, dan tidak invasif dengan menggunakan kombinasi terbaik ombak parameter statistik selepas teknik pemilihan ciri semudah vektor input. Kesalahan pengesanan dan pengelasan algoritma yang dijalankan di bawah set data yang tidak diketahui dan di luar talian telah menghasilkan 98.8% ketepatan .Ini menunjukkan kebolehpercayaan yang tinggi bagi kaedah yang dicadangkan di dalam mengenalpasti tahap kerosakan pada bar patah pemutar.

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This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Master of Science.The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BP	Back-propagation
CBM	Condition-Based Monitoring
CI	Computational Intelligence
CV	Cross-Validation
DWT	Discrete Wavelet Transform
FFNN	Feed forward neural network
GUI	Graphical Unit Interface
IM	Induction Motor
LOO	Leave-One-Out
MCSA	Motor Current Signature Analysis
MLP-NN	Multi-layer Perceptron Neural Network
NEMA	National Electrical Manufacturers Association
MRA	Multi-resolution Analysis
RMS	Root Mean Square
RMSE	Root Mean Square Error
STFT	Short-Time Fourier Transform
SCIM	Squirrel-cage Induction Motor
StD	Standard Deviation
StD-WPC	Standard Deviation Of Wavelet Packet Coefficients
WPSA	Wavelet Packet Signature Analysis
WPT	Wavelet Packet Transform
WPD	Wavelet Packet Decomposition
WPR	Wavelet Packet Reconstruction
WPC-SCS	Wavelet Packet Coefficients of Synchronized Current Signal

LIST OF SYMBOLS

db	Daubechies
f_b	Broken Rotor Bar Frequency
f_s	Fundamental Frequency
n_s	Synchronous Speed
n	Rotor Speed
N_s	Number of Samples
S_f	Sampling frequency
s	Slip

CHAPTER 1

INTRODUCTION

1.1 Background

The initiation of induction motors by Galileo Ferraris in 1885 and further improvement by Nikola Tesla in 1888 provided industrial process engineers with a simple and rugged mechanism for electromechanical conversion [1]. Induction motors are basic segments in commercially accessible equipment and industrial procedures because of being cost effective and their robust performance. Among distinctive sorts of electric engines, more than 60% of the electrical energy produced is because of induction motors contribution [2]. In Europe, it has been reported that 87% of 96.2% AC motors shipment are devoted to three-phase induction motors [2]. Electric motors have transformed the form of human living and shaped in the convenient lifestyle. In every item that we consume or utilize these days or in any facilities that we profit, there is an electric motor involved [3]. Therefore, electrical machine condition monitoring assumes a critical part in modern industries.

An AC induction motor consists of two key parts: rotor and stator. The rotor core is affixed on a steel shaft to form a rotor congregation. The stator is mounted in the middle of the frame and the rotor turns interior the stator. There is a slight air gap separating rotor from the stator. The name induction motor is used because there is no direct physical and electric connection between stator and rotor and electricity is induced in the rotor by magnetic induction rather than electric connection [4]. Nevertheless, induction machines are subjected to the unavoidable burdens in the practical applications.

The rotor is subjected to different types of tensions that severely affect its normal condition and consequently create failures in it. In addition, localized rotor heating around the broken bars may progressively break the adjacent bars and the motor will be finally out of service. Rotor bar breakages rarely cause immediate failures. However, it can become quite a dangerous fault since no clear symptom is reflected over the machine behavior in the early stages. In the case with enough broken rotor bars, the motor possibly will not start as it could not develop sufficient accelerating torque [5]. Nonetheless, the presence of broken rotor bars precipitates deterioration in other components that can lead to an unexpected breakdown of the machine and result in time-consuming and expensive maintenance. Therefore, detection of broken bar faults is a crucial issue.

It is well known that fault detection in induction machine at an early stage may not only lessen maintenance time and minimize breakdowns but also prevent propagation of the fault or slow down its escalation to severe degrees. Therefore, a health monitoring or intelligent condition-based monitoring program which can diagnose such a failure of electrical machines has received extensive consideration for many years. Accordingly, a signal acquired from one of the prevalent condition monitoring techniques need to be evaluated through an advanced signal processing method to generate fault-representative features for the purpose of decision making. Signal processing is a mathematical transformer used for fault detection and diagnostics, whose aim is to convert the raw complex signal to a more understandable signal which enhances the dominant features of fault signature for decision-making. The three major categories of the signature extraction techniques for the fault diagnosis are time domain, frequency domain and time-frequency domain techniques [6].

Time domain-feature extraction techniques include statistical methods, time synchronous averaging methods and other methods. The most frequently used time domain statistical features are root-mean-square, skewness, kurtosis, crest factor and so forth. Time domain features are useful for machinery fault diagnosis, especially for short-duration feature detecting. However, clear symptoms of the fault still may not be directly visible in the time domain. Literally, each fault is associated with the presence of a explicit harmonic in the spectrum. The frequency domain is another signal processing tool which describes the frequency information of a signal and extracts the energy of a particular frequency component. Motor Current Signature Analysis (MCSA) was extensively used based on the monitoring of the sideband components at (1 $)f$, where f_s is the fundamental frequency and s is the slip [7][8]. When the waveforms examined are stationary or periodical, feature extraction using Fourier transform produces good results, but they are not suitable for non-stationary signals.

In an effort to correct this insufficiency, as reported in Wavelet Toolbox ™, Dennis Gabor adapted the Short-Time Fourier Transform (STFT). The difficulty with STFT is that the information obtained with limited precision is determined by the size of the window. This means the chosen time window with a particular size is same for all frequencies. Therefore, the time and frequency resolutions cannot increase simultaneously using STFT. Experimental diagnostic via spectral analysis is more complicated due to the subsequent reasons [9]:

- the precise measurement of slip and fundamental frequency,
- the simultaneous presence of numerous transitory and other various kinds of non-stationary characteristics such as noises, load torque fluctuations, voltage oscillations, and abrupt changes, and
- discrimination of several faults frequency span for different categories of faults may exist at the same time [10].

Hitherto, many non-stationary signal processing methods have been suggested in the literature to those published after the 1990s [11]. A straight forward solution for these difficulties is Discrete Wavelet Transform (DWT), because of zooming and adaptive windowing capability. Frequency resolution and time localization nature of time-scale analysis have been used to extract and describe a more precise behaviour of the stator current signal which is widely used for electrical machine diagnosis [10]. However, DWT iteratively decomposes the approximation signals of lower frequencies but does not further work on the detail signals of higher frequencies. Therefore, due to the coarse decomposition of the high-frequency components in the signal, the resolution in the high-frequency region is quite poor. As a subtle multi-resolution analysis algorithm, Wavelet Packet Transform (WPT) can multi-decompose the signal into multi-levels and provide the different frequencies to obtain the localized impulse signals.

1.2 Problem Statement

According to the background, the specific issue is designing and developing a sensitive signal processing with a great concern of no-load condition. As a sensitive signal processing method, wavelet transform is a time-scale representation of a signal. Moreover, most time-varying machine operational conditions lead to non-stationary characteristics which contain rich information about machinery health condition. The way wavelet analysis localizes signal's information in the time–scale plane makes it especially more advisable in processing the non-stationary signals [12]. Therefore, conclusive fault features can be extracted from these signals for early identification of faults through the identification of time variant features superimposed at different scales. However, because wavelet transform is a time-scale domain technique, it does not provide frequency information on characteristic feature components. Consequently, one of the important point which needs to be affirmed in wavelet packet-based techniques is the fact that frequency order is not the same as the node order due to down sampling [13] [14]. Moreover, in order to choose the most appropriate subset instead of investigating all wavelet packet coefficients, care must be taken to manage the computational complexity, especially in practical circumstances. The next important point is to determine which mother wavelet has more distinctive wavelet coefficients for different conditions in fault identification as an ill-selected base may return false diagnosis result.

The next challenge is extracting the most appropriate feature indices which play an essential role in accomplishment of the performance of intelligent condition monitoring. In contrast to many researches in which only one feature extracted , this research mainly focuses on finding perfectly permissible features for broken rotor bar fault detection , in order to examine the arbitrary working conditions with focus on no-load case [15]. Different topologies of neural networks have been exploited to solve complex problems in various areas of almost all sophisticated fault classification tools. However, a tradeoff exists so that increasing the complexity the fault detection capability is also increased together with computational cost [16]. Therefore, one more step is taken toward an intelligent fault-severity classification with small set of data, by utilizing generalized, simple, small-sized and efficient multi-layer perceptron neural network.

1.3 Aim and Objectives

The aim of this study is focused on the application of an effectiveness signal processing through linking the strong points of both the time-scale and frequency domain techniques, a unified Wavelet Packet Signature Analysis (WPSA) technique that pinpoints the fault signature in special frequency bands with suitable sensitivity and a great concern of no load cases. Moreover, the necessity of sufficient and efficient maintenance policies according to the literature review on intelligent decision-making algorithms for BRBs fault classification and severity identification in induction motor could be essential. Therefore, the following objectives were pursued in this research work.

i. To define the exact localized fault frequency sub-bands based on WPSA associated with the most appropriate mother wavelet through investigating the ability of different types of wavelet functions for BRB detection.

ii. To develop statistical features extracted from wavelet packet coefficients of stator current signal (WPC-SCS) for BRB fault detection with a great concern of no load condition.

iii. To classify fault-severity of BRBs in arbitrary working conditions using simple multi-layer perceptron neural network (MLP-NN).

1.4 Thesis Scope

This thesis provides a comprehensive study on broken rotor bar detection and severity classification in assorted load in squirrel-cage induction machines. In the first step, the wavelet packet transform was applied to the stator current signal which has been acquired by previous research [17]. In order to enhance the effectiveness of defect feature extraction, FFT combines with WPT which can be called as WPSA in the current study. WPSA can accurately differentiate between healthy and faulty machines in more concentrated fault-related depths and nodes. Next step to assist the most relevant feature extraction was the definition of mother wavelet function. Finally, in order to examine the effect of load variations and fault severity on the fault signatures, the statistical parameters of wavelet packet coefficients along with the slip speed formed the input vector to the classifier. On the one hand, detection of fault-oriented sub bands and classification of fault severity on the other hand make the proposed algorithm clearly different with the base research in 2011 [17] with same database.

1.5 Research Contributions

The main contributions of this work are as follows:

1. In the signal processing step, exact localized fault frequency sub bands is determined based on the combination of WPD and FFT named as WPSA under arbitrary load conditions.

2. In the feature extraction step, wavelet statistical parameter of transformed stator current is applied after an advanced signal processing technique as an input vector to NN.

In the classification step, a straightforward, small-sized, low-cost multi-layer perceptron neural network (MLP-NN) is used in order to have an intelligent, reliable, and non-invasive classifier.

1.6 Thesis Organization

The dissertation is organized as follow: In Chapter 2, the required background knowledge for the rest of the thesis is introduced briefly. The mechanical structure of an AC induction motor is described in particular also; the induction motor's performance which causes broken rotor fault has been discussed. To deal with this serious malfunction and the diagnosis of fault in an early stage, data processing along with the related difficulties and artificial intelligent decision-making will be highlighted as main subsections of intelligent condition-base monitoring, which have been used for induction motors fault detection and severity classification.

The gaps in the field of BRB fault detection and classification will be fulfilled by manipulated methodology in Chapter 3 to extract a reliable method that allows a better separation of anomaly cases from the normal operating condition modes of the motor and severity assessment. In Chapter 4, the findings of the research will be presented highlighting the role of broken rotor bar detection based on application of wavelet packet decomposition integrated with Fast Fourier transform to track the most appropriate depth and nodes. These results can be used to optimize the scheduling and clustering, and support the maintenance decision making, by implementing a simple cost-effective multi-layer perceptron neural network. Finally, the conclusion of the thesis and possible areas for future research will be presented in Chapter5.

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APPENDICES

A. Wavelet Packet Signature Analysis MATLAB Command Line

```
clear all;close all;clc;

%% Simple sinusoids signal

f=50;

t=0:(1/2000):(1-(1/2000));

y=10*sin(2*pi*f*t);

%% Wavelet Packet Transform

Level=5;

wpt=wpdec(y,Level+1,'db44');%wavelet packet tree

for node = 0:2^Level;

        data = wprcoef(wpt,[Level node]);%wavelet packet
Reconstructed coefficients

        FFT;

     MAX= max(AMPLITUDEmat(:,2));

     [m n]=find( AMPLITUDEmat(:,2)==MAX);

     MaxFund(node+1,1)= AMPLITUDEmat(m,1);

     MaxFund(node+1,2)= AMPLITUDEmat(m,2);

End

MAX2= max(MaxFund(:,2));

[p q]=find(MaxFund(:,2)==MAX2);

clear node

node=p-1;

%% Plot
```

```
f=figure;
subplot(1,3,1)
plot(y);
title('Original Signal')
%% Wavelet Packet Transform
wpt = wpdec(y,Level+1,'db44');
data = wprcoef(wpt, [Level node]);
subplot(1,3,2)
plot(data);
title('Reconstructed Signal')
FFT %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
samptime  = (1/2000);
N2 = length(data);
[FFTData, amp, ang, freq, NFFT] = fft_signal(data,samptime);
x = NFFT/2+1;
amp=amp';
for j = 0:1;
for i = 1:x;
        AMPLITUDEmat(i,1) = freq(i,1);
        AMPLITUDEmat(i,j+1) = amp(i,1);
End
End

for k=1:x
    plotAm(k,1)=AMPLITUDEmat(k,1);
    plotAm(k,2)=AMPLITUDEmat(k,2);
```

```
End

subplot(1,3,3)

plot (plotAm(:,1),plotAm(:,2));

title('FFT')

xlabel('Frequency (Hz)')

ylabel('Amplitued (A)')

clear AMPLITUDEmat FFTD at a MAXMAX2 Max Fund N2 NFFT...
amp ang f data freq i j k m n p plot Amq samptimet wpt
x

fft_signal%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [FFTData, amp, ang, freq, NFFT]=fft_signal(data,samptime)

    options.sampFreq = 1/samptime;

    N = 2^(nextpow2(length(data)));

    N2 = length(data);

    FFTData = fft(data,N);

    amp = abs(FFTData) * 2/N2;

    ang = angle(FFTData);

    NumUniquePts = ceil((N+1)/2);

    amp = amp(1:NumUniquePts);

    freq=(0:NumUniquePts-1)' / (NumUniquePts)*(options.sampFreq/2) ;

    NFFT=N;

End
```

B. Mother Wavelet MATLAB Command Line

```
close all;

clear all;
```

```
clc;

%% Load Data

% Stator current signal for different loads,as an example NoLoad   condition


load Hnoload1 %Healthy No Load condition, it is also tested for F1NoLoad, F2NoLoad, F3NoLoad

y = Hnoload1;

load MotherwaveletPacket

Level= 5; %(5,1)[31.25-62.5]

Depth= 1;

%Wavelet packet calculation based on different mother wavelet

for motherorder = 1:82;

  wpt=wpdec(y,Level,MotherwaveletPacket{1,motherorder}); % WPD of signal y with level and mother wavelet

  cfs = wpcoef(wpt,[Level Depth]);

  StD=std(cfs);% Standard Deviation of WPD coefficients

  MW(motherorder,1) = MotherwaveletPacket(1,motherorder);

  MW{motherorder,2} = num2str(StD);

End


S1 = char(MW{:,2});

clear ft Frequency Sampling y mother order
```

C. Feature Extraction MATLAB Command Line

```
clear all;close all;clc;

%% Stator current signal for different loads,as an example NoLoad   condition

load F1NoLoad;% 1BRB of No Load condition, it is also tested for HNoLoad, F2NoLoad, F3NoLoad
```

```
for i=1:20;
  y   = F1NoLoad(:,i);
  wpt = wpdec(y,11,'db44');
  cfs = wpcoef(wpt,[9 21]); %wavelet packet coefficients
  X   = cfs;
%% Wavelet statistical parameters
RMS = rms(X);% Root-mean-squares
RSSQ = rssq(X);% Root-sum-of-squares
KURTOSIS = kurtosis(X);
SKEWNESS = skewness(X);
Mean = mean(X);
PtoP = peak2peak(X);
PtoRMS = peak2rms(X);% CrestFactor
LogDectect = exp(mean(log(abs(X))));
PAPR = ((max(X))^2)/((rms(X))^2);% peak-to-average power ratio(dB)
ShapeFactor = rms(X)/mean(X);
ImpulseFactor = max(abs(X))/mean(X);
Energy = sum(X.^2);
StD = std(X); %Standard Deviation
Moment = moment(X,6); %sixth order centrl moment
ResultTime(i,1)  = RMS;
ResultTime(i,2)  = RSSQ;
ResultTime(i,3)  = KURTOSIS;
ResultTime(i,4)  = SKEWNESS;
ResultTime(i,5)  = Mean;
```

```
ResultTime(i,6)  = PtoP;
ResultTime(i,7)  = PtoRMS;
ResultTime(i,8)  = LogDectect;
ResultTime(i,9)  = PAPR;
ResultTime(i,10) = ShapeFactor;
ResultTime(i,11) = ImpulseFactor;
ResultTime(i,12) = Energy;
ResultTime(i,13) = StD;
ResultTime(i,14) = Moment;
i=i+1
Ed

clear RMS RSSQ KURTOSIS SKEWNESS Mean...
PtoP PtoRMS PAPR ShapeFactor ImpulseFactor...
Root X Margin Factor LogDectect Energy StD Moment
```

D. MultiLayer Perceptron NN-based Classifier MATLAB Command Line

```
 clear all;close all;clc;
%% Load Data
load NN_Input; %is defined based on the best combination of features in various loads
Inputs = NN_Input';
load fault_type;
%% Define training set
in=[];
for i=1:15
    temp=[Inputs(i,:);Inputs(20+i,:);Inputs(40+i,:);Inputs(60+i,:)]';
```

```
    in=[in temp];
End

%% Define targets
A =[0.1 0.1 0.1 0.9]';
B =[0.1 0.1 0.9 0.1]';
C =[0.1 0.9 0.1 0.1]';
D =[0.9 0.1 0.1 0.1]';
temp = [repmat(A,1,1) repmat(B,1,1) repmat(C,1,1) repmat(D,1,1)];
Target=repmat(temp,[1 15]);
%% Create a Fitting Network
hiddenLayerSize = 13;
TF={'tansig','purelin'};
trainFcn='trainlm';   %Levenberg-Marquardt backpropagation.
net.performFcn = 'msereg';  %'msereg' improve generalization
net = feedforwardnet(hiddenLayerSize,trainFcn);
CVO = cvpartition(fault_type,'Leaveout');%Create cross validation partition for data
err = zeros(CVO.NumTestSets,1);
cp = classperf(fault_type);%Evaluate performance of classifier
single_error = zeros(1,CVO.NumTestSets);
numNN = 10;%Multiple Neural Network
nets = cell(1,numNN);
for i = 1:numNN
   disp(['Training ' num2str(i) '/' num2str(numNN)])

for j = 1:CVO.NumTestSets
```

```
%% Train the Network
    trIdx = CVO.training(j); % training Index
    trIdx = trIdx';
    trainInputs = in(:,trIdx);
    trainTargets = Target(:,trIdx);
    nets{i} = train (net, trainInputs,trainTargets);

%% Test the Network
    teIdx = CVO.test(j); % test Index
    teIdx = teIdx';
    testInputs = in(:,teIdx);
%% Classification
    class = classify(in(:,teIdx)',in(:,trIdx)',fault_type(trIdx,:));
    classperf(cp,class,teIdx);%To modify properties
    err(j) = sum(~strcmp(class,fault_type(teIdx,:)));
    single_error(1,j) = cp.ErrorRate;
    single_correct(1,j)= cp.CorrectRate;
end
end
get(cp);
cp.ErrorRate;
cp.CorrectRate;
mean_error = mean(single_error);
mean_correct = mean(single_correct);
STD_correct = sqrt(var(single_correct));
```

```
%% TEST and Evaluate the Network with TEST DATA

%Load Test Data

in_ts=[];

perfs = zeros(1,numNN);

y2Total = 0;

for i=1:5

    temp_ts=[Inputs(15+i,:);Inputs(35+i,:);Inputs(55+i,:);Inputs(75+i,:)]';
    in_ts=[in_ts temp_ts];

End


targets=repmat(temp,[1 5]);

for i=1:numNN

  neti = nets{i};

  Tsoutputs = neti(in_ts);

  perfs(i) = mse(neti,targets,Tsoutputs);

  y2Total = y2Total + Tsoutputs;

  PlotResults(targets(:),Tsoutputs(:),'Test Data');

  saveas(subplot(2,2,4),'Test Data.png')

End


y2AverageOutput = y2Total / numNN;

perfAveragedOutputs = mse(nets{1},targets,y2AverageOutput);

Mean_iter=[cp.ErrorRate    cp.CorrectRate    mean_error    mean_correct    STD_error
perfAveragedOutputs];

save Mean_iter;


result=[targets; y2AverageOutput]';

save result
```

```
%% Test Correct class
testCor = 100 * length(find(targets.*y2AverageOutput > 0)) / length(targets);
fprintf('TestCorrect class = %.1f %%\n',testCor/4)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
PlotResults
function PlotResults(t,y,name)

    figure;
    % t and y
    subplot(2,2,1);
    plot(y,'k');
    hold on;
    plot(t,'r:');
    legend('Outputs','Targets');
    title(name);
    % Correlation Plot
    subplot(2,2,2);
    plot(t,y,'ko');
    hold on;
    xmin=min(min(t),min(y));
    xmax=max(max(t),max(y));
    plot([xmin xmax],[xmin xmax],'b','LineWidth',2);
    R=corr(t',y');
    %title(['R = ' num2str(R)]);
    % e
    subplot(2,2,3);
```

```
    e=t-y;
    plot(e,'b');
    legend('Error');
    MSE=mean(e.^2);
    RMSE=sqrt(MSE);
    title(['MSE = ' num2str(MSE) ', RMSE = ' num2str(RMSE)]);

    subplot(2,2,4);
    histfit(e,50);
    eMean=mean(e);
    eStd=std(e);
    title(['\mu = ' num2str(eMean) ', \sigma = ' num2str(eStd)]);

End
```

BIODATA OF STUDENT

Sahar Zolfaghari was born in Isfahan, Iran. She got his B.S. degree in Electrical and Electronic Engineering from Islamic Azad University, Najaf Abad branch. After graduating, she started to work as Instrumentation Engineering on Oil and Gas field projects of the PetroSanat Company, Iran for about 5 years. In 2013, she joined Universiti Putra Malaysia to continue her study and she is currently pursuing Master of Science in Department of Electrical and Electronic Engineering.

LIST OF PUBLICATIONS

Zolfaghari, Sahar, S.B.Mohd Noor, Norman Mariun, Mohammad Hamiruce Marhaban, Mohammad Rezazadeh Mehrjou, and Mahdi Karami. "Broken rotor bar detection of induction machine using wavelet packet coefficient-related features." *In Research and Development (SCOReD), 2014 IEEE Student Conference on, pp. 1-5.* IEEE, 2014.

S. Zolfaghari, et al, “Wavelet-Based Analysis of MCSA for Fault Detection in Electrical Machine,” *in Wavelet Transform and Some of Its Real-World Applications, InTech, 2015*

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