The University of Queensland

ENGG4802

Project Proposal

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Contents

1 Topic Definition

1.1 Motivation

Power systems are integral in the supply and distribution of electricity for use in all facets of society. As a result, it is important to quickly detect and classify any faults in order to prevent catastrophic and potentially permanent failures. Although there are already many pieces of fail-safe equipment and systems put in place to control the severity of a potential fault, real-time event detection and classification is extremely important in gaining insight to the nature and cause of a fault.

Given that a power system has many sub-systems which all have specific purposes, there are many areas where faults can occur. These can range from equipment failures, such as regular deterioration over time or faulty parts, to faults due to the external environment, such as lightning strikes or tree branches brushing up against transmission lines, all of which will produce a certain disturbance signature in the waveform of the power system.

If undetected, faults in a power system are signs of and can lead to permanent failures in the system. One consequence of a permanent failure is power outages in downstream services, which would be detrimental to society if such services are essential. However, a failure can also result in the the breakdown of multiple components that make up a power system whose recommissioning and replacement can be time consuming and extremely costly.

Energy distributors and retailers have an obligation and responsibility to provide energy to consumers at determined standards. When these standards are not met, distributors are required to make guaranteed service level (GSL) payments to consumers, whose value depends on the type of interruption and its frequency and duration.

For the 2018-19 financial year, the Queensland Competition Authority (QCA) reported that Ergon Energy and Energex paid \$1.2 million and \$3.4 million in GSL payments respectively [1]. From this value, 94.6% and 93.6% of the respective payments came from reliability interruptions. Consequently, being able to detect and recognise the cause of an interruption will potentially reduce costs to distribution companies, but also reduce the duration of faults, resulting in higher reliability for consumers.

1.2 Project Outline

The proposed project is the automatic detection of events in a power system caused by faults with data provided by power quality meters. In addition to this, the classification of a detected fault will also be considered. This is due to the many types of faults (steady-state, transient, intermittent) caused by various events and resulting in varying severity as a consequence. A successful automatic detection and classification of a fault and its cause is extremely beneficial to power systems management as it prevents catastrophic failures and costly replacement of equipment as well as reducing the time taken to determine the cause of the fault.

1.2.1 Objectives

Data will be collected from a power quality meter connected to an aged transformer located in a substation at the University of Queensland St Lucia campus. A successful project details the reading and analysis of large amounts of data from the meter which results in a reliable high rate of detection any events. There are currently many algorithms being implemented to automatically detect events in power system waveforms - including digital signal processing methods and neural networks. These methods differ and as a result, will have certain advantages and disadvantages compared with each other. A decision making criteria will be created in order to determine the most successful algorithm(s) and will be chosen for the final demonstration. The majority of the programming and computation will be completed with Python.

After a high rate of detection is achieved, the fault is then classified into one of three main disturbance categories: Steady-state, Transient or Intermittent. Within these subsections, the specific type of fault will be classified from analysing and researching waveform signatures of known disturbances. A detected fault will be classified using the standards and indices as defined by the the Institute of Electrical and Electronics Engineers (IEEE) Std. 1159-2009 [2].

Depending on its cause, some faults may be self-clearing and never occur again. However, some of these self-clearing faults are incipient to permanent failures which will require the operation of protective devices such as breakers. As a result, it is extremely important to classify not only the type of power system fault, but also whether such fault will result in costly permanent failures. Analysis and research into various causes of faults will be conducted in order to further define and classify the consequence of any particular power system event.

2 Background

2.1 Power Quality Disturbances

A non-disturbed power system should supply three-phase AC (sinusoidal) voltage and current to consumers. When faults in the system occur, we can see interference in one or more of the provided waveforms. Power Quality disturbances are separated into three main categories as characterised by IEEE 1159-2019[2].

Disturbance Type	Characteristics	Potential Causes and Consequences
Steady-state	**$>$ 1 min**	
Over-voltages & Under-voltages	One or more phases of voltage is higher than 1.1pu or lower than 0.9pu.	Load variations or system switching.
Sustained Interruptions	Supply voltage is reduced to less than 0.1pu.	Typically permanent - will require operation of protective devices or manual intervention.
Voltage & Current Imbalances	Refers to the ratio between the magnitudes of negative and positive sequence components of a three phase system.	Commonly occurs when multiple single phase loads are unbalanced on a three phase system.
Transient	**$<$ 1 min**	
Voltage sags & swells	One or more phases of voltage is higher than 1.1pu or lower than 0.9pu.	High starting currents from load energisation/switching or faulty physical connections/equipment.
Interruptions	Supply voltage is reduced to less than 0.1pu.	Faulty equipment, power systems faults.
Impulsive transients	Sudden, large and unidirectional changes in a waveform.	Lightning Strikes.
Oscillatory transients	Waveforms exhibit a rapid increase in frequency, changing polarity with each period before the disturbance clears.	Capacitor/cable switching.
Frequency variation	Deviation from the fundamental frequency.	Imbalance between load and generator capacity.
Intermittent	**$<$ 25 Hz**	
Flickering	Small fluctuations in the voltage waveform.	Arcing, loads with reactive cyclic variations.

Table 1: Disturbance Types & Characteristics

2.2 Existing Event Detection Methods

2.2.1 Waveform Abnormality Methods

There are many types of waveform abnormality detection methods, but the general method is:

1. Calculate the differential waveform between two periods
2. Determine if the differential waveform exceeds a certain threshold for a disturbance to have occurred

For some chosen threshold, varieties of this method can include:

Description	Disturbance Criteria	Notes
The difference of two consecutive cycles calculated for each sample	Magnitude and duration of disturbance	Choosing a meaningful threshold value can be difficult
The difference of the square of two consecutive cycles calculated for each sample	Absolute value of difference	Squaring a sample not technically sound and can remove some sensitivities
RMS of the difference of two consecutive cycles calculated	Percentage difference between 'healthy' RMS value	Considers the RMS value of a whole cycle and disturbances which last less than a cycle may not be detected

Table 2: Waveform Detection Method Variations

The above methods are computationally simple, but have drawbacks in the choosing of thresholds and detection sensitivity. Furthermore, choosing two consecutive cycles may not detect steady-state events such as over- and under-voltages.

A hypothesis test based detection method is detailed by Li et al. [3] by considering the expected random noise of a (current) waveform. Consider two hypotheses, H_0 being the waveform of a power system under normal operation and H_1 being the waveform of a power system under abnormal operation:

$$H_0 : i(t) = \sum_{k=0}^{K} A_k \cos(2\pi k f_r t + \phi_k) + n(t)$$

$$H_1 : i(t) = \sum_{k=0}^{K} A_k \cos(2\pi k f_r t + \phi_k) + n(t) + a(t)$$

where:

$$\begin{aligned} n(t) \rightarrow &\quad \text{Random noise} \\ a(t) \rightarrow &\quad \text{Abnormal component} \\ A_k \cos(2\pi k f_r t + \phi_k) \rightarrow &\quad \text{Steady state component} \end{aligned}$$

Removing the steady state component for abnormality detection:

$$\begin{aligned} H_0 &: i(t) = n(t) \\ H_1 &: i(t) = n(t) + a(t) \end{aligned}$$

It can be seen that under normal operation, only random noise should be left and under abnormal operation, there is superposition of random noise and an abnormal component. Differential waveforms that contain noise that doesn't resemble a normal distribution (Gaussian) is considered to be abnormal and contain an event.

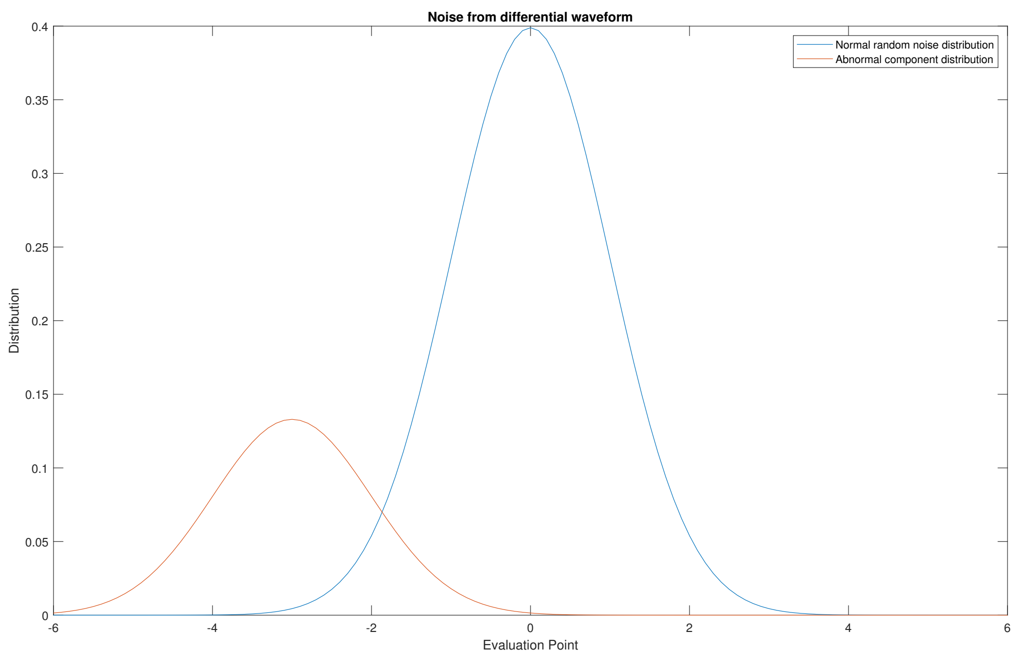

Figure 1: Expected random noise distribution (blue) vs. abnormal noise distribution (red)

2.2.2 Wavelet Analysis

The wavelet analysis is often used to detect transient faults by transforming a waveform into its frequency domain using the Fourier Transform. This is then decomposed into multiple approximations of the signal using various digital signal processing methods until sufficient bands of frequency ranges have been extracted (including the fundamental frequency).

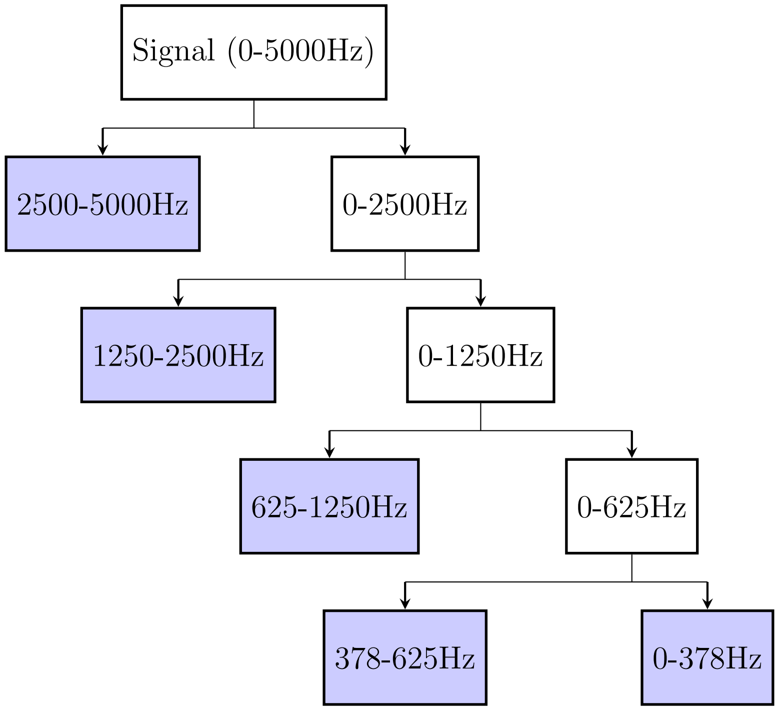

Figure 2: Example decomposition of 5000Hz signal with chosen frequency bands in blue

Once the decompositions have been completed to satisfactory ranges, a disturbance is deemed to be detected if the magnitude in the decomposition exceeds a specified magnitude. We also note that disturbances in the high frequency detail typically occur from transient faults.

Detection based on these approximations are defined in [4] through the following equations. For decompositions on or near the fundamental frequency, a disturbance is detected for some threshold ϵ if:

$$RMSCR = \frac{RMS_{\text{latest half cycle}} - RMS_{\text{one cycle before}}}{RMS_{\text{one cycle before}}} > \epsilon$$

For decompositions of higher frequency, a disturbance is detected for some threshold ϵ if:

$$ENGR = \frac{\text{Energy}_{\text{latest}} - MEAN(\text{Energy}_{\text{past}})}{STD(\text{Energy}_{\text{past}})} > \epsilon$$

Additionally, the patent by Mousavi et al. [5] discusses methods in determining events from the fundamental frequency approximation:

1. Complete DFT for $\frac{1}{2}$ a period of an input signal every $\frac{1}{8}^{th}$ cycle
2. Determining the threshold:
    - Fixed
    - Dynamic

Methods such as the S-Transform and the Fourier Transform and its variations (discrete (DFT), short-time (STFT)) are similar in its methods in that an input signal is decomposed into its spectrum components.

The wavelet transform's advantages lie in the decomposition of the waveform, allowing for the detection of both transient and steady-state disturbances, whereas other methods such as waveform analysis may only detect transient faults.

2.2.3 Artificial Neural Networks (Adaline)

Artificial neural networks (ANN) look to mimic biological neural networks in the brain by 'learning' to classify certain input data. ANNs are commonly used for modelling and prediction for a multitude of applications. The general structure for an ANN is:

- Input Layer
- Hidden Layer(s)
- Output Layer

The hidden layers are composed of specific weights and functions which are programmed by training the network: a recursive method where inputs with known outputs are fed into the system. The desired and actual outputs are compared and any errors are propagated back into the hidden layers so their weights and functions can be altered until the output is achieved.

Adaptive Linear Neuron (Adaline) is a single layer neural network which takes in time delayed samples of the power system waveform and predicts the future waveform.

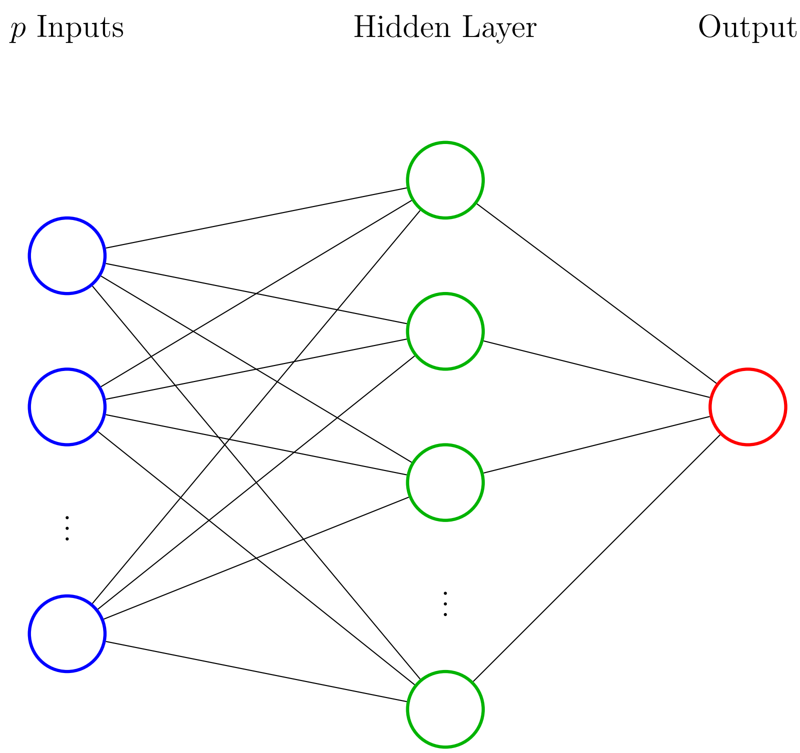

Figure 3: Adaline Neural Network structure for p inputs

Training of the Adaline network is completed by minimizing the error function $J(\omega)$ expressed as:

$$\begin{aligned} J(\omega) &= \frac{1}{N}\sum_{N} E(k)^2 \\ &= \frac{1}{2N} e(k).e(k)^T \end{aligned}$$

Where the error $e(k)$ is the difference in expected output and actual output. The resulting minimizing ω vector is the set of weights used for the hidden layer.

The predicted waveform output from the Adaline network will then be compared to the signal. The square root of the differential waveform is then used to detect disturbances and faults in the system. Abdel-Galil et al. concluded that using Adaline for event recognition was successful for transient voltage sag, swells, interruptions and harmonic disturbances [6].

Adaline has advantages over other methods due to its simplicity in minimizing one function and does not depend on any specific parameters such as the fundamental frequency compared to the wavelet transform. By nature, neural networks are an adaptive method and will minimise false positive detections for small variations in frequency. Furthermore, due to its simplicity, Adaline can be trained online in contrast to taking the system offline to reprogram. This is particular important for an autonomous detection system.

2.3 Existing Event Classification Methods

Depending on the detection method used, the output may be fed into a classification algorithm/network. Existing classification methods are currently only classifying the type of disturbance as in Table 2 and not determining the cause of the fault.

2.3.1 Artificial Neural Networks

As in section 2.2.3, ANNs can also be used to classify an event in a power system. In contrast to Adaline, a multi-layer neural network was used in [7] with a resilient backpropagation (RPROP) minimising function. Uyar et al. defines rules for each PQ disturbance type and from these, the ANN is able to best match the event to the rule:

PQ Disturbance	Equation
Normal	$y(t) = A\sin(\omega t)$
Sag	$y(t) = A(1 - \alpha(u(t-t_1) - u(t-t_2)))\sin(\omega t)$
Swell	$y(t) = A(1 + \alpha(u(t-t_1) - u(t-t_2)))\sin(\omega t)$
Interruption	$y(t) = A(1 - \alpha(u(t-t_1) - u(t-t_2)))\sin(\omega t)$
Flicker	$y(t) = A(1 + \alpha_j \sin(\beta\omega t))\sin(\omega t)$
Oscillatory Transient	$y(t) = A[\sin(\omega t) + \alpha e^{-(t-t_1)/\tau}\sin\omega_n(t-t_1)(u(t_2) - u(t_1))]$
Harmonic	$y(t) = A(\alpha_1\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t) + \alpha_7\sin(7\omega t))$
Sag and Harmonic	$y(t) = A(1 - \alpha(u(t-t_1) - u(t-t_2)))(\alpha_1\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t))$
Swell and Harmonic	$y(t) = A(1 + \alpha(u(t-t_1) - u(t-t_2)))(\alpha_1\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t))$

Table 3: Rules for PQ Disturbance types for parameters α, t_1, t_2, ω defined in [7].

The ANN will train by reading in test cases and changing the weights of its hidden layers into the output matches up with the corresponding rule set in Table 3. The RPROP is a back propagation optimising algorithm which considers the sign of the partial derivative of the the error function and changes the weights accordingly. As a result, the RPROP algorithm is first-order and increases speed efficiency at low computational efforts.

For 100 training cases, the ANN produced a classification accuracy of 99.67%. Additionally, when confusion noise was added, the network was still able to produce an accuracy of above 90%.

2.3.2 Probabilistic Neural Networks

Another type of neural network that is commonly used is the Probabilistic Neural Network (PNN) which differs from the traditional ANN in that it is implemented using the probabilistic model and a PNN is guaranteed to converge to a classification as long as enough training data is provided.

The underlying principal behind a PNN is Bayes' Rule:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

where $P(A|B)$ is the probability of A occurring given that B is true. This statistical logic is what is used in the hidden layers which updates the weightings of the nodes in the hidden layer. Mishra et al. [8] used a PNN to classify events detected using the S-Transform into 11 different classifications:

- Normal
- Pure Sag
- Pure Swell
- Transient Interruption
- Harmonics
- Sag with Harmonics
- Swell with Harmonics
- Flicker
- Notch
- Spike
- Transient

With 550 training events, the PNN was able to successfully classify the event at a rate of 98.64%. It can be seen that the PNN is relatively successful at classifying a given event and over a wide range of classifications.

2.3.3 Fuzzy Expert Systems

Boolean logic uses the binary variables 0 and 1 to represent false and true. By contrast, fuzzy logic has multiple truth values between 0 and 1, which represent partial truths. When implemented, this logic is able to better represent complicated systems that are vague and unable to be accurately depicted by well known models. Abdelsalam et al. uses the discrete wavelet transform output from a Kalmain filter in [9] to produce the amplitude, slope and standard deviation from the mean of a detected event. These values were then fed into a fuzzy expert system. The output classification of the method was determined depending on the level of the amplitude and slope:

Fuzzy 'AND'	Positive Slope	Zero Slope	Negative Slope
Very Small Amplitude		Interruption	Interruption
Small Amplitude		Sag	Sag
Normal Amplitude	Normal	Normal	Normal
Large Amplitude	Swell	Swell	
Very Large Amplitude	Surge		Surge

Table 4: Brief classification rules from fuzzy-expert system

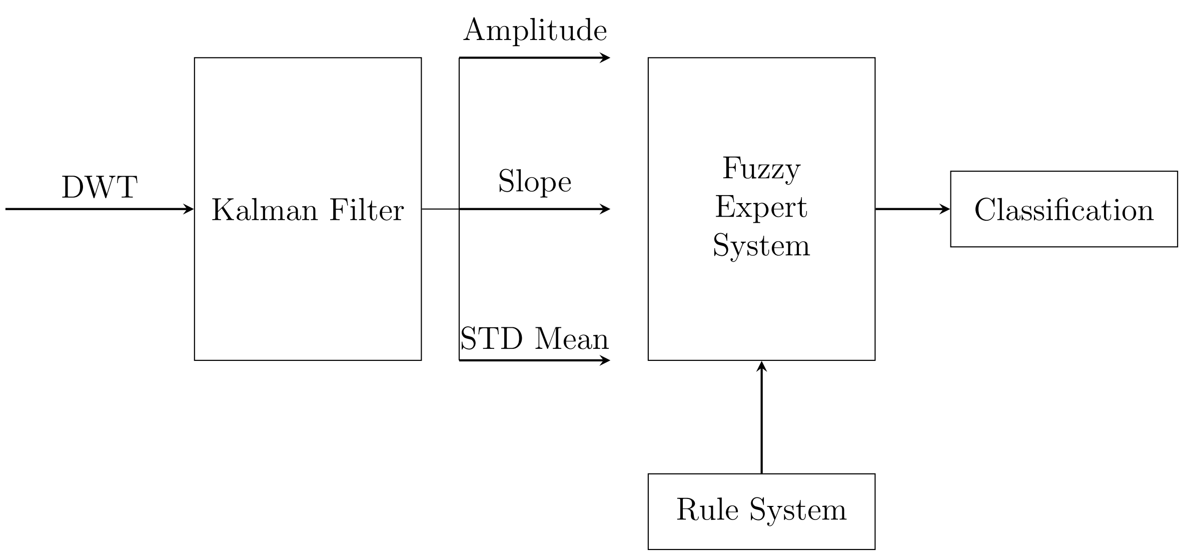

Figure 4: Rough block diagram of system in [9]

Note that the slope is also often used to indicate the beginning and end of transient faults, such as sags and swells, and is therefore also considered when classifying the type of disturbance. For 100 tests of each type of disturbance with 20dB, 30dB and 40dB values of signal to noise ratio (SNR), [9] recorded an acuracy of 92.3%, 97% and 98.71% respectively using the above method.

2.3.4 Support Vector Machines

Support Vector Machines (SVM) are learning models similar to aritifical neural networks. Given training examples, SVMs turn events from input space into a binary feature space divided by a hyperplane as in Figure 4.

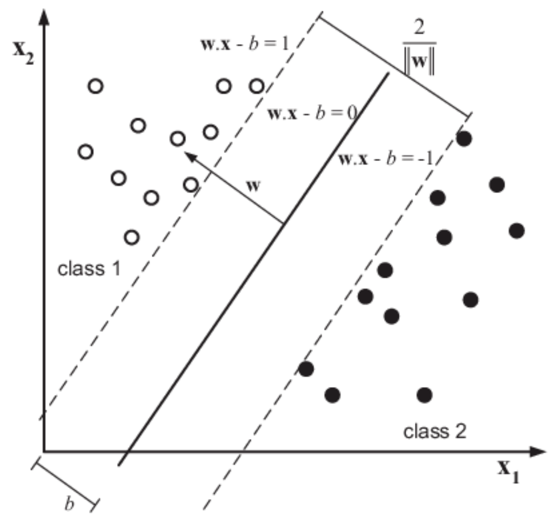

Figure 5: Hyperplane separating two classes of input data [10]

Maximizing the margin of this hyperplane $\frac{2}{||w||}$ is computed by computing $\min\frac{1}{2}||W||^2$, where $W = \sum_{i=1}^{N} \alpha_i^* x_i y_i$. Computation now only involves the minimizing of a quadratic function. For features that cannot be separated linearly, kernel functions which operate in higher dimensions can be used to classify the feature.

Babu and Mohan [11] use SVM to classify various three phase short circuit faults by first extracting event features with the Hilbert Huang Transform (HHT) which outputs instantaneous amplitude, phase and frequency. From the HHT, the following features were used to train a SVM for each of the three phases A, B & C:

- Energy distribution of instantaneous amplitude
- Standard deviation of amplitude
- Standard deviation of phase

For each phase, SVM output 1 if there was a fault detected and -1 if there was no fault detected. Results are further defined in Table 5.

SVM A	SVM B	SVM C	Fault Type
1	-1	-1	Single Line (A) to Ground
-1	1	-1	Single Line (B) to Ground
-1	-1	1	Single Line (C) to Ground
1	1	-1	Double Line (AB) to Ground
1	-1	1	Double Line (AC) to Ground
-1	1	1	Double Line (BC) to Ground
1	1	1	Other

Table 5: Fault Classification using SVM

Babu and Mohan reported a 95.33% accuracy efficiency from the results gathered. We note that this SVM method is only useful in detecting voltage sag and interruptions and not other PQ disturbances. However, this method does take into account all three phases and is able to successfully detect whether the fault is SLG or DLG and classify the fault, whereas other classification methods have not considered the classification of a particular voltage sag or interruption.

3 Project Plan

3.1 Milestones

The following tables outline deadline and objectives of major project milestones to be completed throughout the duration of this thesis project. Milestones in bold are ITEE Thesis Assessment Items. Note that all milestones up to and including Week 5 have been completed.

Deadline	Milestone	Objective & Notes
Week 1	Meet with Supervisor	Discuss project details and expectations
	Begin Literature Review	Gather reputable sources and increase content knowledge
Week 2	Receive Sample Data	Become familiar with data arrangement and exportation Determine best programming language to analyse data
Week 4	Choose literature to be reviewed in proposal	Determine the most relevant and successful algorithms to discuss in proposal
Week 5	**Project Proposal**	Complete Literature Review, Project Plan and summarise objectives and motivation of project
Week 7	Replicate at least one detection algorithm	Using MATLAB or Python on any test data and comment on efficiency and accuracy
Week 8	Replicate at least two detection algorithms	Using Python on any test data and comment on efficiency and accuracy
	Progress meeting with supervisor	Discuss current results and update expectations on result accuracy
Week 9	Replicate at least 2 detection algorithms	Using Python on provided data
Week 10	Continue progress on detection algorithms	Gathering a summary and discussion of results in preparation for the seminar
	Potential Classification Algorithm start	Attempt of classifying events in any language with any test or provided data
	Format Seminar Presentation	Speech, Visuals (PPTX), Demonstrations
Week 11	**Progress Seminar**	Gather and present results from tested algorithms
	Seminar Attendance	

Table 6: Semester 1 objectives and deadlines

Deadline	Milestone	Objective & Notes
Week 2	Progress Meeting with supervisor	Discuss progress after summer break and update expectations
	Thesis Writing	Begin writing non-results based areas
Week 4	Determine most accurate detection algorithm	Journal and record results from previous tests of various algorithms for detection
	Thesis Writing	Results from detection
Week 6	Deploy detection algorithms	On provided data from aged transformer
	Determine most accurate classification algorithm	Journal and record results from previous tests of various algorithms for classification
Week 9	Deploy classification algorithms	On provided data from aged transformer
	Thesis Writing	Results from classification
Week 10	Progress Meeting with supervisor	Discuss progress on project and discuss Thesis writing
	Demonstration Preparation	Gather results and prepare presentation for demonstration
Week 12	**Poster and Demonstration**	Gather and present results from project duration
SWOTVAC	**Thesis**	

Table 7: Semester 2 objectives and deadlines

3.2 Risk Assessment

Table 9 summarises the potential non-OHS risks to the project:

Risk & Impact on Project	Potential Cause & Likelihood	Mitigation Strategy
Data Loss A loss of data will be catastrophic to the project as this would completely halt any progress to the project. Algorithms would not be able to be deployed successfully. Impact: High	• Corruption of data • Damage to hard drive • Misplacement or damage to computer Likelihood: Low	Backing up data to multiple locations, including cloud
Document File Loss Losing a document such as the Thesis file can result in a shortened timespan to complete if a high amount of progress has been made. As a result, the final report submitted may be of a lower quality due to a rush to complete. Impact: Medium	• Corruption of file • Damage to hard drive • Misplacement of damage to computer • LaTeX files corrupted Likelihood: Low	Frequent saving and drafting of TeX files and using GIT for version control.
Insufficient Time This project requires developing and deploying algorithms on large sets of data, which takes up a considerable amount of time. If milestones and the plan are not up-kept, it is possible that no feasible results are achieved. Impact: Medium	• Poor time management • Assessment from other courses • Personal stresses Likelihood: Medium	Frequent meetings with supervisor to motivate progress. Personal initiative to complete tasks for the project.
Health Related Impacts Poor health will hinder the ability to complete the project. Furthermore, a lockdown may be imminent due to COVID-19. Although this project can be completed remotely, mental health risks may also affect quality of work. Impact: Low	• COVID-19 Virus • Other unexpected physical/mental issues Likelihood: Medium	Following QLD Health advice and keeping a healthy work-life balance.

Table 8: Risk Assessment for Thesis Project

3.3 OHS Risk Assessment

The majority of the work undertaken for this project will not be completed in a laboratory environment, so there is a low level of risk which is covered by general OHS rules.

4 Bibliography

[1] Queensland Competition Authority, “Guaranteed service levels: Performance by energex and ergon energy for 2018–19,” Queensland Competition Authority, Compliance, 2019.

[2] Institute of Electrical and Electronics Engineers (IEEE), *IEEE recommended practice for monitoring electric power quality*, 2019.

[3] B. Li, Y. Jing, and W. Xu, “A generic waveform abnormality detection method for utility equipment condition monitoring,” IEEE, Technical, 2017.

[4] Institute of Electrical and Electronics Engineers (IEEE), “Electric signatures of power equipment failures,” IEEE Power and Energy Society, Technical, 2019.

[5] M. J. Mousavi, J. J. McGowan, J. Stoupis, and V. D. Donde, “Apparatus and method for adaptive fault detection in mv distribution circuits,” US 8,390,302 B2, 2013.

[6] T. Abdel-Galil, E. Saadany, and M. Salama, “Power quality event detection using adaline,” Department of Electrical and Computer Engineering, University of Waterloo, Technical, 2003.

[7] M. Uyar, S. Yildirim, and M. T. Gencoglu, “An expert system based on s-transform and neural network for automatic classification of power quality disturbances,” *Expert Systems with Applications*, 2009.

[8] S. Mishra, C. N. Bhende, and B. K. Panigrahi, “Detection and classification of power quality disturbances using s-transform and probabilistic neural network,” IEEE, Technical, 2008.

[9] A. A. Abdelsalam, A. A. Eldesouky, and A. A. Sallam, “Characterization of power quality disturbances using hybrid technique of linear kalman filter and fuzzy-expert system,” *Electric Power Systems Research*, 2012.

[10] M. Papadonikolakis and C.-S. Bouganis. (2010). “Novel cascade fpga accelerator for support vector machines classification,” [Online]. Available: `https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6197724`.

[11] N. R. Babu and B. J. Mohan, “Fault classification in power systems using emd and svm,” *Ain Shams Engineering Journal*, 2015.