Predictive Maintenance of Circuit Breakers

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

For predictive maintenance of circuit breakers, a number of variables must be considered in order to assess the genuine working condition of a circuit breaker [CB]. This thesis selects vibration signatures obtained on the operating mechanisms and arcing chambers as a source of monitoring breaker conditions. The task of analyzing the behavior of a circuit breaker is perennial and difficult but the thesis has an attempt to tackle this problem. Experiments have been devised to monitor CBs; however, these have limitations details of which will be discussed. For example, each circuit breaker has its own unique vibration signature and the shape of the vibration may be different even though breakers confront similar problems. CBs have decades-long service life spans and failure rates are relatively low. Those that fail are not necessarily saved and there have been relatively few samples to base evidence upon.

There are different vibration analysis algorithms available including Dynamic Time Warping [DTW], Resolution Ratio [RR], Discrete Envelope Statistics [DES], event time extraction, Chi-square based shape methods, and fractal theory. Some of these algorithms are based on acoustic properties of materials and rely on assessing extracted time component and the frequency components are extracted. This research applies multi-resolution analysis [MRA] to decomposed signals to in order to assess different sub-wave levels so that wave features may be captured and modeled. There are many ways to analyze the waves. This thesis uses optimizing fuzzy rules with genetic algorithm [GA] as the proposed method.

The simuation part of the thesis uses spring performance as an example of how vibration signature analysis may be implemented. Spring vibrations are evaluated by two classification algorithms: Dynamic Time Warping [DTW] and multi-resolution analysis [MRA] with optimizing fuzzy rules with genetic algorithm [GA]. The first method is competent to identify the faulty cases from the normal ones by looking at the deviation of the vibration signature frequency content. In contrast, it is not capable to identify the degree of how bad it performs from looking at the frequency variation. For the second method, it is capable of not only classifying the abnormal cases from the normal cases, but also distinguishing the vibration signatures into different category so that the spring condition can be retrieved immediately. Fuzzy rules is capable of classify a new case to a category and genetic algorithm is an effective tool to minimize the applicable fuzzy rules. The accuracy of the identification is very satisfactory, which is over 90%. Consequently, the proposed algorithm is very useful for asset management purpose of breaker

since the lifespan of the spring is known. Diagnostic technicians are able to make decision on the replacement scheme of the spring.

There are some areas that this research uncovered that suggests further study is mandated. For example, there are other parameters that can be monitored and compared other than spring constant such as valve position in trip coil and close coil, acceleration parameter in changeover valves, damping in hydraulic cylinders and mechanical linkages, gas pressure in primary contacts and breaker resistance in line system.

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Chapter 1
Introduction

Circuit breakers are mechanical switching devices that carry and disrupt electrical current in a circuit. Circuit breakers must function in normal and abnormal conditions, and must accommodate short circuits and outages. Circuit breakers are used with switching generators, power stations, cable feeders, transformers, and overhead lines in power distribution systems [1].

Circuit breakers are very important to power grid integrity. When there is a fault, the circuit breakers isolates the faulty area so that extremely high currents do not flow into the whole power grid network thereby damaging related electrical devices including generators, transformers, and load transferring equipment used by clients. As a result, utility companies spend money and manpower to utilize and maintain circuit breakers so that the reliability of the power supply can be more secure and the chance of damaging the devices due to extremely high current exposure decreases.

Traditionally, circuit breakers are monitored manually. Technicians are sent to the substations and they regularly check if there are any operating problems. They rarely use measuring instrumentation to assist them in finding a problem or use measuring instrumentation for troubleshooting. Instead, they use eyes to accomplish professional inspection. This way of doing maintenance is insufficiently accurate and results in possible overlooking of breakers faults. It seems obvious that utilities companies would be better served if we are capable of ensuring that their breakers are functioning well all of the time. The old adage, prevention is better than cure, should apply and utility companies would benefit from uncovering potential problems before rather than after a breakdown.

Some researchers found that vibration analysis provides a solution for predictive maintenance of circuit breakers. Vibration analysis is a mature technique for detecting mechanical defects in rotating machinery. It is believed that the same concept, the trend analysis of vibration signature patterns, is also applicable on circuit breakers maintenance [8].

The goal of the research in this thesis is to search and compare signal-processing techniques that work best with the task of analyzing vibration signals. The behaviour of different circuit breaker parts and the mathematics of analysis have been introduced as the subject of interactions between the components. Normal and abnormal range analysis was deployed.

Combining simulated data and actual measured results, a Simulink model that mimics a real circuit breaker is built.

1.1 Resources

The data of the vibration signatures is retrieved from the circuit breaker Simulink model. The model is developed so that it provides analysis-based diagnostic suggestions, applies flexibly and is implemented at a reasonable computational cost. It consists of models of the individual circuit breaker components, including contact travel, voltage and current of the interrupter, and gas pressure of the SF_6 unit, with special focus on the operating mechanism which until now has resisted automated monitoring. The model accommodates behavior under various situations. One part of the model simulates vibration when the breaker is in operation. From the output vibration signals, condition data is obtained and conclusion is formulated from the analysis of the signals.

Vibration monitoring techniques are applicable to different parts of a breaker including the arcing chamber. In this thesis, the spring circuit breaker problem will be simulated. In a circuit breaker with a spring-hydraulic operating mechanism, the spring provides energy to open and close a breaker. If a spring malfunctions, the performance of the breaker will not be satisfactory. The malfunction of a breaker jeopardizes the stability of a power grid in the event of an outage in the power network. The performance of a spring can be affected by the age of the spring, the lubrication, and number of times of compressing and stretching of the spring.

As a control experiment, several vibration signature signals were captured when the circuit breaker was in normal condition. This thesis compares the signals in normal and in abnormal cases and deploys different methodologies.

1.2 Objectives

Vibration is itself a complex term and involves simulation, segmentation, feature extraction, and classification. The focus of this thesis is on how to extract and classify event (normal decaying into abnormal range) vibration data. The task is to select suitable signal processing methods to analyze the vibration signatures and identify the parts in the operating mechanism susceptible to malfunction. If successful, by running a remote program to display waveforms, a technician would not be required to locate and open a circuit breaker to do time-consuming and inefficient maintenance checks. By viewing the waveforms that are captured during operations, they would have the capability of knowing the status of the circuit breakers remotely. It is desirable that the proposed features can satisfy the following criteria:

1. The accuracy is as high as possible; 80% would be a minimum target;
2. The program is easy to use
3. The method is clear and easily understood

In summary, the goal of this thesis is to propose an automatic methodology of predictive maintenance by reviewing the vibration signatures generated by the circuit breakers during operations by using discriminative features and extraction methods. These methods include algorithms from other disciplines including artificial speech recognition and data mining.

1.3 Organization

There are eight chapters in this thesis. *Chapter 1 - Introduction* gives an overview of circuit breakers and the research project related to the diagnosis of the breakers. *Chapter 2 – Background Information on Circuit Breaker Maintenance* gives a brief explanation of circuit breakers in terms of its functionalities and its maintenance methodologies. *Chapter 3 – Literature Review for the vibration signature of a circuit breaker* describes different methodologies historically applied to solve the problem investigated by this thesis. *Chapter 4 – Proposed methods for analyzing vibration signals of a circuit breaker* outlines the methodologies used in analyzing the vibration signatures and how these techniques identify the normal cases and faulted cases. In this thesis, the methodologies involve multi-resolution analysis, fuzzy rules, and genetic algorithm. In *Chapter 5 – Problem Formulation,* the core problem of the thesis is articulated. The objectives of the research and the experimental data used in this research are described. *Chapter 6 – Circuit Breaker Simulink Model* gives a brief explanation on how does a circuit breaker model simulate a real breaker and how the vibration signatures are generated with this model. *Chapter 7 – Experiment* compares the efficiency and accuracy of the result when different methodologies are applied. *Chapter 8 – Future Prospects and Conclusion* suggests the area of the project can be further improved and concludes the result of the research.

Chapter 2
Background Information on Circuit Breaker Maintenance

Circuit breakers are mechanical switching devices that control power flow in a power grid network. They switch circuits on, carry continuous loads, and switch circuits off automatically or manually. In normal conditions, circuit breakers are in closed position and they carry high-voltage electrical loads. In abnormal conditions, circuit breakers must be in open position in order to provide electrical isolation. During the operational span of circuit breakers, switching occurs rarely. On average, one circuit breaker has one switching event annually. This situation makes circuit breaker design more challenging: they must be reliable under relatively static conditions and must become efficient when required to perform a switching operation after idling for long periods of time [2].

The essential design focus for circuit breakers is to maintain the current flow in a circuit under normal as well as abnormal conditions, when the magnitude of the current varies. A good circuit breaker must have two stable states: when it is closed its impedance is very small (ideally the impedance should be zero) and when it is opened its impedance is extremely high (ideally the impedance should be infinite). A circuit breaker must be able to change state in milliseconds. If it takes any longer, the circuit breaker will endanger other power system components as well as generate excess heat energy and reduce circuit breaker service durability. The additional heat load will also compromise the reliability of the grid as well [2].

In order to make such a resistive system featuring rapid breaker response, electric arc technology is applied. The application of electric arc has two advantages: first, it can change its resistance rapidly. Arc plasma resistance can be exponentially increased so that a breaker opens quickly. Arc plasma has no upper limit in current carrying capacity so that any current flow can be passed using an arc in the breaker. Finally, the change of the resistance can be enforced by the changing value of the alternating current, therefore the impedance across the arc is controlled [2].

There are different kinds of circuit breakers utilized in power grid systems today. Circuit breaker typification involves defining the medium of extinguishing the electric arc. There are four primary methods: oil, air-break, SF_6, and vacuum circuit breakers. This thesis concentrates on predictive maintenance of SF_6 circuit breakers.

Today, thousand of SF_6 circuit breakers are in use around the world. SF_6 has been used as an insulation and quenching medium for more than 30 years. A survey taken in France on 5000 circuit breakers over a 12-year time period found only 11 failures. SF_6 is an extremely reliable technology for extinguishing electric arc because of its high dielectric strength and thermal conductivity. Its dielectric strength at atmospheric pressure is about three time greater than that of air. SF_6 is non-toxic, odorless, incombustible, and three times more chemically inert than air [3].

Diagnostic techniques for SF_6 circuit breakers have been improving in recent years. In general, these breakers are rated as excellent after more than ten years of usage with up to 600 operations. Key parts of circuit breakers including the arcing chamber and the contacts have been found to be pristine even if in use for ten years. The cost of maintaining a circuit breaker versus replacement has become subject of common sense calculation; there is a rule of thumb set up by Norwegian power utilities that the maintenance cost of one circuit breaker is between one-third and one-half the price of a replacement [4].

There is a fundamental paradox involved in traditional circuit diagnostic techniques. Examining and inspecting circuit breakers involves disassembly. For example, the technician examines the lubrication of the mechanical parts, the dielectric strength of the contacts, and the pressure of the SF_6 gas. This part, inspection, is done manually; it is simple and the usage of special equipment is minimized; however, the process may be very time-consuming. More significantly, the deconstructing and reassembly of breakers may introduce new faults that affect the reliability of the load's power supply.

Electric utilities perpetually strive to reduce maintenance costs but they may not sacrifice safety and reliability. Because of the reassembly problems, periodic or traditional maintenance was replaced by condition-based maintenance [CBM]. CBM was proposed in the 1970s and became dominant in the 1990s. According to IEC 17A/17C (sec) 422/128, CBM offers a maintenance regime that mandates regarding the condition of the equipment [5] from a disciplined perspective. The advantages of such a regime include lower capital expenses. In comparison between tradition and CBM, CBM extends machinery life, is safer and more eco-environmentally nurturing. However, the change to CBM must be accomplished with integrity; in other words, CBM must be able to detect failure and degradation modes with a reasonably high degree of accuracy. In application, CBM techniques must be able to detect common- and rarely-occurring circuit breaker faults and they must access different types of switching equipment [6].

Industry findings (the second CIGRE enquiry) categorize the origins of failures into five groups. Table 1 shows major and minor failures within each class.

Table 1 Origin of failures in the second CIGRE survey [7]

Problems	Major Failures	Minor Failures
Mechanical in operation mechanism	44%	39%
Mechanical in other parts	10%	10%
Electrical (main circuit)	14%	1%
Electrical (control and auxiliary)	25%	10%
Tightness of SF_6 gas system	7%	40%

Encapsulating Table 1, the most important major failure involves mechanical problems in operating mechanism (44%) and the most important minor failure is the tightness of the SF_6 gas system (40%). In fact, local utilities in Kitchener and Waterloo area including Kitchener-Wilmot Hydro mention in their circuit breaker maintenance manual that circuit breaker technicians must check the gas pressure every time the circuit breaker is repaired and maintained. Some utilities have a remote system to monitor the SF_6 gas pressure in their distribution system. The control room acquires pressure data in real time in order to monitor the status of the breakers. In case of gas leak, the monitoring system sounds an alarm and stops the breaker operation. SF_6 problems are relatively tractable; it is far more difficult to monitor physical problems in operating mechanisms.

With a goal of making it easier to monitor problems in operating mechanisms, this study demonstrates how vibration signatures may be used in the predictive maintenance context. There are three advantages of monitoring circuit breakers using vibration signatures. First, it provides an alternate way of monitoring circuit breakers that does not involve contact, travel and technician time. Second, those most familiar with breaker performance will have historical metrics for comparison purposes. And finally, vibration monitoring techniques are applicable for any type of circuit breakers, regardless the structure of the breakers and the rated voltage [10].

The operating mechanism is the most complicated component of a breaker since it consists of moving parts involving mechanical interactions. As Table 1 survey disclosed, the main problem in breakers involves mechanical failure. Circuit breaker operating mechanisms have three units: energy storage, controller, and power transmitter. The energy storage unit is used to store energy for an auto-reclosure cycle. Depending on the material used for energy storage, there are different kinds of operating mechanisms: spring, pneumatic, hydraulic, and the hybrid and most effective, hydraulic spring. In this thesis, hydraulic spring-operated mechanism is used in the circuit breaker Simulink model. Energy is stored in a spring set which is compressed by the hydraulic pump. In a pure hydraulic mechanism, a piston integrates into the actuation unit in order to generate actuating force for the circuit breaker contacts.

But a pure hydraulic mechanism system lacks rapid repeatability. In contrast, the hydraulic spring operating mechanism has advantages of high repeat operating time accuracy, meets standards of high mechanical endurance, and is easily adaptable to different breaker types. There are different components such as relays, solenoids, valve, latches, linkages, and rods. They stop, move, and are impacted during the operation. The vibration propagates to the external structure through the internal mechanism and the interrupting medium [1].

In this chapter, the background of failures in operations of circuit breakers is described. The current diagnostic techniques of breaker malfunction are discussed. The method of applying vibration analysis for predictive maintenance of circuit breakers is introduced. Vibration analysis is a mature technique for detecting mechanical defects and it is believed that the same concept, the trend analysis of vibration signature patterns, is also applicable on circuit breakers maintenance. The advantages of monitoring circuit breakers using vibration signatures are examined. In the following chapters, signal-processing techniques are searched, compared and implemented in order to find the method that work best with the task of analyzing vibration signals.

Chapter 3
Literature Review for the vibration signature of a circuit breaker

There are several journal papers describing the experiment applicability of testing vibration on a circuit breaker. All of these journal papers are based on a real circuit breaker in order to capture real vibration signatures. In this chapter, the set up of the actual breaker experiment and how vibration signatures are obtained from a breaker are discussed. In addition, several methods that detect vibration signatures from the failure of breaker are described. They include dynamic time warping [DTW], resolution ratio [RR], discrete envelope statistics [DES] and event time extraction, chi-square based shape methods, and fractal theory.

3.1 Experimental set up

By using accelerometers and a data acquisition system triggered by the command signal to the breaker, vibration "signatures" are obtained when opening and closing operations take place.

Researchers [8] and [9] have provided detailed descriptions of vibration monitoring systems. Each system executes acquisition, management, analysis, and data evaluation after each breaker operation. The instrumentation consists of accelerometers which attach on the cover of an operating mechanism of a circuit breaker, a preamplifier which installs at the breaker, connection cable which link the preamplifier to a computer located in the control room, a standard four channel 16-bit computer-based data acquisition system with a sampling rate up to 51,200 samples per second per channel, a built-in anti-aliasing filter, an optical coupling unit which converts the signal in the breaker to a transistor-transistor-logic [TTL] triggering signal for the data acquisition system, and software on the computer which analyses and stores the vibration measurement data. An open or close command signal starts up the data acquisition system. If the recorded vibration signals are below a designated amplitude level, the triggering is ignored. Otherwise, the vibration is recorded. The procedural vulnerability lies in the fact that it is very important to situate the accelerometers at the right spot in order to capture accurate results. Ideally, one accelerometer is mounted in each phase of the operating mechanism, and the preamplifier is located in its own cabinet installed at the breaker. Also, the computer and the data acquisition system must be installed internally to avoid climate-caused interference.

One research study [10], describes accelerometer installation. There are three or four accelerometers mounted externally on each single-phase unit. There is usually one on each arcing chamber (given that the circuit breaker is disconnected and grounded, or that the circuit breaker is a dead tank type), one in the operating mechanism, and one somewhere in between. Figure 1 [10] shows a 2-g accelerometer installed on a rotating shaft of a circuit breaker operating mechanism.

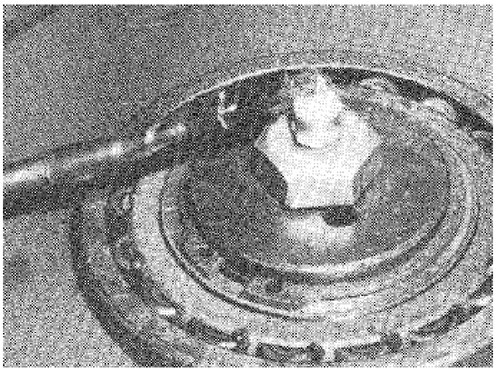

Figure 1 An accelerometer is installed on a circuit breaker [10].

In [9], the instrumentation of the accelerometer used in the testing is outlined. The accelerometer is designed for a nominal shock of 5000 g and a maximum shock of 50000 g. It gives out 1 mV/g (g is the parameter for gravity, g = 9.81 ms^{-2} on Earth). The –3-dB low frequency point is at 0.16 Hz and the natural resonance frequency is at 130 kHz. In testing, several accelerometers are mounted in solid metal in the operating mechanism of a 145 kV SF_6 circuit breaker close to the main shaft. In order to compare the vibration and the operation between each of the phase, the location is deviated more than 1 centimeter. In order to reduce damaging high potentials and electrical noise, the accelerometers are insulated from ground. Further, the accelerometers are mounted on a good acoustic and bad electric conductor so that the noise on the data captured is minimized. In the experiment done in this paper, a 1.5-cm thick stiff thermoset polymer is used. The polymer transmits mechanical vibration but decreases the capacitive coupled noise.

By putting the accelerometers at the correct position, it is possible for the vibration monitoring system to distinguish numerous events in an opening and closing operation by considering the time domain signals. Optimally, for capturing a more accurate result, the accelerometers should be located at the sources of the sound-generating mechanical movements.

3.2 Vibration signature captured from circuit breaker

Generation and propagation of vibration in a circuit breaker is a very complicated process. This derives from the fact that there are numerous sound sources during an operation and there are multiple boundaries and interfaces in the breaker that scatters, attenuates, and alters the propagation of acoustic waves. Due to the complexity of tracing the vibration energy flow, there are few published works attempting the exploration of acoustic properties of circuit breakers analytically [4].

Although there are few analytical analyses on circuit breaker vibration, some quantitative explanations are available. For example, a vibration signature includes a sequence of transients that represent mechanical events when the circuit breaker is operated. Some vibration events occur during particular opening and closing operations. Each event has its specific amplitude, frequency, and decay exponential parameter. By analyzing these transients, an engineer may obtain the mechanical condition of various parts involved and thus be able to assess the overall performance of the breaker operation [11,12].

Experiment has shown that breakers of the same type generate vibration signatures in similar shape. If there are some changes in mechanical conditions such as mechanical malfunction, excessive contact wears, maladjustment, or other irregularities and faults, the signature will be affected and a significant effect will be shown on the signature. Therefore, a diagnostic test can be implemented by comparing different vibration signatures so that the maintenance engineer knows the part of the circuit breaker that has problems. For instance, the engineer can compare each of the phases in a three-phase unit. Since the vibration signature of each of the phase are supposed to be similar, if there is variation, a phase can be used as a control experiment and the signal from the faulted phase may be analyzed to find out which part of the breaker is out of order [11,13].

Figure 2 shows a typical vibration signature obtained for one phase for closing and opening.

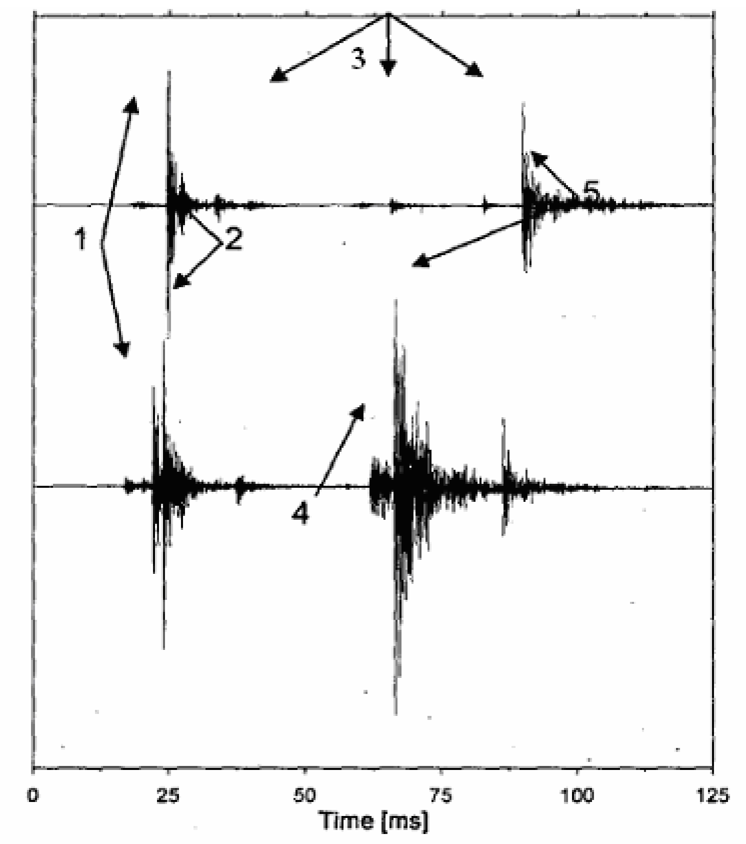

Figure 2 Closing (upper trace) and opening (lower trace) reference signals for one phase. Main events: 1. Main shaft releases (contact movement starts) 2. Latch hits main shaft. 3. Various latching. 4: Dash pot. 5. End stop [8]

For live tank circuit breakers, the dominant frequency components of the obtained signals are usually below 20 kHz. However, at times, components of 30-40 kHz are detected [13].

Figure 3 shows some acoustic and mechanical events from a closing of the breaker. Figure 3(a) shows the movement on the shaft between the driving mechanism and the crank housing. The optical device gives one voltage pulse per 1.9 degrees of rotation. The waveform indicates when the shaft and the lower contact are moving. Figure 3(b) shows the state of the contact (open/close). Figure 3(c) and figure 3(d) show the vibration signatures when the breaker is closing [4].

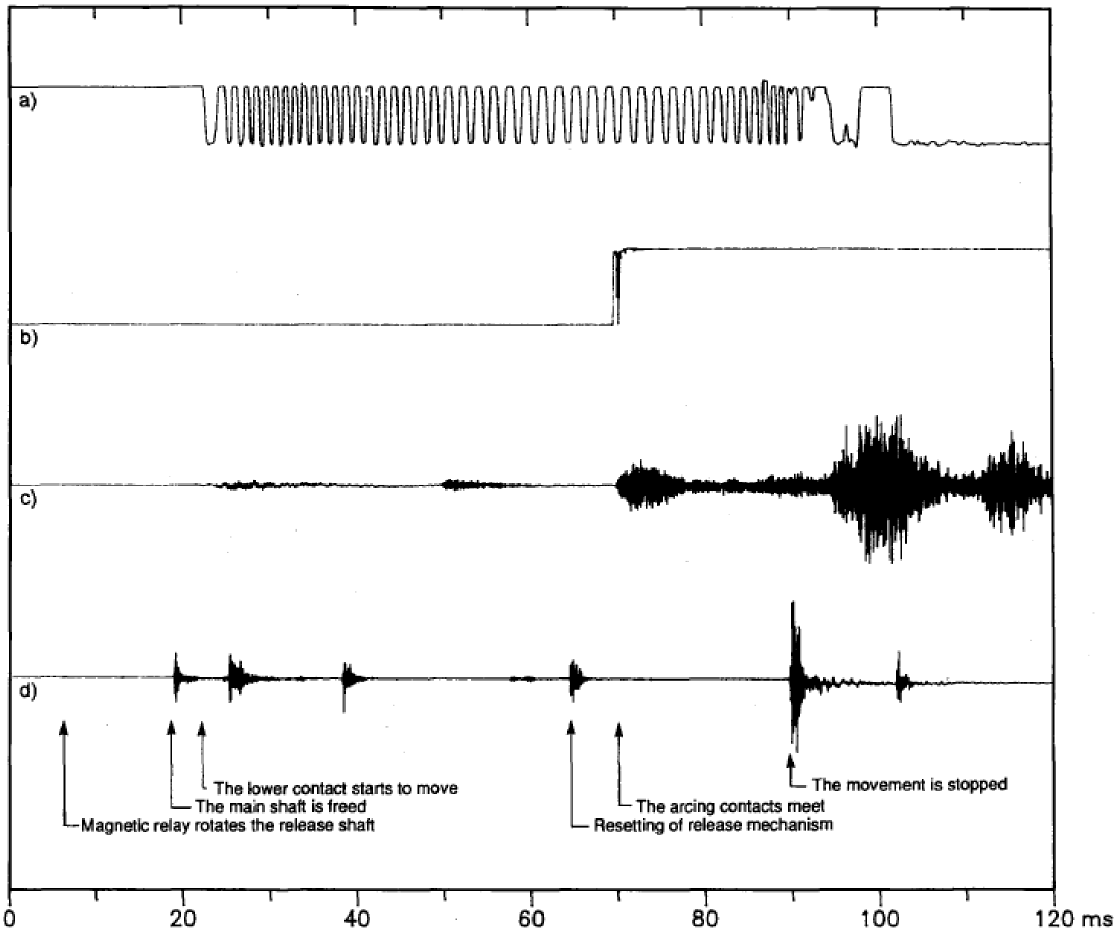

Figure 3 (a) Synchronic traces showing contact movements (b) contact mating (c) acoustic signature from the pole and (d) acoustic signature from the driving mechanism [4]

In addition, studies shows that electric and acoustic noise from the arc does not affect the vibration recordings on the operating mechanism of the circuit breaker in service [3]. If the noise is significantly dependent on the arc current, continuous vibration monitoring is not possible [9].

According to the research team of H. K. Hoidalen in Sweden [9], there are two main problems related to the process of obtaining comparison between the reference and the test results. They are, namely, electrical noise in the vibration pattern and the vibration pattern quality. As to electrical noise, it lasts for a short period of time at a specific location during all closing operations. In order to solve this problem, the analysis program should be modified in order to ignore the vibration pattern where the predefined noise is located. Moreover, the acquisition technique should be improved in order to reduce the influence of noise. For instance, a different amplifier and signal transmission system should be used. The length of the coaxial cable between the sensor and the system should be reduced so that less noise is induced. For vibration pattern quality, comparison of vibration pattern depends on the signals with distinct events. When the circuit breaker is opened or closed, ringing effects (echo) and lack of distinct events can result in large wrong timing deviations. In order to resolve this problem, careful examination of the vibration signatures is necessary. The unrelated portion of the signature should be distinguished. There is a further deduction. As experiments have proven that the opening signature is harder to monitor than the closing signature, due to the fact that opening signature contains most of the low frequency response components, it would be better not to include the opening signals in order to maintain the stability of the result. Consequently, more work has to be done on analysis of opening signatures in the future in order to definitively complete this research.

Some practical issues of the experiments [9] must be described. For example, overvoltage may occur in the data recording system. In order to prevent the damage of the recorder, overvoltage protection should be installed. The accelerometer should be isolated from ground in the operating mechanism. The optocoupler that converts command signal (110-220V) to a TTL triggering signal should have high insulation values. Moreover, there is evidence showing that circuit breakers after a short period of idle will have slower operations. When the user does the test on the circuit breaker when it is re-activated, the alarm must be adjusted carefully.

3.3 Signal processing methodologies

With respect to developing an algorithm for analyzing and comparing the vibration signature, different researchers propose their own methodologies. The most popular contenders are Dynamic Time Warping [DTW], Resolution Ratio [RR], Discrete Envelope Statistics [DES] and event time extraction, Chi-square based shape methods, and Fractal Theory.

3.3.1 Dynamic time warping (DTW)

There is no shortage of research [8], [10], and [11] applying dynamic time warping [DTW] when analysis is needed. DTW is a method that finds an optimal match between two warped non-linear sequences (with restrictions). The restrictions of DTW include continuity and monotonicity. With respect to continuity, no large gap exists in the sequences. For instance, there is only one item of a sequence which may be dropped at one time. For monotonicity, the order of the elements in a sequence for matching should not be inverted or altered [25].

There are two types of output produced when the normal vibration signal and the abnormal vibration signal are compared. They are the deviation in frequency content and amplitude, and deviation in the time of the events of the two signatures that exist. Both deviations are in terms of time.

DTW was originally used in speech recognition. According to the research team of M. Runde in the United States [4], this method is also applicable to vibration signature monitoring for circuit breakers and the reasons are twofold. First, comparison of the transients in two signals are involved in both applications. In speech recognition the transients are sounds and in circuit breakers the transients are mechanical transients. Second, the order of the events is fixed when the appearance of those events may be changed. Comparison of the timing of the events is applicable.

There are detailed explanations on how DTW is used for signal analysis [4]. The original time domain signal is divided into several frames defined by a specific signal time interval. Fast Fourier Transform [FFT] with a Hanning window is used to find the frequency content of each signal frame. In order to detect the events that yield weak signals, the frequency components are plotted in logarithmic scale. At this stage, rescaling of the time axes is necessary so that the events in the signal are matched for comparison. By using DTW, the Euclidean distance between the frequency vectors are calculated by looking at the similarity of the event signals. DTW algorithms ensure that the accumulated Euclidean distance between the frequency vectors of two signals is minimized when two vibration signatures are aligned. The optimized time alignment may be plotted in a time/time diagram. Figure 4 shows an example of a time/time diagram. In this chart, if the line is going along the diagonal, it represents that the two compared signals match in terms of the timing of the events. If the experimental data is higher than the reference data, the experimental data has a slower operation. Conversely, if the experimental data is lower than the reference data, the experimental data has a faster operation [8]. There are three constraints for frame matching: first, the matching paths cannot go backwards in time; second, every frame in the input must be used for matching so that the allowable steps in the warping path to adjacent paths are restricted; and third, the warping path must start and finish along the diagonal of the chart [32].

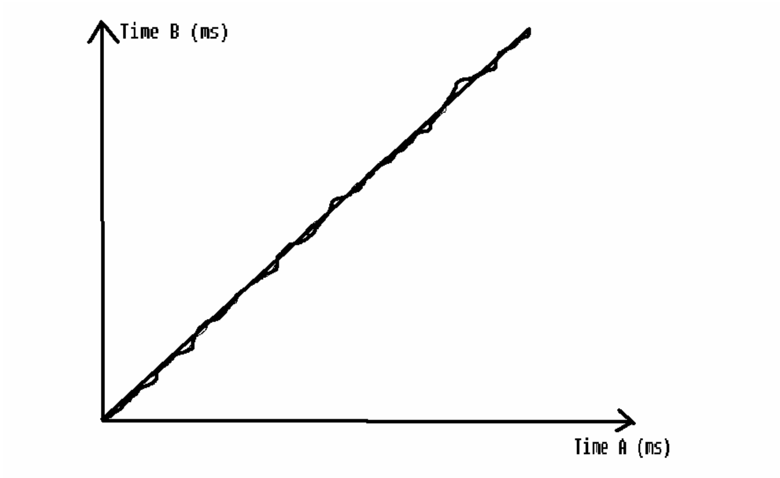

Figure 4 A typical example of a time/time diagram in DTW [4]

After the optimized time alignment is found, the two frequency vectors are aligned. The difference between two corresponding frequency vectors is called spectral distance and it is expressed in decibels (dB). Since an event increases the spectral distance at the time that event occurs, a chart of spectral distance is very useful for diagnostic purposes.

Figure 5 shows an example of spectral distance plot. Normal deviation shows that there is no abnormal event in the signal and it fluctuates at a certain range. In case of irregular deviation, the spectral distance increases compared to the normal deviation. In this way, mechanical events of a circuit breaker may be detected.

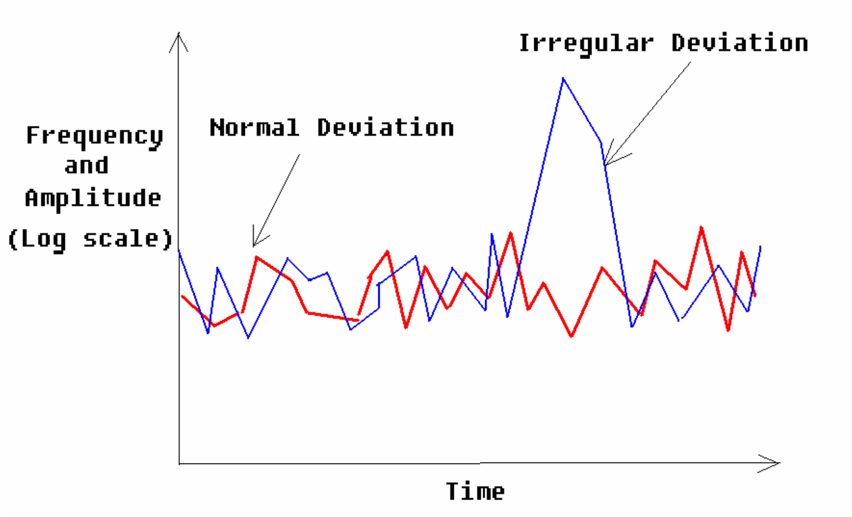

Figure 5 A typical example of a spectral distance diagram in DTW [8]

Dynamic time warping is a simple method for signal analysis and does not involve any complicated calculations. However, this algorithmic approach has its shortcomings. First, the deviations are very sensitive to the signatures in both quiet and noisy regions of the signal. Even though two circuit breakers seem to be the same, some deviations in their vibration signals are noticeable. As no vibration signal can be perfectly reproduced, deviations always exist and, sometimes, it is not an easy task to recognize any irregularities when two signals are compared. Second, some faults are not detected with this method as long as they have the same frequency content and timing in the signal. Finally, lack of vibration can totally alter the timing of the vibration signature by slowing down the circuit breaker operations when there is no problem in the mechanical parts of the operating mechanism. Merely by finding signal deviations does not guarantee that events will be detected [10].

3.3.2 Resolution Ratio (RR)

The research team of D. P. Hess in the United States devised another method of comparing normal and test signals [26]; they proposed entitling it resolution ratio (RR). Resolution ratio looks for the ratio of the normal Euclidean distance, which is defined between normal base and normal reference signals, and the test Euclidean distance, which is defined between normal base and test signals.

The first step of RR is to prepare two sets of data featuring: base normal (S_B) and reference normal (S_R) values. Each set of the data contains several operations and the features are expressed as:

$S_B = \{Z_{Bi}, 1 \le i \le l\}$……………………………………………(1)

$S_R = \{Z_{Ri}, 1 \le i \le l\}$……………………………………………(2)

Where i represents the number of operations of the circuit breaker.

In the second step, several test data are captured from the breaker. The data is expressed as:

$S_T = \{Z_{Ti}, 1 \le i \le l\}$……………………………………………(3)

In order to reduce randomness of the signals, average of the signals are calculated. Therefore, the average of S_B is A_B, the average of S_R is A_R, and the average of S_T is A_T.

In the next step, the Euclidean distance is calculated between the normal averages and the test average. The normal Euclidean distance, d_{N_i} ,is calculated by:

$$d_{N_i} = \left[\sum_{k=0}^{N_D} \left[\overline{A_B}(k) - \overline{A_{R_i}}(k) \right]^2 \right]^{\frac{1}{2}} \quad \text{.................................(4)}$$

The test Euclidean distance, d_{T_i}, is calculated by:

$$d_{T_i} = \left[\sum_{k=0}^{N_D} \left[\overline{A_B}(k) - \overline{A_{T_i}}(k) \right]^2 \right]^{\frac{1}{2}} \quad \text{.................................(5)}$$

where N_D is the length of the signal.

The average of d_N and d_T are $\overline{d}_N$ and $\overline{d}_T$ respectively.

RR is defined by:

$$RR = \frac{\overline{d}_T}{\overline{d}_N} \quad \text{...(6)}$$

RR is a useful indicator for describing the condition of a circuit breaker. RR works well when there are structural changes in the circuit breaker such as fractured and defective components. For a circuit breaker in normal condition, the value of RR is close to 1. Any RR that is above three standard deviations on the normal value is said to be in critical condition. For STS, any RR that is above 2 standard deviations on the normal value is said to be in critical condition. For short-time energy, any RR that is above 2.5 standard deviations on the normal value is said to be in critical condition [26].

According to the research group of A. A. Polycarpou in the United States [27], RR works satisfactorily in most cases. However, there are two disadvantages: first, sometimes overflow of the data may occur. Second, RR requires the average of several input signals in order to minimize the randomness effect of the data. However, it is not easy to retrieve several sets for one group of data, especially for test data.

3.3.3 Discrete Envelope Statistics (DES) and event time extraction

Discrete envelope statistics (DES) is another method of finding the envelope (amplitude) of the vibration signal [27], The envelope is then used as the input of event time extraction.

In the first step, DES is calculated by using this equation:

$$S(i) = \sqrt{s^2(i) - s(i-1)s(i+1)} \quad \text{..............................(7)}$$

where $s(i)$ is the vibration signal , i is the sample point, $s(i\text{-}1)$ is the previous sample and $s(i + 1)$ is the next sample. The term $s(i\text{-}1)s(i{+}1)$ is used to reduce the harmonics produced by $s^2(i)$. On the other hand, $S(i)$ contains high frequency components that is not important to signal analysis. Therefore, in the second step a low pass filter is used to filter out these components so that the output signal is smooth enough for signal analysis.

In the third step, the signal is sampled (commonly from 8000 samples to 512 samples) by eliminating the outlier. In this case, the outlier is defined as any sample that is out of ±20% of the median of the signal. Then, the average of the envelopes captured in each operation is calculated. Next, the average signal is filtered by a low pass filter again in order to minimize the noise. This noise is produced by the nonlinear processing during the outlier rejection stage.

Event timing extraction is used to locate the physical event in a signal. An event is characterized by large time derivative of the signal or sharp transition in amplitude. Event timing extraction is developed so that sharp transition is captured and the time of the event is known.

Time derivatives of a signal envelope S(t) is calculated by:

$$\frac{dS(t)}{dt} = F^{-1}\left[j\omega F\left(S(t)\right)\right] \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (8)$$

where F^{-1} is the inverse Fourier transform. The sequence is divided into several portions so that each portion has the same time interval ΔT. The largest derivatives are selected from each of the portions of the sequence. These derivatives represent that an event exists in the signal.

In this method, the timing of the event is investigated. The timing of the events in the normal data are compared with the timing of the events in the test data by finding the correlation. Also, the time shift between the time location of events in the normal data and that of test data is calculated. If the time shift is larger than a certain threshold, the circuit breaker is classified as in abnormal condition.

However, the derivative-correlation method has one shortcoming: it is not easy for this method to detect the location of the first event in the signal. In this case, an algorithm is built in order to find a point where there is an obvious and continuous increase in amplitude of the signal compared to the background noise. This point is considered to be the time location of the first event.

3.3.4 Chi-square based shape methods

Chi-square Goodness-of-fit Test is a famous method in statistics for comparing observed data with data expected based on the particular distribution, such as the one based on theory (for example, if the difference between the observed distribution and normal distribution is not significant) or one based on some kind of known distribution. Reference [27] proposes a statistical shape analysis test called variation of the Chi-square test [VCS] for goodness-of-fit. This test compares the local differences between two signals.

In the first step, cumulative amplitude, $A(t)$, is calculated by using this equation:

$$A(t) = \frac{1}{m}\sum_{i=1}^{m} e_i(t) \text{ ....(9)}$$

where $e_i(t)$ [i = 1,2,…,m] represents the number of amplitudes in a circuit breaker.

In the second step, the standard deviation of the amplitude values, δ(t), is calculated by using this equation:

$$\delta(t) = \sqrt{\sum_{i=1}^{m}\left(e_i(t) - A(t)\right)^2} \text{ ....(10)}$$

In the third step, the value of the square-chi is calculated by using this equation:

$$\chi^2\left(x(i), s(i)\right) = \frac{\left[x(k) - s(k)\right]^2}{\left|x(k) + s(k)\right|} \; when\, k = 1,...,N \text{ ....(11)}$$

where N is the total number of points for comparison. For the purpose of comparing the test data and reference data , S(t) is the amplitude of the test signal, A(t) is the average amplitude of the reference signal, and d(t) = A(t) + δ(t) is the sum of the average amplitude and one standard deviation signal of the amplitudes. The value of VCS is defined as:

$$VCS = \frac{\chi^2\left[A(t), S(t)\right]}{\chi^2\left[A(t), d(t)\right]} \text{ ....(12)}$$

where VCS is the normalized value of χ^2. The normalization shown here is one standard deviation of amplitude.

This method is applicable to classification of vibration signature problems since it fits the assumptions of the goodness-of-fit test. The primary advantage of VCS is that it is quite general. It can be applied to any distribution of data, either discrete or continuous, for which the cumulative distribution function can be computed. Also, it is an excellent tool for classification of circuit breaker problems as the nominal variable is grouped into classes (categorical). On the other hand, there are two disadvantages. First, the test is sensitive to how the classification of the data is performed. Second, it requires significant data streams for the test in order to yield accurate results.

3.3.5 Fractal Theory

One research group developed a methodology to evaluate the vibration signature signals with fractal theory and wavelet transforms [33]. Fractal theory is used to analyze the signals and wavelet transform is used to calculate the fractal characteristics of the signals. Given that two signatures are captured from the same mechanical conditions, the fractal characteristics are very similar. When there is a change in the condition, the fractal parameter changes accordingly so that the fault can be classified.

The principle of fractal operation is to express complex physical phenomena in terms of simple analytical processes. Fractal theory has philosophic implications, discussion of which is beyond the boundary of this effort. By identifying simple but infinitely iterative processes as essential to complexity, fractal theory attempts to model complex processes by analyzing "self-similarity." "Self-similar" means that the original signal is broken down into an arbitrary number of small pieces when each of those pieces combined is a duplicate of the entire signal. The primary parameter that measures the complexity of the signal is called fractal dimensions. It is based on the observation scale and the number of objects that are seen under the given observation scale. In the methodology proposed, three definitions of fractal dimensions are used. Reliance on only one variable set would not do justice to the complexity of signal physics. In fact, there are several fractal parameters that affect the characteristics of the fractal phenomena. The first one is the fundamental definition of fractal dimensions and it is expressed as:

$$D = -\frac{\log N(r)}{\log r} \qquad \text{...(13)}$$

where parameter r is observation scale and N(r) is the number of the objects that are seen under the given observation scale.

The second one is a modified version of the fundamental definition. It is the gradient of the point (r, N(r)) from the curve N(r)~r and it is expressed as:

$$D = -\frac{d\log N(r)}{d\log r} \qquad \text{..(14)}$$

The third one is the local fractal dimension and it is defined as:

$$\alpha = \lim_{L \to 0} \frac{\ln P_i}{\ln L_i} \ ,i = 1, 2, 3, ..., N \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

where N is the number of pieces of the signal, L_i is the scale of the L^{th} piece of the signal, P_i is the fractal body's developing interface probability and α is the local fractal dimension.

α has no intrinsic meaning on comparing the characteristics of different signals. With the help of wavelet transform, signals can be compared and the detail of the signals can be captured. Wavelet transform is discussed in section 4.1.

The method of using fractal theory to analyze vibration signals has an advantage that once the fractal characteristics are obtained for one breaker the result tends to be repetitive for every normal operation. Therefore, when there is a failure in that breaker the problem is detected. However, the disadvantage of this method is the process of obtaining firm fractal characteristics requires a large number of vibration samples.

This chapter introduces the experiment set up of a breaker and how vibration signatures are obtained from an actual breaker. Also, this chapter has demonstrated a number of applicable algorithms including dynamic time warping [DTW], resolution ratio [RR], discrete envelope statistics and event time extraction, chi-square based shape methods, and fractal theory in terms of their principle, advantages, disadvantage, and the ability of solving the problem of analyzing vibration signatures of a breaker. Comparing these methods, DTW appeared to be the best of the current methods since it is simple method in terms of the computation involved. Also, it does not require lots of input data in order to yield stable results. It does not have problem of data overflow.

In the following chapters, a new method that analyze vibration signature will be proposed. The new method and DTW are applied to analyze a modelled breaker whose spring is faulty. Both methods will be implemented and compared and the result will be analyzed and discussed.

Chapter 4
Proposed methods for analyzing vibration signals of a circuit breaker

In the previous chapter, several methods of analyzing vibration signals of a circuit breaker are discussed. They are capable to detect the breaker whether the breaker is in the normal state or in the abnormal state. However, they are not able to tell the diagnostic personnel how bad the breaker performs. As a result, the lifespan of certain component in a breaker will not be known by solely knowing if a part is working or not. Therefore, a method that can classify and distinguish different states of failure is needed so that the degree of the malfunction can be captured. In this chapter, a method for analyzing vibration signals is proposed which is based on fuzzy classifications. This is implemented using fuzzy rules and genetic algorithms.

4.1 Multi-resolution analysis

There are many ways to analyze distorted signals in terms of feature extraction. In reference [14], Fast Fourier Transform [FFT] is proven to increase the capability of analyzing signals. However, in order to do thorough manipulations of the signal, a large amount of data has to be stored and this method is not efficient enough for analyzing large amount of signal data.

For multi-resolution analysis, wavelet transform is a tool chosen to perform multi-resolution signal decomposition. Wavelet transform expresses the signal as a sum of wavelet signals at different positions and different scales. The wavelet coefficients represent the weights of the wavelets to shows the signal at these positions and scales [15].

There are three ways to do wavelet transform. First, the Continuous Wavelet Transform [CWT] is defined as the sum of all of the time signals multiplied by scaled, shifted versions of the wavelet function ψ. The equation of CWT is:

$$C\left(scale, position\right) = \int_{-\infty}^{\infty} f\left(t\right)\psi\left(scale, position, t\right)dt \text{ ....(16)}$$

The parameter *C* represents the wavelet coefficient in terms of scale and position. By multiplying each coefficient by the corresponding scaled and shifted wavelet, the original signal is obtained [18]. The Wavelet Series [WS] is a representation of a square-integrable function by a certain orthonormal series generated by a wavelet [19]. It maps a function of continuous variables into a sequence of coefficients. Discrete Wavelet Transform [DWT] decomposes a discrete signal into different resolution levels providing a range of easily identifiable normal and abnormal data. In this thesis, DWT is used.

DWT invokes the application of multi-resolution analysis [MRA] to analyze the signal by extracting information from any abnormal signals encountered. DWT is sufficient to decompose and reconstruct the signal in terms of the amount of information provided and the runtime. The transform features an increased scaling factor in order to reduce the number of coefficients so that the runtime is shortened. A function *f(t)* can be expanded in terms of its orthogonal basis $\varphi(t)$. Orthogonal basis can be scaled to give multiple resolutions of the original signal. At scale *j*, the signal *f(t)* can be expressed as:

$$f(t) = \sum_n c_j(n) 2^{\frac{j}{2}} \phi\left(2^j t - n\right) \quad \text{.....................................(17)}$$

where c_j is the *j* level scaling coefficient.

Function *f(t)* can be manipulated by using low- and high-pass quadrature mirror filters. A quadrature mirror filter is an array of filters which splits an input signal into two bands which are subsampled by a factor of 2. Low frequencies are encoded as high frequencies and vice versa. In the context of wavelet transform, quadrature mirror filter consists of low- and high-pass decomposition filters, and their associated reconstruction filters. Figure 6 shows a quadrature mirror filter system.

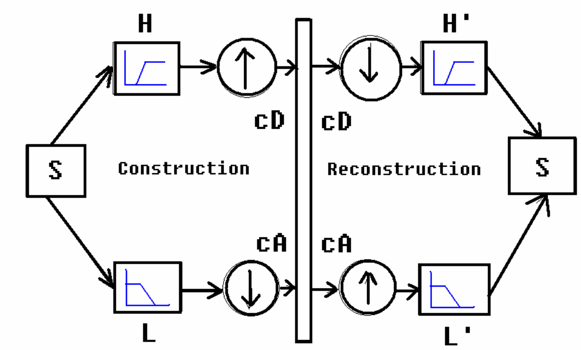

Figure 6 Quadrature mirror filter

In fact, many of the common wavelets such as Daubechies, Coifman, and Mallat and their scaling functions are in a quadrature mirror filter relationship [17]. As a result, equation (18) can be represented in terms of both scaling functions and wavelet functions:

$$f(t) = \sum_n c_o(n)\phi(t-n) + \sum_n \sum_{j=0}^{J-1} d_j(n) 2^{\frac{j}{2}} \varphi\left(2^j t - n\right) \quad \text{..........(18)}$$

Where c_0 is the zero level scaling coefficient and d_j is the wavelet coefficient at scale j. $\varphi(t)$ and $\psi(t)$ are the scaling function and wavelet function respectively. n is the translation coefficient. $\psi(2^j t - n)$ is the translated and scaled version of the wavelet.

In addition, $d_j(k)$ is an expression in terms of wavelet function coefficients, $h_1(m-2k)$ and scaling coefficient $c_{j+1}(m)$:

$$d_j(k) = \sum_m h_1(m-2k)\,c_{j+1}(m) \quad \text{.................................(19)}$$

In other words, in order to calculate the wavelet coefficient at scale j, convolution of wavelet function coefficients and scaling coefficients at scale j+1 and downsampling the result by a factor of 2 are required. The definition of $h_1(n)$ is:

$$h_1(n) = (-1)^n\, h(1-n) \quad \text{..(20)}$$

where $h(n)$ are the scaling function coefficient and $h_1(n)$ are the wavelet function coefficient. In fact, $h_1(n)$ is a high pass filter for the input signal in order to get the detailed coefficient. Here, impulse response $g(n)$ is defined in order to find the low pass filter for the input signal in order to get the approximated coefficient. The equation of calculating the wavelet coefficient is:

$$c_j(k) = \sum_m g(m-2k)\,c_{j+1}(m) \quad \text{.................................(21)}$$

Figure 7 shows the input signal (s), high pass filter, low pass filter, downsample modules, detail coefficient (cA), and approximation coefficients (cD).

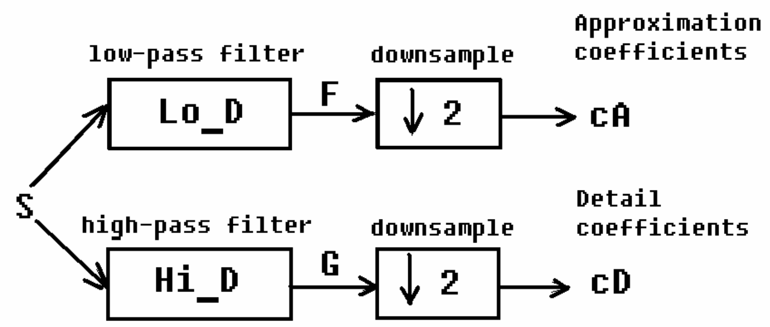

Figure 7 Discrete Wavelet Transform [18]

The decomposition of the signal has halved the time resolution since half of the low pass filter and high pass filter represents the signal. On the other hand, each output has half of the frequency band of the input so the frequency resolution is doubled. The changes of the time resolution and frequency resolution obey the Heisenberg Uncertainty Principle, which states a tradeoff has to be made between finer time resolution and finer frequency resolution [20] [21].

MRA builds a time-frequency picture of the decomposed signal. Wavelet functions and scaling functions are important since they reconstruct the signal at different resolution levels. The wavelet functions give the detail of the decomposed signal and the scaling functions give the approximation of the decomposed signal.

Multi-resolution signal decomposition provides two characteristics on the signal. First, it localized the signal in time for any transient phenomena. At the time of disturbance, localization appears by the presence of large wavelet coefficients. Second, it does partitioning of the signal energy at different frequency bands. Therefore, the frequency content of the signal is useful in order to do transient phenomena analysis.

Figure 8 shows an illustrated example of MRA. The detail signals are composed by wavelet functions and the approximate signals are composed by scaling functions. Different levels of the composition are used so that the signals are "mathematically magnified." In the figure, four levels of MRA are done. Four detail signals and an approximated signal are captured. One can reconstruct the original signal by adding all of these detailed and approximated signals. The DC offset of the original signal can be captured from the lowest level of approximated signal [14] [15].

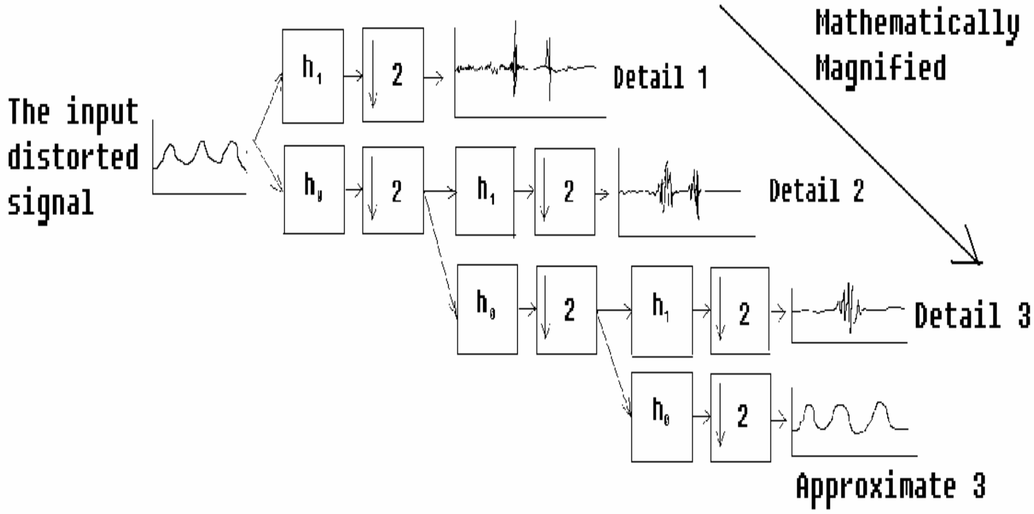

Figure 8 Multi-Resolution Analysis [15]

In fact, feature extraction is the pre-processing operation that converts a pattern from its original domain to a new form suitable for processing [16]. MRA is one of those feature extraction techniques.

After decomposing the input signal, it is important to detect and localize the features found in the output signals. In fact, the work of detection and localization is better in wavelet domain than in time domain. After the signal is processed with multi-resolution signal decomposition, the signal is separated into different resolution levels. For detail coefficients, any pattern changes in the signal can be detected and localized at the finer resolution levels due to the change of the magnitude of these coefficients. As these patterns are found, they are correlated to classification stages. However, the noise signal may hide the desired pattern as the noise level increases. This may cause a failure in wavelet detection and localization. One way to overcome this problem is to use approximated signal instead of detail signal and the duration of the signal is measured in order to filter out the unwanted portion of the signal pattern [22] [23].

Multi-resolution analysis is a well-known method for speech recognition. By decomposing the speech signal into different resolution levels, vast amount of knowledge is obtained by extracting the features from the waves. Multi-resolution analysis is proposed for analysing circuit breaker vibration signals since the signal for speech recognition is very similar to the signal generated by vibration in terms of the formation of signals. In fact, speech signals are also generated by the vibration of object and the mechanical energy of the vibrating object is converted to sound energy. Therefore, it is feasible to apply MRA for analyzing signals that are generated by breaker. At this stage, once the signal from the circuit breaker is disintegrated, the sub-components of the waves are analyzed and classified by the method discussed in the next section; fuzzy classifications using fuzzy rules and genetic algorithms.

4.2 Fuzzy classifications using fuzzy rules and genetic algorithms

This method is proposed by Ishibuchi which applies fuzzy IF-THEN rules and genetic algorithms (GA) to classify the classes of the data. IF-THEN rules are used to describe and classify the data when GA is used to minimize the number of fuzzy rules. Actually, this method is an optimization problem with three objectives: to maximize the number of correctly classified patterns, to minimize the number of incorrectly classified patterns, and to minimize the number of fuzzy IF-THEN rules.

Fuzzy IF-THEN rules are generated in grid type fuzzy partitions in a pattern space. The fuzzy partitions can be small to represent a fine partition or it can be large to represent a coarse partition. In a pattern space, it is given that there are m patterns $x_p = (x_{1p}, x_{2p})$, $p = 1, 2, \ldots, m$ from M classes $C_1, C_2, \ldots, C_M$. A pattern x_p is classified into one of those M classes by using fuzzy IF-THEN rules as these rules divide the pattern space into M disjoint decision area. An example of fuzzy IF-THEN would be:

R_{ij}^K = IF x_{1p} is A_i^K AND x_{2p} is A_j^K, THEN x_p belongs to G_{ij}^K.

Where K is the number of fuzzy intervals in each axis, R_{ij}^K is the name of the fuzzy IF-THEN rule, G_{ij}^K is outcome of the classification, and A_i^K and A_j^K are fuzzy sets with triangular membership function $\mu_i^K(x_{1p})$ and $\mu_i^K(x_{2p})$ defined by:

$$\mu_i^K(x) = \mu_{A_i^K}(x) = \max\left\{1 - \frac{\left|x - a_i^K\right|}{b^K}, 0\right\}, \; i = 1, 2, \ldots, K \ldots\ldots (22)$$

where $a_i^K = \dfrac{i-1}{K-1}$ and $b^K = \dfrac{1}{K-1}$, $i = 1, 2, \ldots, K$. a_i^K is the center of the membership function where the function equals to one. b^K represents the width of the membership function. Figures 9, 10, 11, and 12 represents fuzzy pattern with different values of K.

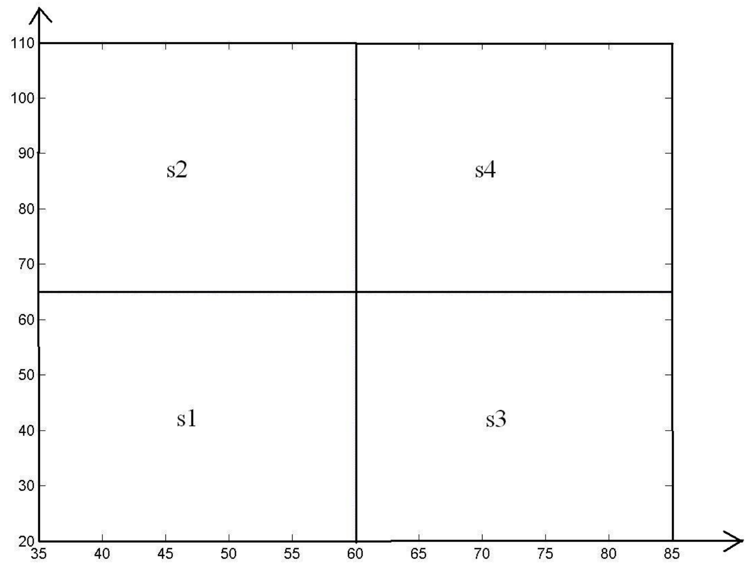

Figure 9 The fuzzy pattern and string element for $K = 2$

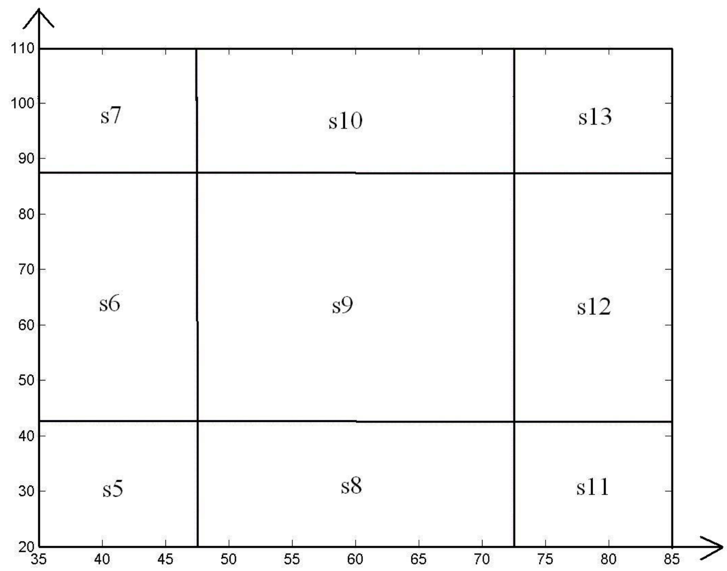

Figure 10 The fuzzy pattern and string element for $K = 3$

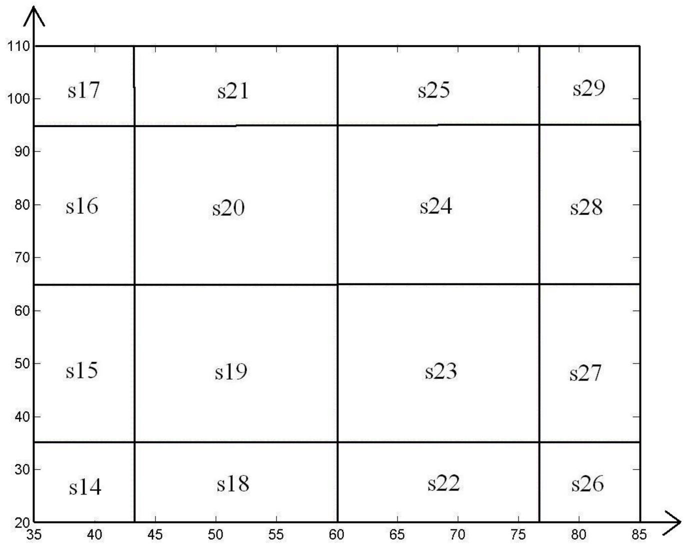

Figure 11 The fuzzy pattern and string element for $K = 4$

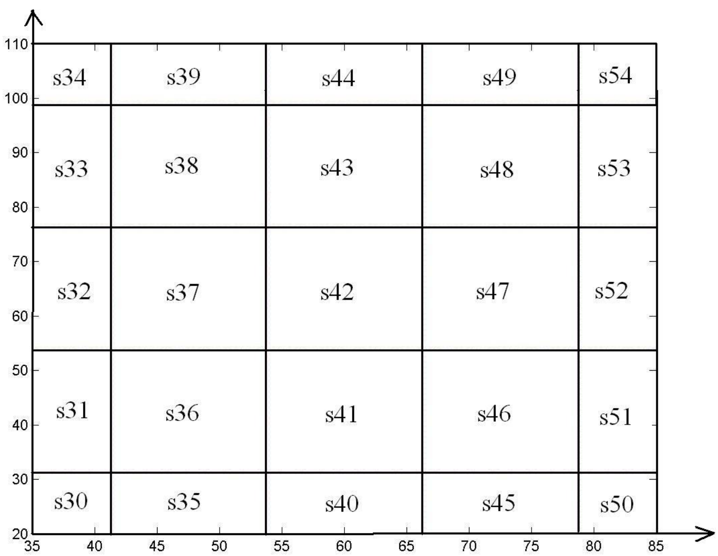

Figure 12 The fuzzy pattern and string element for $K = 5$

Sometimes, when there is no pattern in a certain fuzzy subspace $A_i^K \times A_j^K$, a dummy rule is produced. In terms of classification, the area represented by a dummy rule is neutral in deciding which fuzzy subspace belongs to which class. In a pattern space whose interval is dividend into K sections, there are $K \times K$ partitions. Therefore, it has K^2 fuzzy rules. The set of all fuzzy rules are expressed as S_{ALL} for $K = 2, 3, .., L$, where L is the maximum value defined in K :

$S_{ALL} = \{R_{ij}^K \mid i,j = 1, 2, \ldots, K; K = 2, 3, .., L\}$……………………….(23)

The rule set S_{ALL} consists of $2^2 + 3^2 + \ldots + L^2$ fuzzy rules. The objective of this classification method is to find a rule set S that minimizes the rules defined in S_{ALL} in order to do the classification of the given patterns. On the other hand, it is important to control the classification error to a reasonable level. The optimization is expressed as:

Maximized $f(S) = w_{NCP} \times NCP(S) - w_{NCP\_WRONG} \times NCP\_WRONG(S) - w_S \times |S|$, $S \subseteq S_{ALL}$..(24)

where $NCP(S)$ is the number of patterns that is correctly classified, $NCP\_WRONG(S)$ is the number of patterns that is incorrectly classified, $|S|$ is the number of rules in the rule set S, and w_{NCP}, w_{NCP_WRONG}, and w_S are the weighting constants of the parameters $NCP(S)$, $NCP\_WRONG(S)$ and $|S|$ respectively.

The optimization is done using Genetic Algorithm (GA). In order to apply GA, a string is composed with the fuzzy rules so that it is in the form of $s_1, s_2, s_3, \ldots, s_N$, where $N = 2^2 + 3^2 + \ldots + L^2$. The value of each s_r value in the string is "1", "-1" or "0". "1" represents that the r^{th} rule belongs to the rule set S. "-1" represents that the r^{th} rule does not belong to the rule set S, and "0" represents that it is a dummy rule. Since dummy rule has no functionality on classification procedures, it is valued as zero and these rules are excluded from the rule set S.

There are four steps in operations of GA that can be done on the string. First, in reproduction phase a portion of the parent string is chosen in order to generate children strings. The selection probability depends on the value of $f(S)$, the optimization function. The higher the value of $f(S)$, the higher chance the string is picked for reproduction. Second, in crossover phase each of the strings is paired with other strings and parts of the elements are exchanged. The number of elements exchanged is randomized. Third, in mutation phase one element of a string is chosen randomly and that element is multiplied by –1. That is $s_r = s_r \times -1$. Each element of each string is mutated with the mutation probability of P_m. Fourth, the worst individual (the string which has the lowest $f(S)$) is eliminated and it is substituted by the best individual (the strong which has the highest $f(S)$).

The algorithm is very flexible and there are modifications that can be made for the purpose of analyzing circuit breaker signals. For example, in the above example, the signal consists of two elements: $x_p = (x_{1p}, x_{2p})$, $p = 1, 2, \ldots, m$. In reality, the number of elements can be changed according to the characteristics of the input data. In other words, the fuzzy patterns are required to change accordingly since the grid of fuzzy rules is no longer two-dimensional but it can be n-dimensional in order to accommodate the additional fuzzy rules for each for the additional dimension.

The flexibility of this algorithm provides the most important advantage of applying fuzzy classifications using fuzzy rules and genetic algorithms: it is able to classify the failure cases into different categories in order to visualize the degree of the failure rather than applying dichotomy on the signals to distinguish between normal signals and abnormal signals. It is an important tool for asset management of circuit breaker so that the diagnostic personnel can make decision on replacing the faulty part depends on the lifespan of the part. For example, let say a failure scale is created between zero and three, where zero indicates that replacement is necessary and three indicates that the part is in mint condition. When moving part shows its failure state is two, the personnel can justify if it is a good decision to do the replacement today rather than waiting the part to deteriorate further until the failure state turns to one or zero so that a replacement can take place.

In this chapter, multi-resolution analysis, fuzzy classifications using fuzzy rules and genetic algorithms are examined. In the following chapters, the problem and target of applying vibration signature analysis to find the failure of circuit breaker is defined. The circuit breaker model that generates the input data for multi-resolution analysis algorithm is examined in detail. Next, the simulation part of the thesis will show the analysing results of applying fuzzy rules and genetic algorithms and compare the analysing results with DWT covered in chapter 3.

Chapter 5
Circuit breaker Simulink model

Simulink is a graphical simulation tool manufactured by Mathworks Inc. which simulates models in engineering, mathematics, economics, and science. The data for the simulation in this thesis is retrieved from a circuit breaker Simulink model built for ABB. In this chapter, the description of the model is divided into two parts: the circuit breaker model and the vibration-sensing model.

5.1 Circuit breaker model

The circuit breaker model used in thesis is a modification and an extension of the model presented in the PhD thesis written by Michael Stanek [28]. The model visualizes the breaker components by using systems that consist of inputs, outputs, and processing unit. The processing unit functions are represented by blocks of equations, logic expression, and inequalities in Simulink. Three modifications have been made to Michael Stanek's circuit breaker model in order to improve the accuracy of the output signal of a breaker. These modifications are: the calculation of withstand voltage, the implementation of arc model, and the addition of vibration sensing model. The change of withstand voltage and arc model is discussed in section 6.1.3 and the vibration sensing model is discussed in section 6.2.

Figure 13 [28] shows a figure of a generic SF_6 circuit breaker. It shows a modern live-tank SF_6 self-blast breaker with a spring-hydraulic operating mechanism. A circuit breaker consists of three parts: breaker control, operating mechanism, and interrupter. Breaker control monitors the status of the actuators, auxiliary contacts, and charging system in an operating mechanism by using control logic, limit switches, and sensors. The operating mechanism provides the force needed to establish the connection of the breaker and extinguish the arc in the interrupter. The force is transmitted by mechanical linkage to the interrupter. The interrupter is where the connection and disconnection of the circuit actually take place. Live wire in power distribution system is connected to the interrupter. SF_6 gas is located in the interrupter in order to quench the arc.

All circuit breaker types have their own unique behavior characteristics. The model built in this thesis is based on ABB ELF SP 6-2 with an AHMA 8 drive mechanism.

The ELF SP is a SF_6 high voltage AC circuit breaker with up to four interrupters per phase. The 6-2 model has two T-shape interrupters per pole. The interrupting chambers are constructed on a puffer piston principle and are equipped with double contacts. Wide space between the open contacts provides high dielectric strength. The interrupting chambers are driven by an actuating rod with a pneumatic operating mechanism. Model 6-2 was designed for 420 kV-rated voltage, 4 kA-rated current, and 63 A-rated breaking current. Figure 14 shows a picture of ABB ELF SP. The rated operating sequence is O-0.3s-CO-1 min-CO or CO-15s-CO [29].

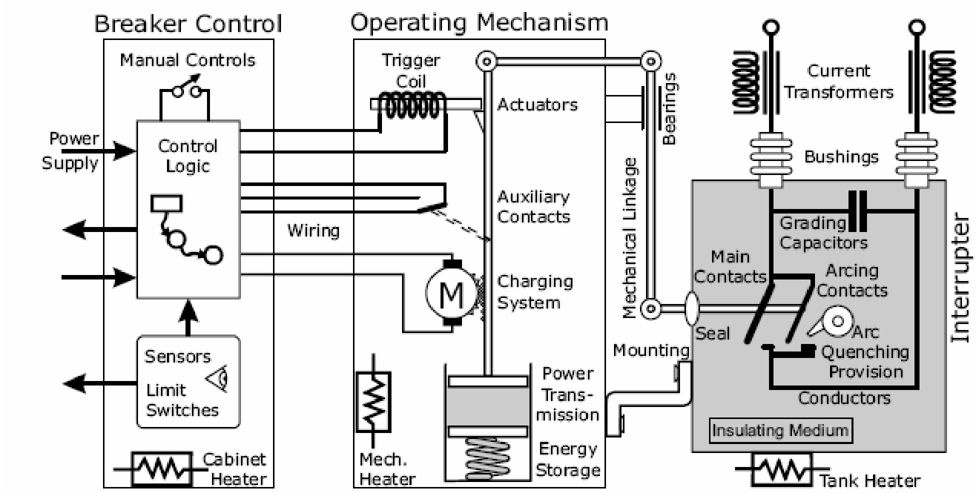

Figure 13 A generic description of a high voltage circuit breaker [28]

Figure 14 A picture of ABB ELF SP [29]

The AHMA 8 is a hydraulic spring operating mechanism. It is a combination of a hydraulic operating mechanism and an energy storage disk spring assembly. Tripping of the operating mechanism and energy output are based on hydraulic operating techniques and include control valves and hydraulic cylinders. In detail, the activation of open coil and close coil actuates change-over valves which adjust the pressure in the main piston. The location of the main piston determines the opening position and closing position of the breaker. On the other hand, the tension of the spring is released according to the amount of oil needed for switching. Oil required from the high pressure storage is replaced immediately by a hydraulic pump [28][30]. The hydraulic pump is controlled by a limit switch and the limit switch is controlled by the position of the spring column. Figure 15 shows a picture of AHMA operating mechanism.

Figure 15 AHMA model 8 [30]

Figure 16 [6] shows the complete view of the Simulink model. This model consists of 23 subsystems. The important input of the model includes open command, close command, motor voltage supply, oil leak size of high pressure volume, gas pressure, travel limit of cylinder, damping limit of cylinder, source voltage, contact resistance, and contact mass. The important output of the model includes close coil current, trip coil current, motor voltage, motor current, load side voltage, and contact travel. Based on the extract of the circuit breaker layout and the previous measures have done experimentally on circuit breaker, the simulink model for spring and primary contact is modified. Improvement is done step by step to make the output signals to be more closely to measured signals. The improved part of the model is highlighted by blue line in Figure 16.

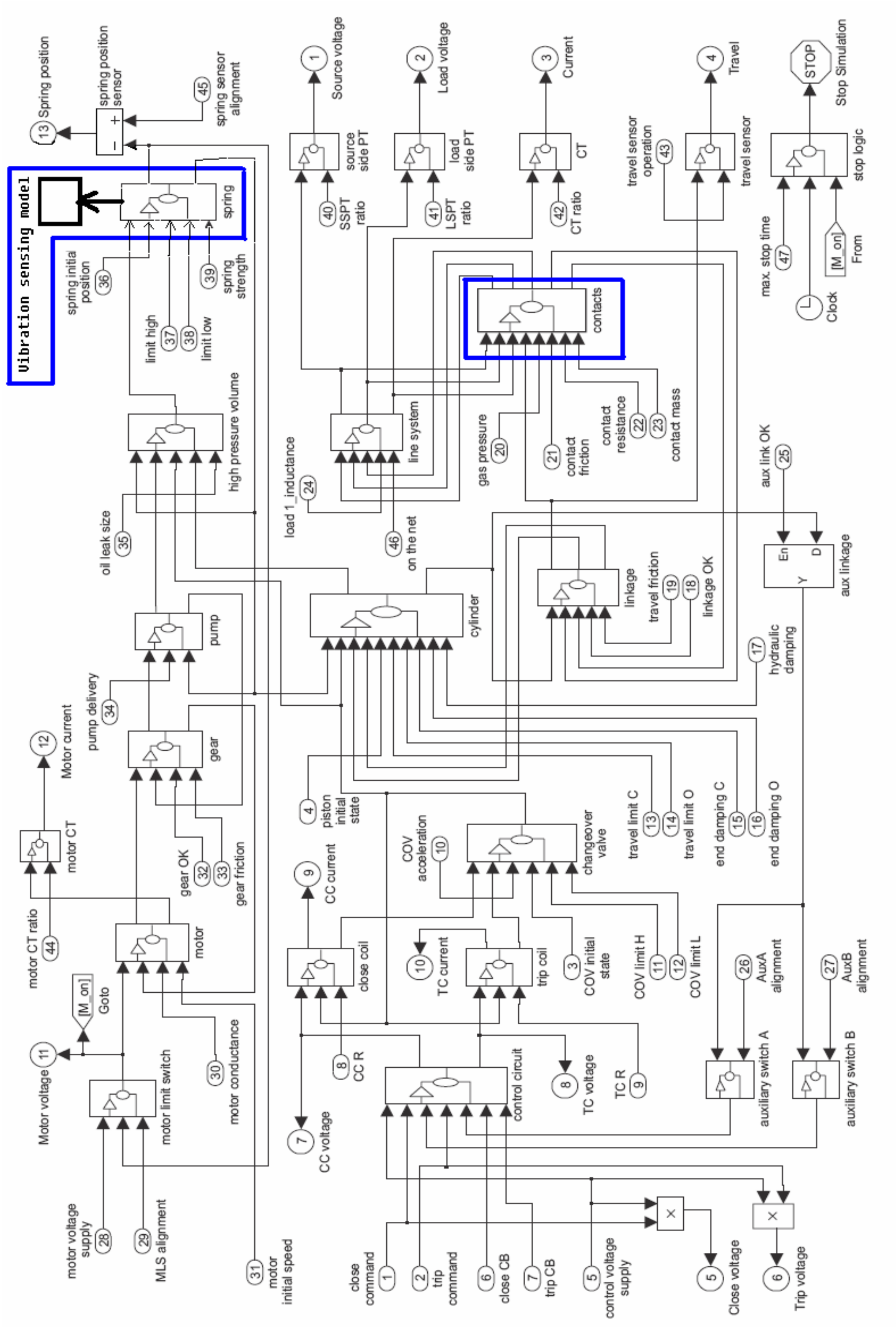
Vibration sensing model
Spring position
spring position sensor
spring sensor alignment
spring
spring initial position
limit high
limit low
spring strength
Source voltage
source side PT
SSPT ratio
Load voltage
load side PT
LSPT ratio
Current
CT
CT ratio
Travel
travel sensor
travel sensor operation
STOP
Stop Simulation
stop logic
max. stop time
Clock
[M_on]
From
contacts
gas pressure
contact friction
contact resistance
contact mass
aux link OK
En
D
Y
aux linkage
line system
load 1_inductance
on the net
high pressure volume
oil leak size
pump
pump delivery
cylinder
linkage
travel friction
linkage OK
hydraulic damping
Motor current
motor CT
motor CT ratio
gear
gear OK
gear friction
piston initial state
CC current
COV acceleration
changeover valve
travel limit C
travel limit O
end damping C
end damping O
motor
Goto
Motor voltage
motor limit switch
motor conductance
close coil
TC current
trip coil
COV initial state
COV limit H
COV limit L
AuxA alignment
AuxB alignment
CC R
TC R
control circuit
TC voltage
auxiliary switch A
auxiliary switch B
CC voltage
motor voltage supply
MLS alignment
motor initial speed
close command
trip command
close CB
trip CB
control voltage supply
Close voltage
Trip voltage

Figure 16 The model of a high voltage circuit breaker built by Michael Stanek [28]

The vibration of the model has several sources. Main spring, hydraulic cylinder, and primary contact contribute most of the vibration produced in a circuit breaker.

5.1.1 Main Spring

The spring in the spring hydraulic operating mechanism is the power source for operations in a circuit breaker. It provides pressure to the hydraulic pump and the hydraulic cylinder. The strength of the spring provided depends on nonlinear spring characteristics. Figure 17 shows the Simulink model of main spring. The inputs include the oil flow into high pressure volume and data on spring specification such as limit and strength. The outputs of the model are spring position and spring force. Notice that the spring force is the input of the vibration sensing-model [28].

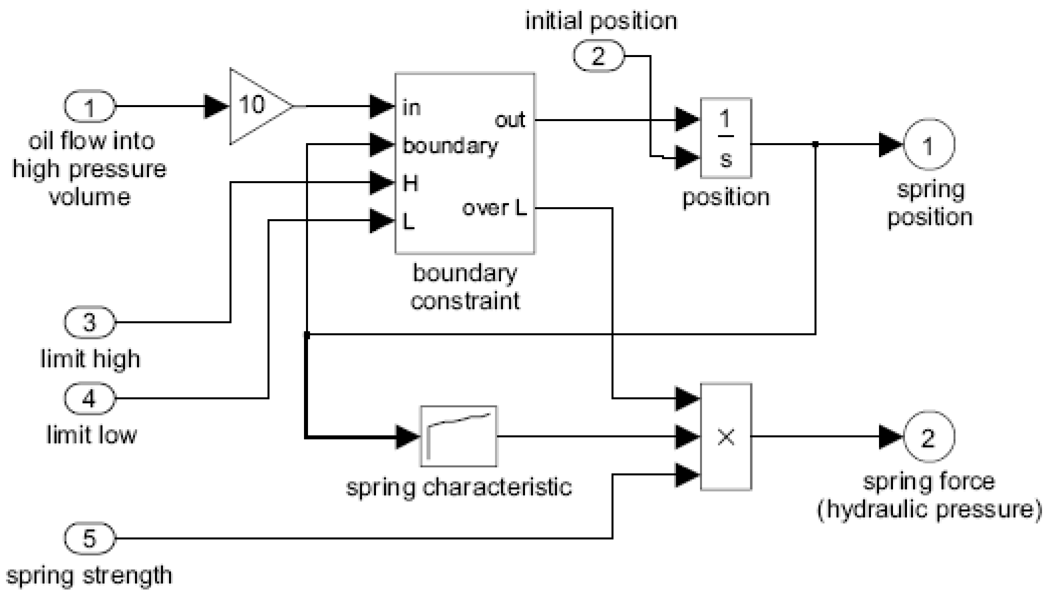

Figure 17 The Simulink model of main spring [28]

5.1.2 Hydraulic cylinder

A hydraulic cylinder consists of a piston which moves the circuit breaker contacts. Figure 18 shows the cross section diagram of the hydraulic cylinder. The arc extinction unit includes fixed continuous current (1), fixed arcing contact (2), movable arc contact (3), and movable continuous current contact (4). For opening operations, the piston moves the contact to the open position as hydraulic pressure of the enclosed gas increases and is applied to the top of the piston. The contact separately produces an arc that further increases the pressure of the SF_6 gas. When the pressure of the gas reaches a certain level, gas is released from the quenching nozzle (8) and 'blows' the arc. The nozzle shape of the contacts is tailor-made to allow airflow and optimized quench time. For close operation, the piston moves the contact to the closed position as hydraulic pressure is applied to both ends of the piston. Due to the area differences of both ends, the piston is moved to the desired position [1]. Figure 19 shows the Simulink model of hydraulic cylinder [28].

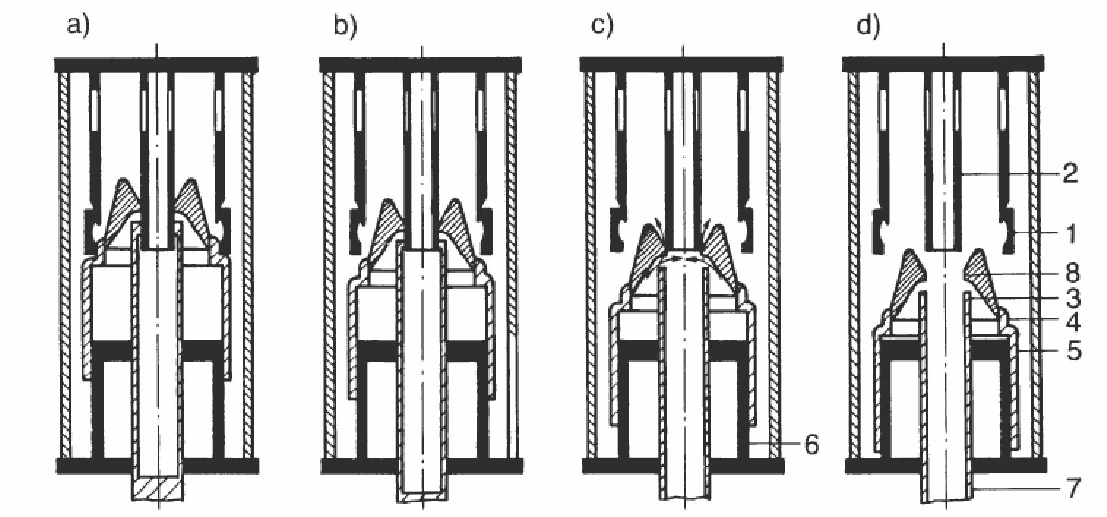

Figure 18 The four stages of hydraulic cylinder: (a) closed position of arc contact; (b) starting of the contact opening movement; (c) separation of arcing contacts; and (d) open position of arc contact. Parts: 1) fixed continuous current contact, 2) fixed arcing contact, 3) movable arcing contact, 4) movable continuous current contact, 5) compression cylinder, 6) compression piston, 7) actuating rod, and 8) quenching nozzle [1].

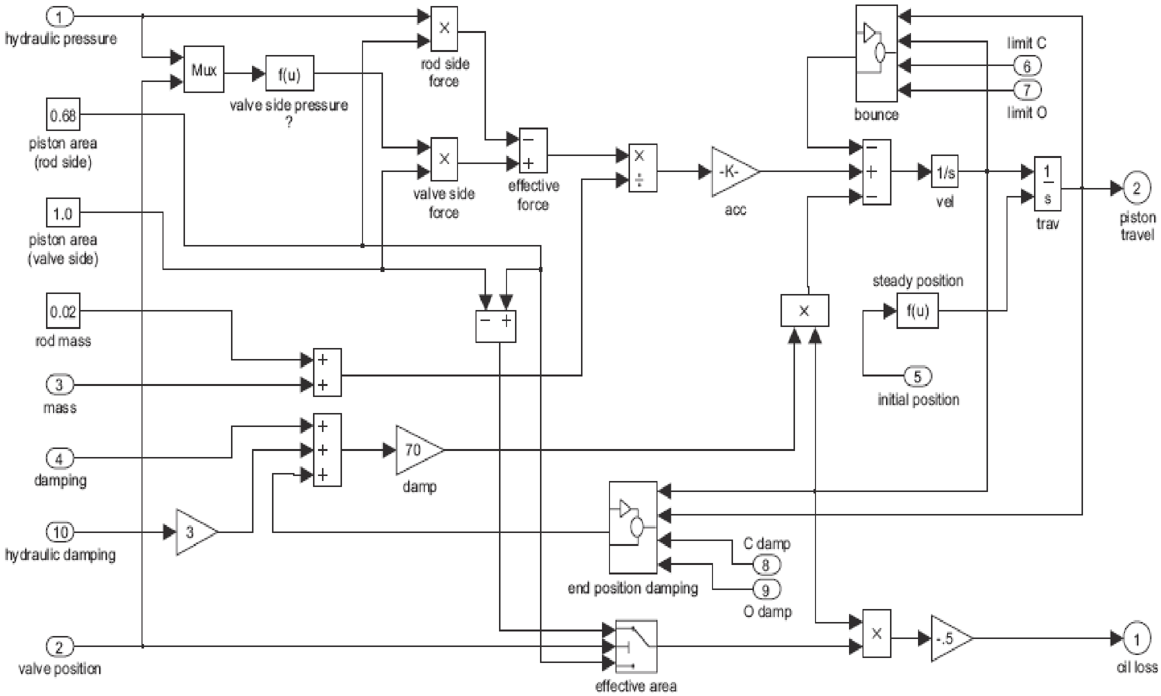

Figure 19 The Simulink model of hydraulic cylinder [28]

5.1.3 Primary contact

Primary contact is the location where the interruption of the current going through a circuit breaker takes place. In Michael Stanek's model, load current flows through the contact when the contact voltage, the difference between the source voltage and the load side voltage, is larger than the dielectric withstand voltage of SF_6 gas. Figure 20 shows the original primary contact Simulink model of Michael Stanek. There are two refinements on this model and they are highlighted with blue line in the figure. The left block represents the refinement of withstand voltage and the right block represents the refinement of arcing model.

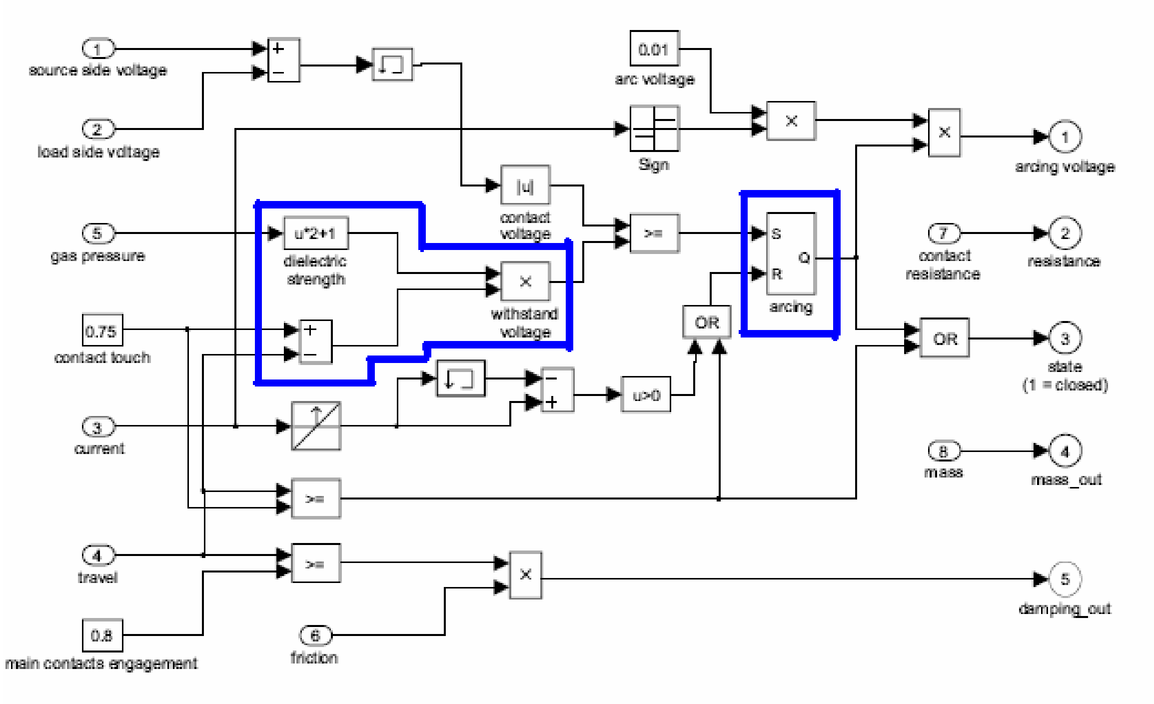

Figure 20 The Simulink model of primary contact [28]

The first refinement in Michael Stanek's model is to recalculate the value of withstand voltage to reflect the fact that SF_6 gas is an excellent current interrupting and insulating medium in an interrupter and SF6 is in effect when the breaker model demonstrate the opening and closing of the breaker. The withstand voltage can be calculated by using this equation:

$$V = \left(\frac{P}{RT}\right)^{\alpha} \times d^{\beta} \times \tau \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(25)$$

where V is the withstand voltage, P is the absolute pressure in atm, R is a constant (0.08205 liter-atm/mole-°K), T is the temperature in °K, d is the gap length in mm, and α,β, and τ are the empirical coefficients. For SF_6 gas, $\alpha = 0.995$, $\beta = 1.01$, and $\tau = 214$. The equation of withstand voltage is applicable when the temperature is between -50°C and 800°C [31] Figure 21 shows the new Simulink model for withstand voltage.

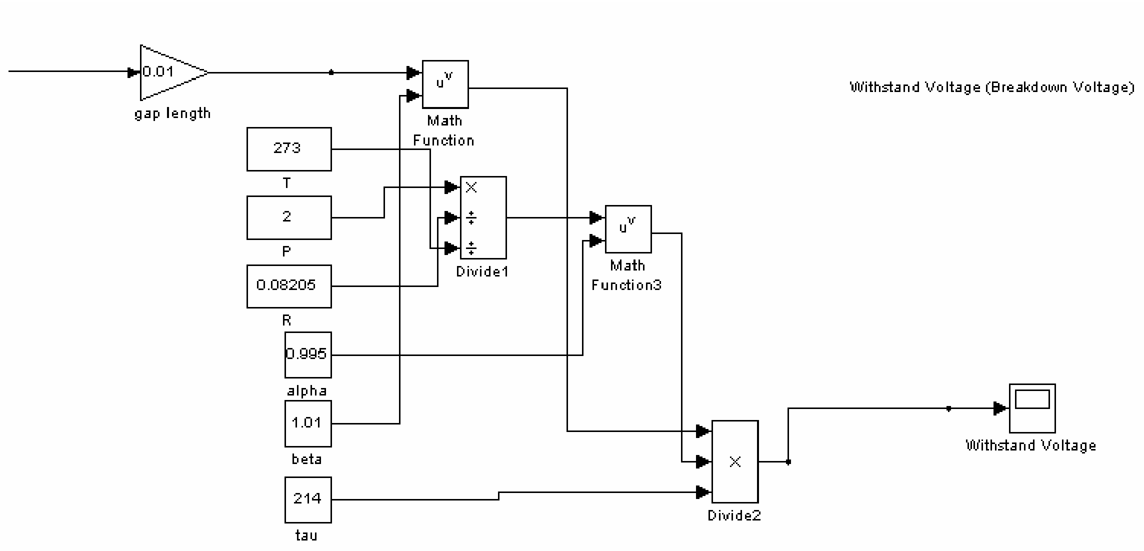

Figure 21 The Simulink model of withstand voltage

The second improvement on Stanek's model is the implementation of Mayr arc model in the primary contact component. Arc model is formulated for better understanding of the current interruption behaviour and interrupting chamber operation in a circuit breaker. Mayr arc model is one of the most common tools to study the non-linear behaviour of the circuit breaker arc. The equation is:

$$\frac{1}{g}\frac{dg}{dt} = \frac{d\ln g}{dt} = \frac{1}{\tau}\left(\frac{ui}{P} - 1\right) \qquad \text{..........................(26)}$$

where g is the conductance of the arc, u is the voltage across of the arc, i is the current through the arc, τ is the arc time constant, and P is the cooling power in the interrupting chamber. Figure 22 [35] shows the Simulink model that demonstrates the Mayr arc model.

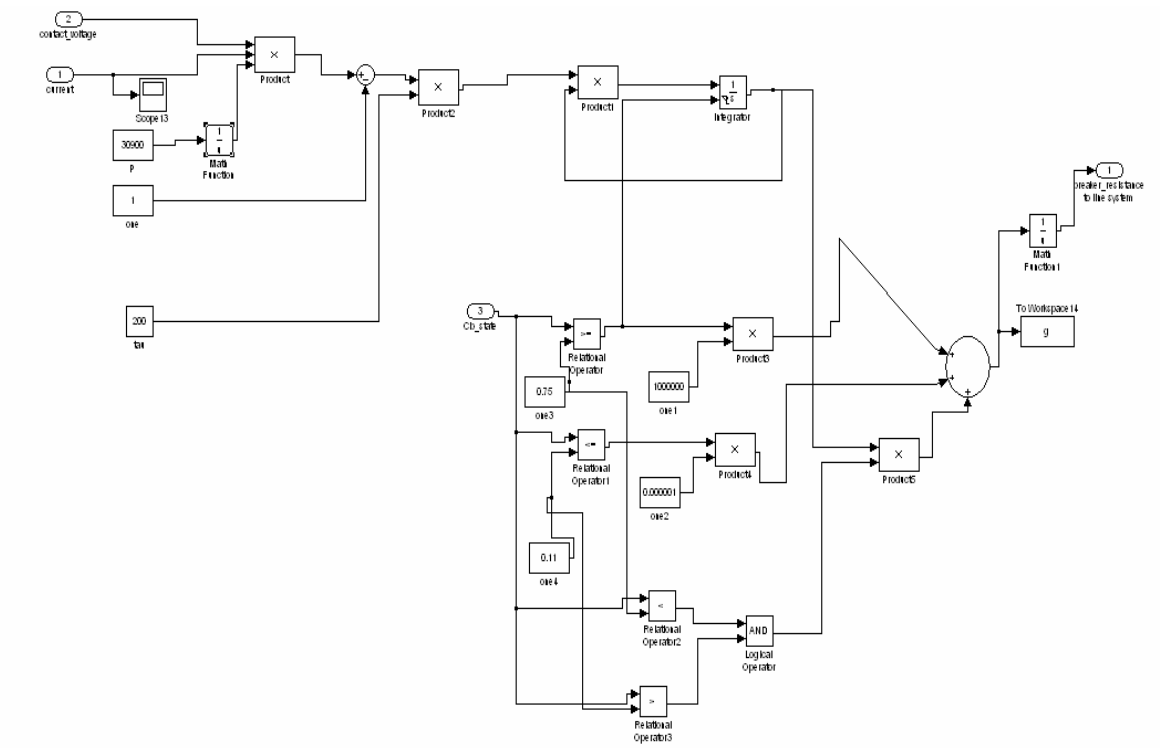

Figure 22 Mayr arc model [35]

5.2 Vibration-sensing model

The third improvement on Stanek's model is the addition of vibration-sensing model. The vibration-sensing model of the breaker model is derived from [24]. In this model, a silicon micromachined accelerometer is simulated. Acceleration of the vibrating object prevents the mass of the sensor from resting and a differential change in capacitance is made which is proportional to the acceleration. This model reflects the dynamic performance of the sensing element and the control strategy (closed loop), and electrostatic force.

A micromachined sensing element consists of three layers. The top layer is "top electrode," the middle is "seismic mass," and the bottom is "bottom electrode." Differential change of the capacitance between each of the layers determine the output voltage which represents the vibration signal. As the seismic mass is vibrating, it is no longer at the centre position of the accelerometer. At that time, electrostatic force exists and it pulls the seismic mass back to its original position. In the model, the electrostatic force is represented by a spring.

The sensing element is a second order system with a mass, spring, and a form of damping caused by the mass that the accelerometer is detecting. On the other hand, the damping is not linear since the gap between the electrodes and the mass is much smaller than the area of the accelerometer. As the mass moves, the air in the gap cannot escape in a sufficiently short period of time. As a result, pressure builds up between the electrode and the mass. When the accelerometer is installed in different locations of the mass, damping coefficients may vary.

Figure 23 shows a Simulink model of the vibration-sensing model used for this thesis's simulation. The input of the model is the damping coefficient of the mechanical part and the states of the open/close of that part in the circuit breaker to make sure that vibration occurs when it is operated. The output is the vibration signature of the mechanical part and it is shown in Figure 24. The transport delay block and its corresponding +/- block ensure that the input of the model is a very-short-time-duration pulse. The saturation block shows that there is a physical restraint in the movement of the mass due to the top and bottom electrodes. The "50" gain block represents the spring constant of the accelerometer. The "10" gain block represents the seismic mass of the accelerometer. The feedback loop from the two integrators represents the nonlinear viscous damping.

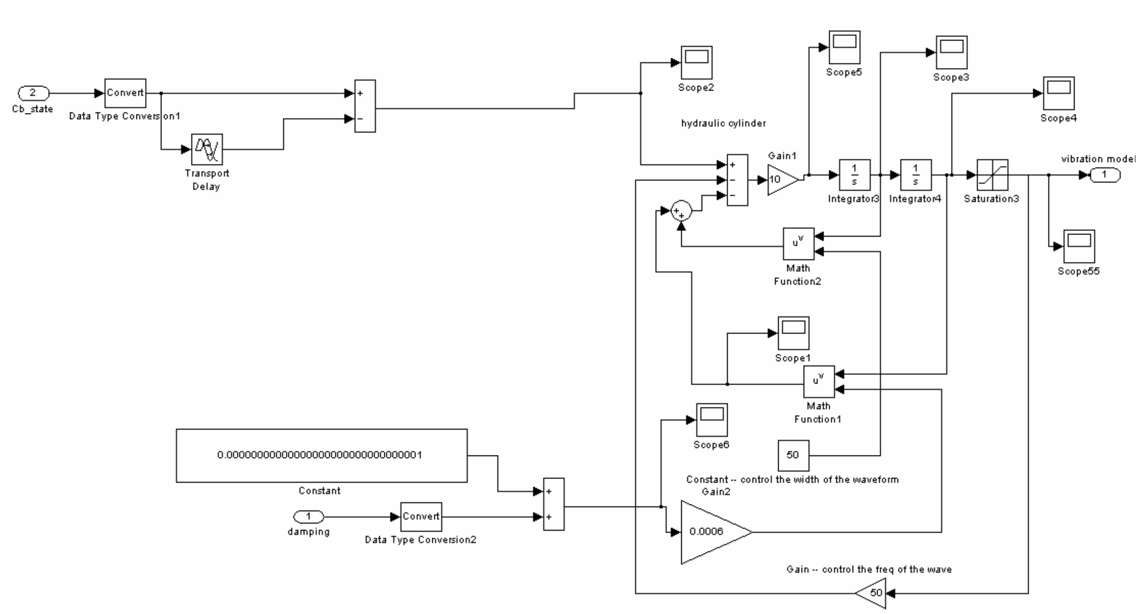

Figure 23 The Simulink vibration-sensing model

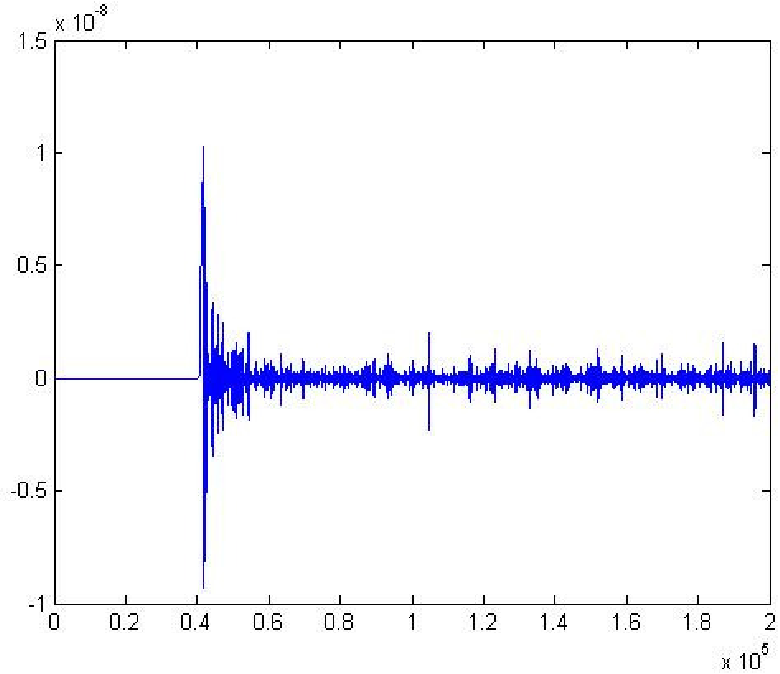

Figure 24 The vibration signature generated by the Simulink vibration-sensing model

Figures 25 and 26 compare the vibration signature when the spring gain (The "50" triangular block in fig. 11) is changed to 0.05, 5, 50, 50000, and 5000000. The first 200000 samples are compared in these charts. From the figures, it is observed that the shape of the vibration signature is very similar for each level of spring gain, but as the spring gain increases, the amplitude of the fluctuation increases. This results because the spring gain in the diagram represents the spring constant in the accelerometer. If the spring constant is large, the spring has more force to place the seismic mass back to its original position. As a result, the seismic mass experiences more vibration as shown. On the other hand, as spring constant is low, the force provided by the spring is low, therefore it takes shorter time for the spring to place the seismic mass back to its original location. As a result, the vibration is larger in terms of the amplitude.

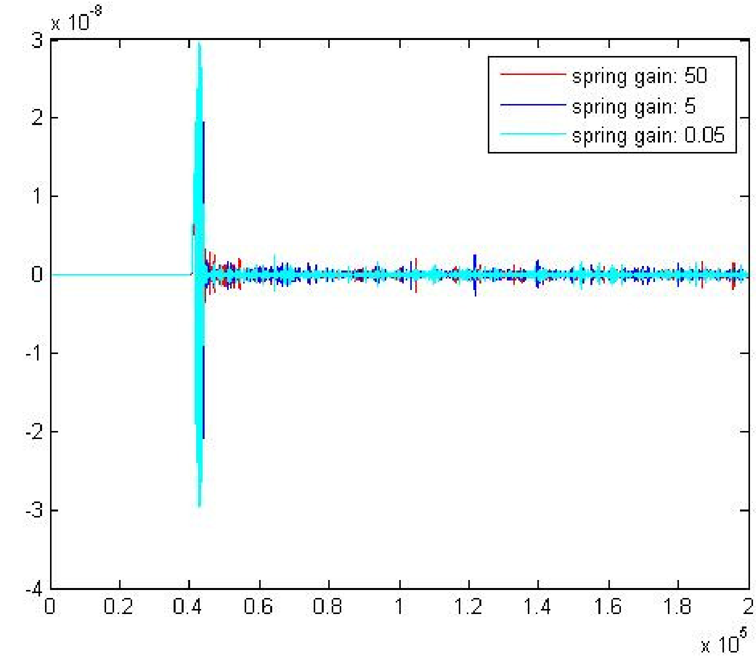

Figure 25 A comparison of the vibration signature for spring gain is 50, 5, and 0.05

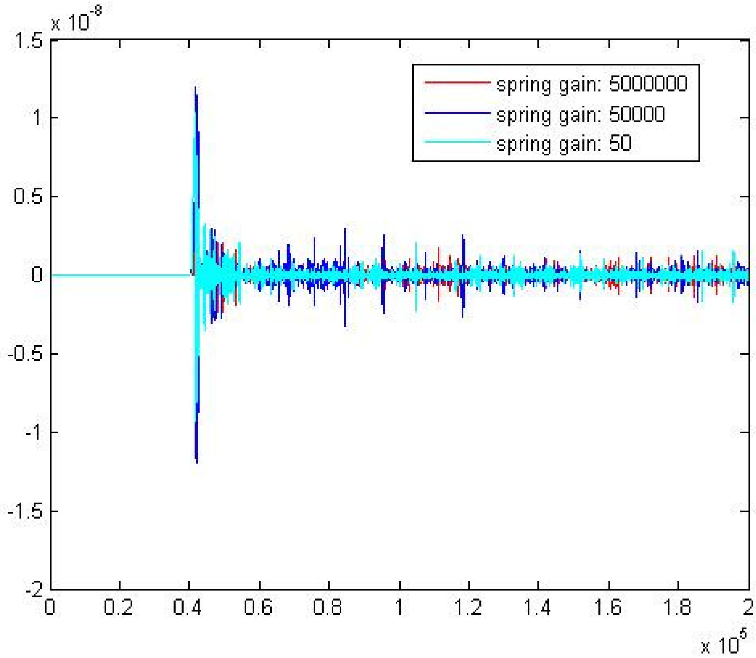

Figure 26 A comparison of the vibration signature for spring gain is 5000000, 50000, and 50

Figure 27 compares the vibration signature when the damping constant (The "50" rectangular block in figure 11) is changed to 0.5, 50, and 5000. The first 200,000 samples are compared in these charts. As the value of damping increases, the amplitude of the vibration signature decreases.

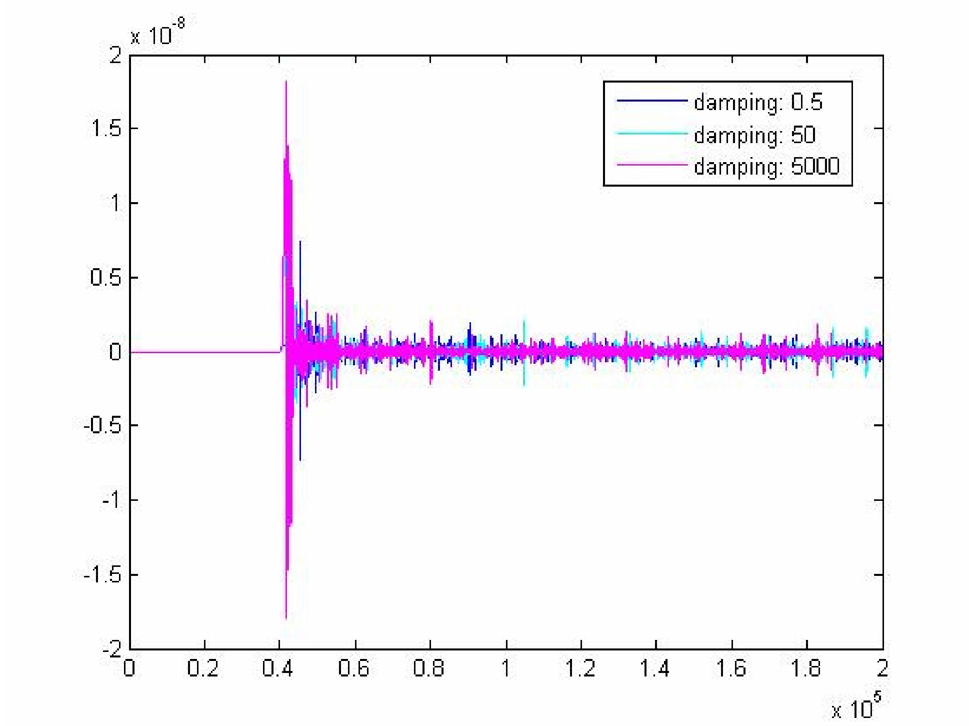

Figure 27 A comparison of the vibration signature for damping constant is 0.5, 50, and 5000

Figures 28 and 29 compare the vibration signature when the gain (The "10" rectangular block in figure 11) is changed to 0.5, 1, 2, 5, 10, 20, and 50. The first 150,000 samples are compared in these charts. It is observed that as the value of gain deceases, the amplitude of the vibration increases. Since the value of gain represents the mass of the seismic mass, as the mass decreases, the vibration is likely to increase.

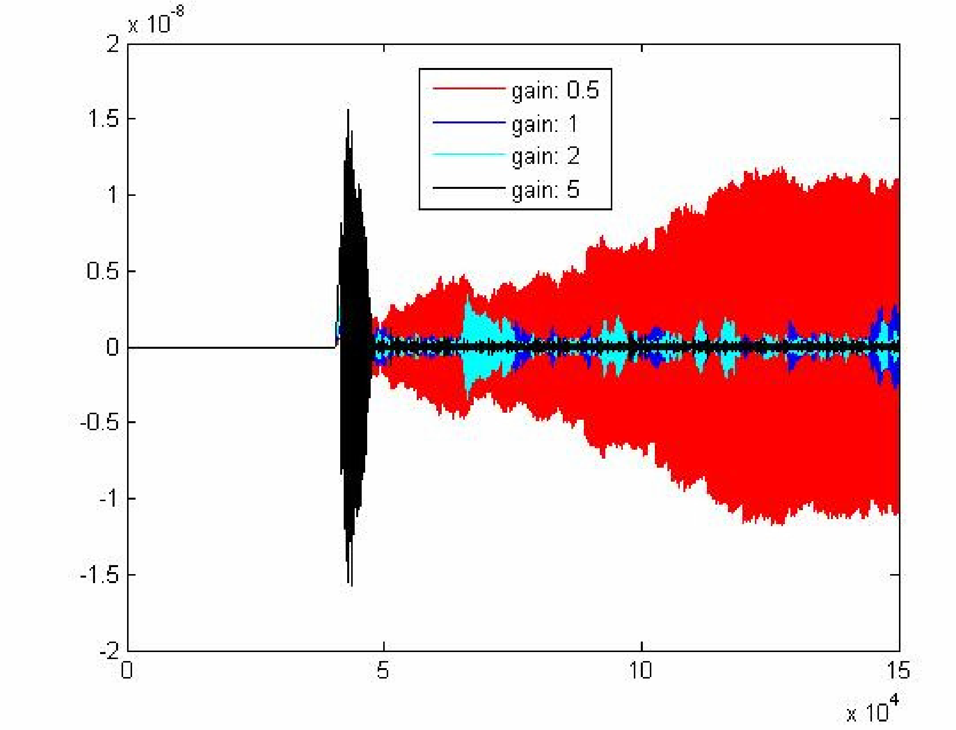

Figure 28 A comparison of the vibration signature for gain constants are 0.5, 1, 2 and 5

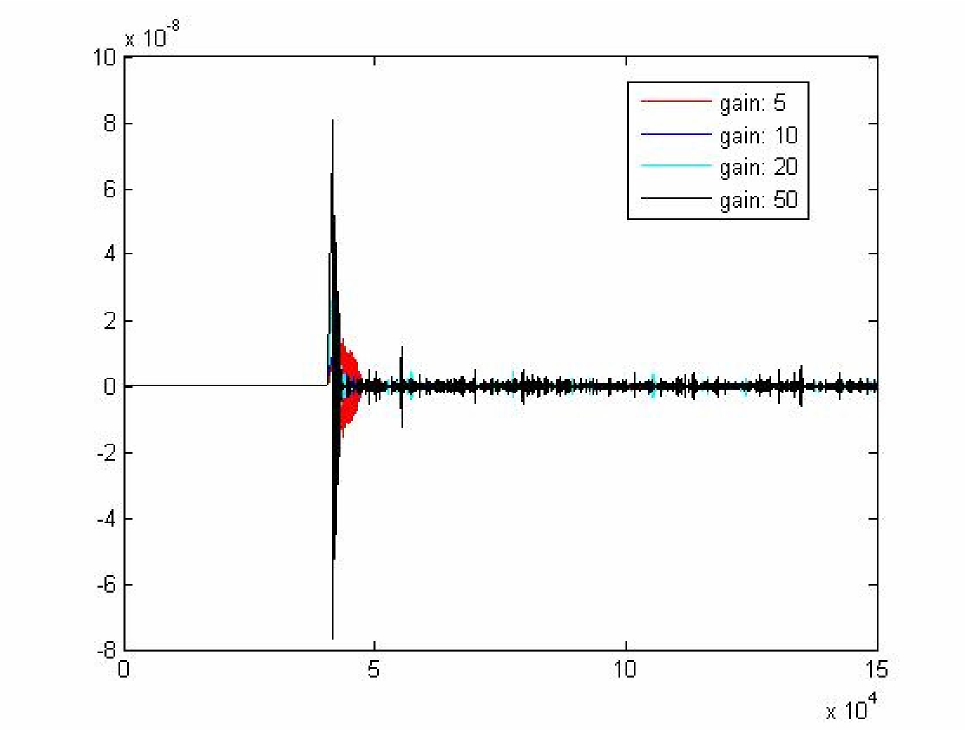

Figure 29 A comparison of the vibration signature for gain constants are 5, 10, 20 and 50

This chapter discussed the circuit breaker model used to mimic an actual circuit breaker. In chapter 3 and chapter 4, different methods of analyzing vibration signals are introduced and compared in terms of their advantages, disadvantages, and their ability to analyze breaker vibrations in order to find the failure of a breaker. In chapter 5, the problem and the target of how to find a failure of a circuit breaker using vibration signatures are formulated. In this chapter, the method of how vibration signals are generated is examined. In the breaker model, the interactions between the components are demonstrated in terms of equations, logic, and inequalities. Some modifications are made so that it is more customized to the opening and closing operations of a breaker. In addition, a sensor model is created so that any failure in a breaker is converted to a form that makes the signal visible for diagnostic purpose. In the next chapter, there are demonstrations of the detection of failure of a simulated breaker by using proposed vibration analysis method. There is a discussion of why this proposed method is better than the conventional method.

Chapter 6
The simulated results and the analysis

In the previous chapters, different methods of analyzing vibration signals are introduced and compared in terms of their advantages, disadvantages, and their ability to analyze breaker vibrations in order to find the failure of a breaker. Moreover, the breaker model and the sensing model that are used for generating vibration signals are described. In this chapter, there are demonstrations of the detection of failure of a simulated breaker by using proposed vibration analysis method. There is a comparison of the results between the proposed method and the conventional method.

In the diagnostic process of a breaker, a tool that describes the degree of wear of a mechanical part is helpful for asset management of circuit breaker since the diagnostic personnel can make a better decision on replacing the faulty part depends on the lifespan of the part. For example, the state of a part is described by a failure scale between zero and three, where zero represents replacement is crucial and three represents the part is in mint condition. When moving part shows its failure state is one or two, the personnel can apply cost-benefit analysis to justify if it is a good decision to do the replacement today rather than waiting the part to deteriorate further until the failure state turns to one or zero so that a replacement can take place. In order to perform this task, an algorithm that solely divide the cases into two categories “pass” and “fail” may not be capable to do this job, Instead, an algorithm that can demonstrate the degree of corrosion of a certain part is applicable in this case.

In the simulation, spring is chosen for the study since spring is one of the most active parts in a breaker when a breaker is opened or closes. The spring in the spring hydraulic operating mechanism is the power source for operations in a circuit breaker. It provides pressure to the hydraulic pump and the hydraulic cylinder. When there is a failure in a breaker, it is likely that spring is the part that causes the problem. In order to measure the performance of a spring in terms of its elasticity, spring constant is applied. Therefore, spring constant is chosen as the variable of the simulation.

The simulation data comes from the model of circuit breaker described in chapter 6. The data is collected when the model breaker is changing from the state of closing to the state of opening. For the purpose of classifying the normal cases and abnormal cases, the spring force is manipulated. According to the specification of ABB AHMA 8, the nominal value of spring force is 90000 N. In order to classify the fault cases, four categories are created. In the first category, spring constant is below 20000N. In the second category, spring constant is between 20000 N and 40000 N. In the third category, spring constant is between 40000 N and 80000 N. In the last category, the spring constant is between 80000 N and 100000 N. The first three cases are considered as faulty state and the last case is considered as healthy state. In terms of the severeness of the spring, category 1 requires immediate replacement of the spring while category 2 and category 3 do need attention from the diagnostic personnel but no immediate replacement of spring is necessary.

In the first part of the simulation, the vibration waveforms are analyzed using dynamic time warping. The original time domain signal is divided into several portions defined by a constant time interval. Fast Fourier Transform is used to find the frequency content of each signal frame. The frequency components are plotted in logarithmic scale so that the events that yield weak signals are detected. The Euclidean distance between the frequency vectors are calculated by looking at the similarity of the event signals. DTW ensure that the accumulated Euclidean distance between the frequency vectors of two signals is minimized when two vibration signatures are aligned. Normal deviation shows that there is no abnormal event in the signal and it fluctuates at a certain range. When there is an irregular deviation, the spectral distance increases compared to the normal deviation. Consequently, mechanical events of a circuit breaker may be detected.

In the second part of the simulation, the vibration waveforms are analyzed and decomposed using multi-resolution analysis (MRA), as mentioned in Chapter 4.1. Nine levels of resolution levels are captured. After the waveforms are produced, the standard deviations of each level of approximate signals are calculated and it is shown in Figure 30. From the figure, it is observed that level 2, 3, and 4 have the highest standard deviations among all of the levels. In other words, level 2, 3, and 4 contain the highest level of signal energy and are suitable for classification. Each of the case is plotted three-dimensionally according to the standard deviations of level 2, 3, and 4 and fuzzy rules and genetic algorithm which described in Chapter 6.4 are applied to categorize the cases.

After analyzing the vibration signals with these two methodologies, the accuracy results are compared and the conclusion of which method is the best can be made.

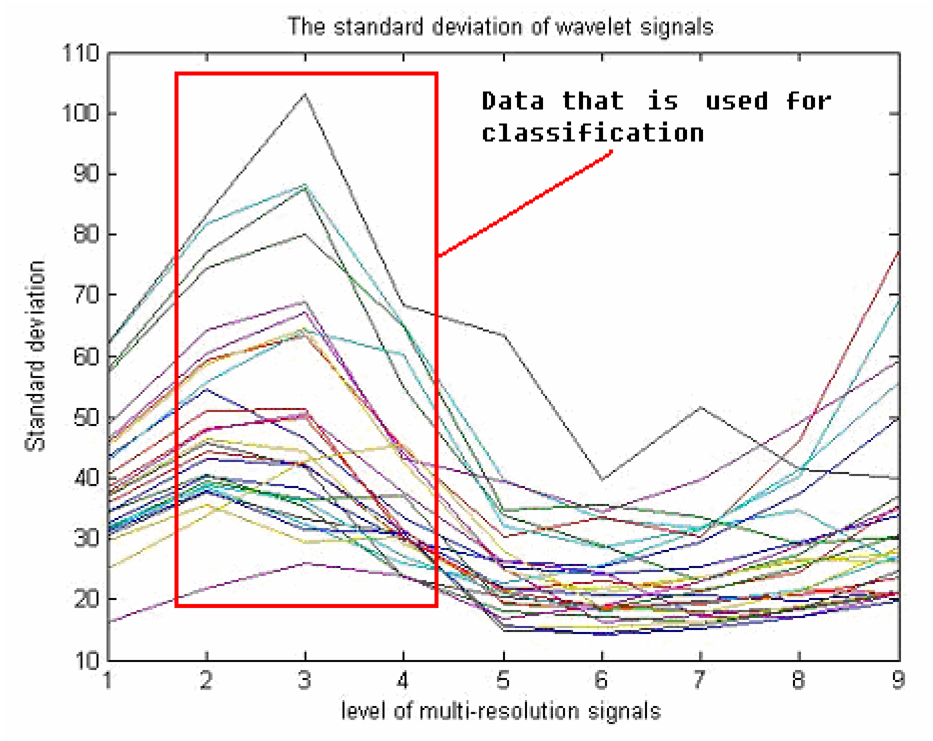

Figure 30 The standard deviations of the vibration signals of nine levels

6.1 Result of Dynamic Time Warping [DTW]

This Chapter will discuss the result of applying dynamic time warping to analysis the vibration. In the simulation, waves from each of the four categories are obtained from the model. In Figure 31, the scenario of category 1 (spring constant 3600 N against 85500 N) is compared with the scenario of category 4 (spring constant 90000 N against 85500 N). Blue line represents the deviation from category 1 and green line represents the deviation from category 4. From the figure, normal deviation is shown except the time between 0.225 second and 0.275 second, when there is irregular deviation.

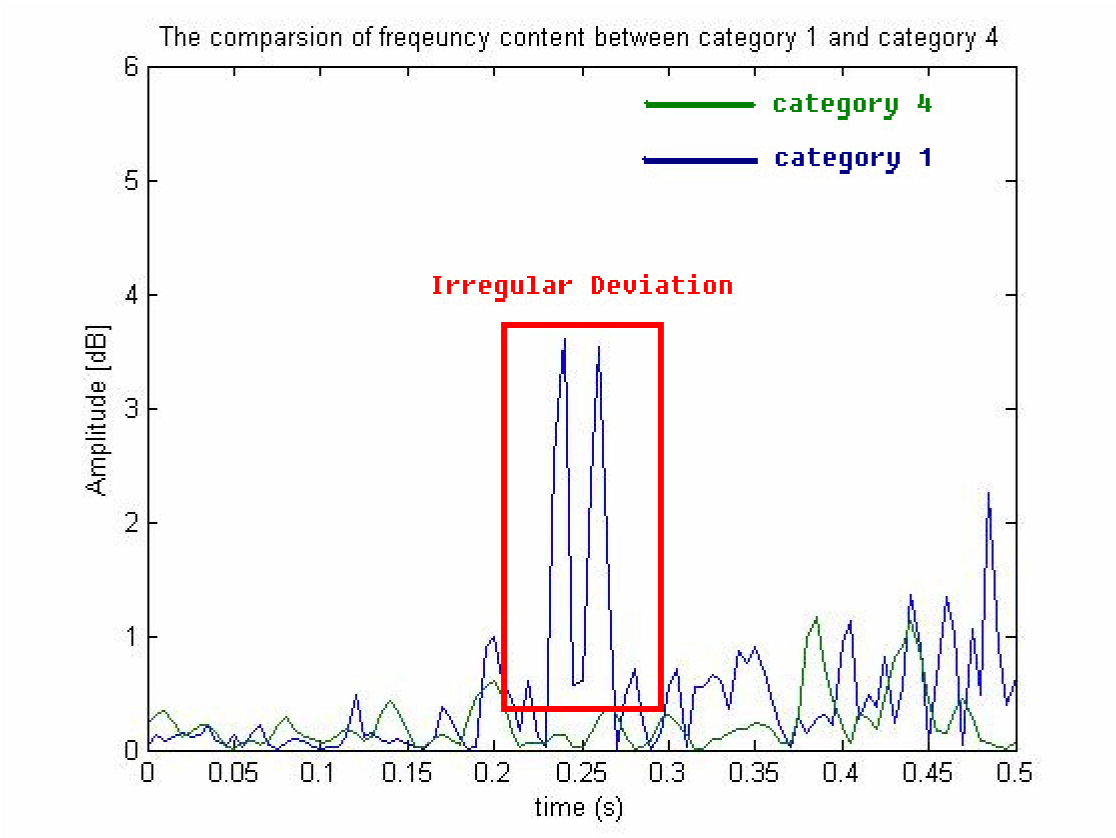

Figure 31 The comparison of frequency content between category 1 and category 4

In Figure 32, the scenario of category 2 (spring constant 28800 N against 85500 N) is compared with the scenario of category 4 (spring constant 90000 N against 85500 N). Blue line represents the deviation from category 2 and green line represents the deviation from category 4. From the figure, normal deviation is shown except the time between 0.37 second and 0.47 second, when there is irregular deviation.

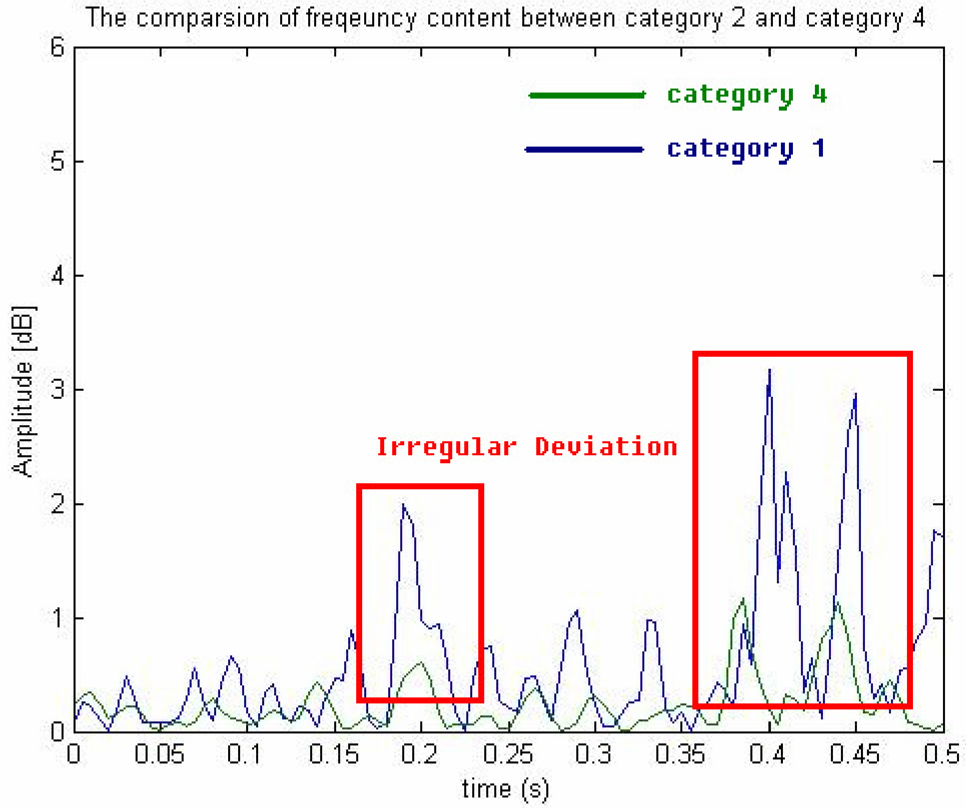

Figure 32 The comparison of frequency content between category 2 and category 4

In Figure 33, the scenario of category 3 (spring constant 55800 N against 85500 N) is compared with the scenario of category 4 (spring constant 90000 N against 85500 N). Blue line represents the deviation from category 3 and green line represents the deviation from category 4. From the figure, normal deviation is shown except the time between 0.1 second and 0.17 second, between 0.31 second and 0.34 second, and between 0.42 second and 0.44 second, when there is irregular deviation.

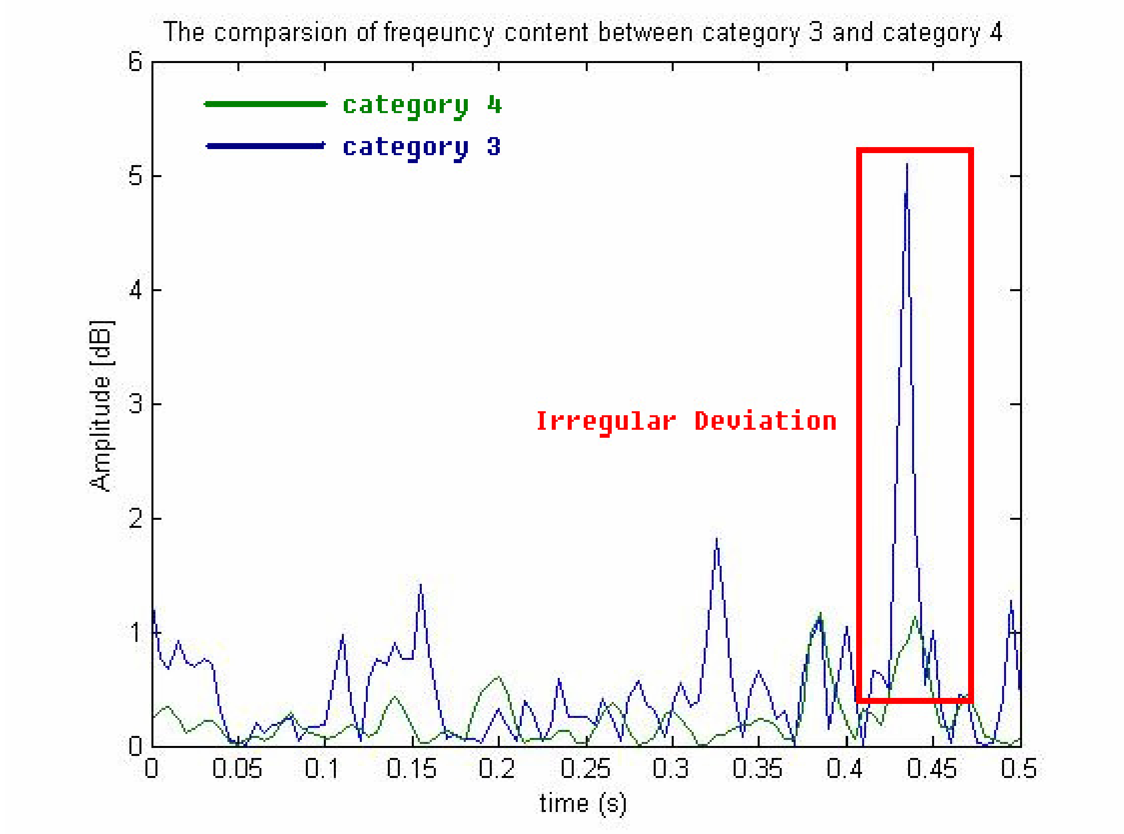

Figure 33 The comparison of frequency content between category 3 and category 4

In Figure 34, the scenario of category 4 (spring constant 84600 N against 85500 N) is compared with the scenario of category 4 (spring constant 90000 N against 85500 N) as a control experiment. Blue line represents the deviation from category 4 (spring constant 84600 N against 85500 N) and green line represents the deviation from category 4 (spring constant 90000 N against 85500 N). From the figure, normal deviation is maintained in the entire period of time.

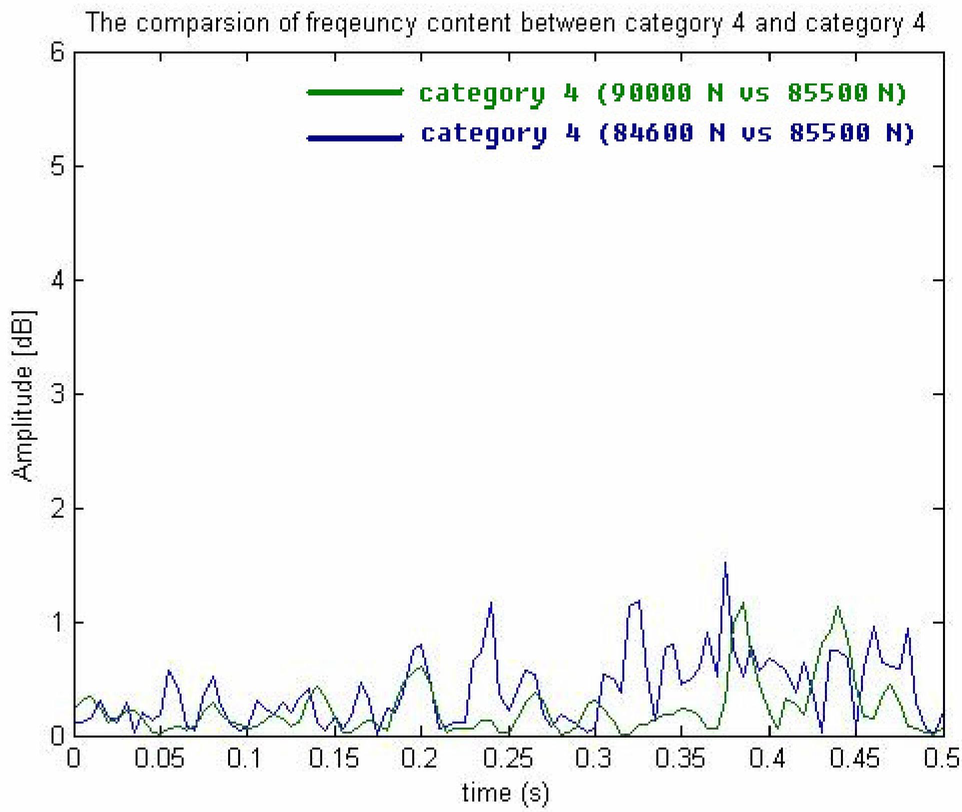

Figure 34 The comparison of frequency content between category 4 and category 4

From the above figures, it is observed that DTW is an effective method to classify the abnormal cases from the normal cases in case of malfunction of spring. However, it is very difficult to distinguish each of the failure case. It is almost not possible to know how the spring performs and it does not give enough information on the decision making process of whether the replacement of the spring is necessary or not. DTW is not an ideal solution for asset management of circuit breaker since it does not provide the full picture of the situation.

6.2 Result of optimizing fuzzy rules with genetic algorithm

In Chapter 6, when the algorithm of fuzzy rules and genetic algorithm is introduced, the pattern is descried in two-dimensions. However, it is not enough to allocate all of the wave features (Standard deviations of level 2, 3, and 4 of approximate signals). Therefore, the fuzzy rules are modified so that it is now in three-dimensions in order to accommodate adequate information for classifications. Figure 35, 36, 37, and 38 shows the new fuzzy rules for different value of K in three-dimensions, according to equation (22).

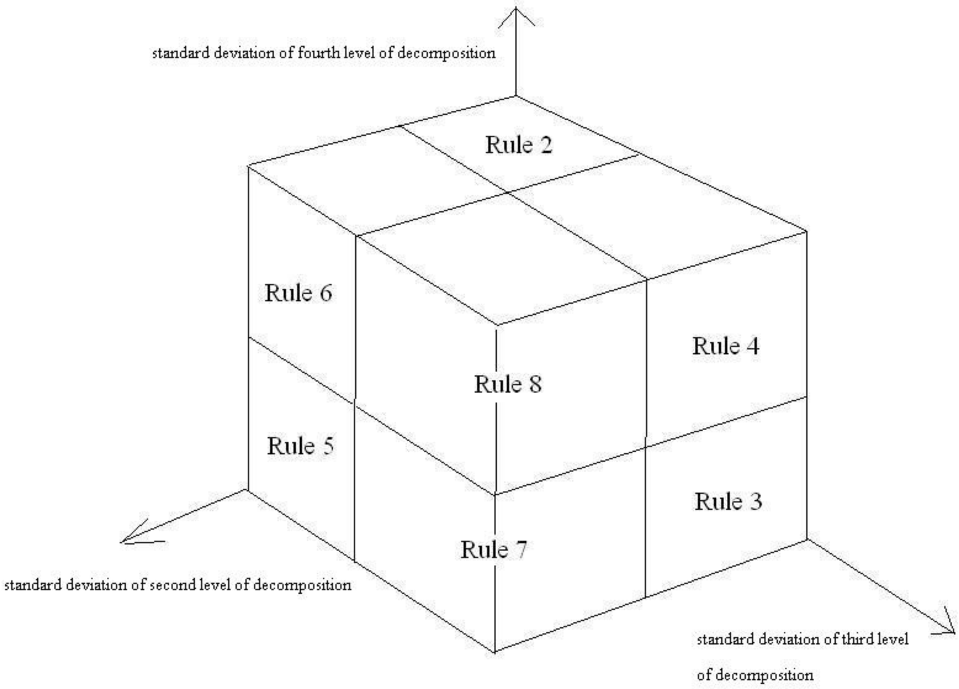

Figure 35 The fuzzy pattern and string element for $K = 2$ in three dimensions (compare this figure with Figure 9)

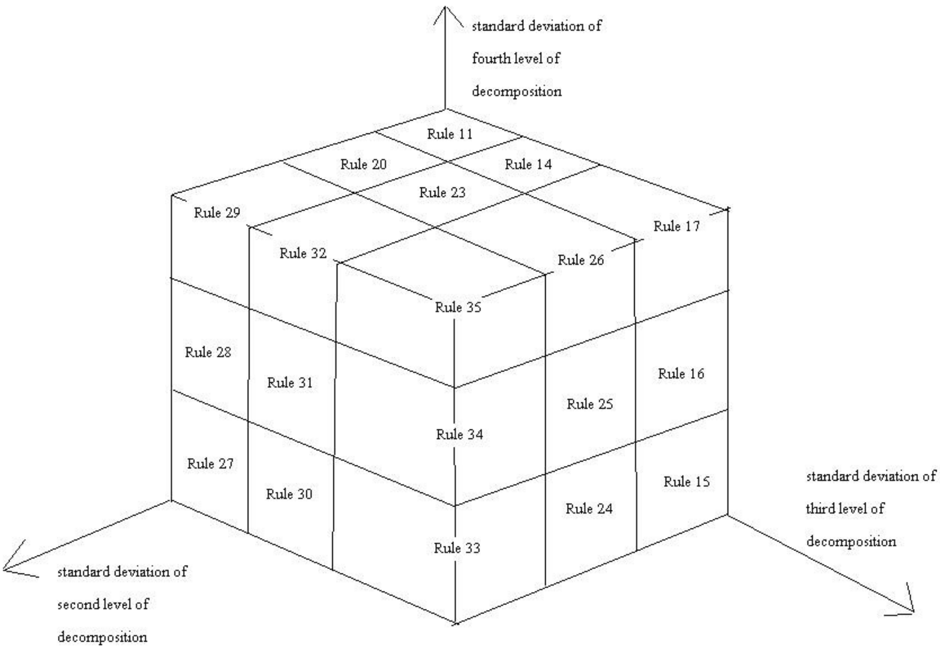

Figure 36 The fuzzy pattern and string element for $K = 3$ in three dimensions (compare this figure with Figure 10)

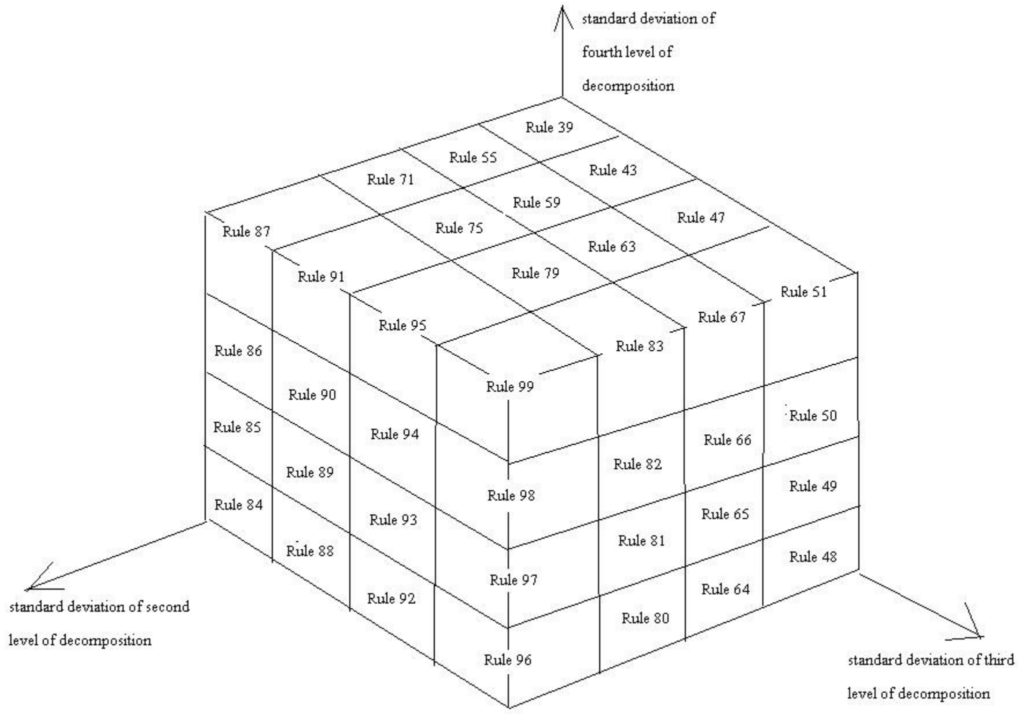

Figure 37 The fuzzy pattern and string element for $K = 4$ in three dimensions (compare this figure with Figure 11)

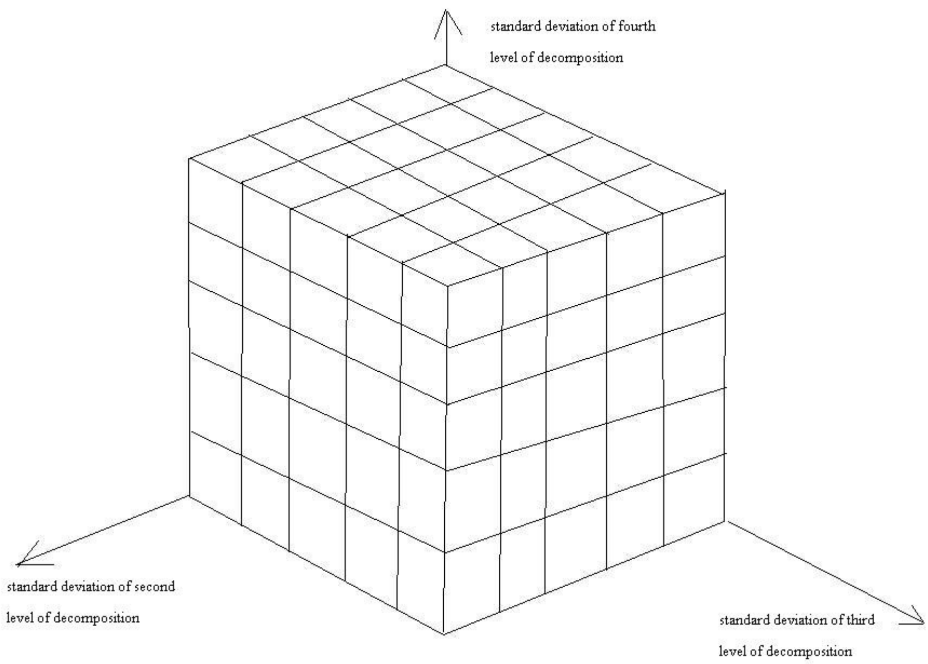

Figure 38 The fuzzy pattern and string element for $K = 5$ in three dimensions (compare this figure with Figure 12, the name of the rules are omitted)

According to equation (23), there are $2^3 + 3^3 + 4^3 + 5^3 = 224$ fuzzy rules in total. After the standard deviations of the decomposed signals are calculated as shown in Figure 30, these three-dimensional points from level 2, 3, and 4 signals are classified into different rules. Table 2 shows the rules in each of the category *before* running the genetic algorithm.

Table 2 Fuzzy rules defined in each of the category before running the genetic algorithm

Category	Applicable fuzzy rules that defined in the category	Number of fuzzy rules
Category 1 (Spring constant: less than 20000 N)	1,7,8,9,18,22,35,36,52,56,57,77,78,98,99,130,131, 156,162,193,219	21
Category 2 (Spring constant: between 20000 N and 40000 N)	1,2,7,9,22,23,36,57,59,77,100,105,125,162,164	15
Category 3 (Spring constant: between 40000 N and 80000 N)	1,8,9,13,35,36,56,57,79,99,101,131,194,224	14
Category 4 (Spring constant: between 80000 N and 100000 N)	1,9,10,21,36,42,52,100,107,131	10

From the above table, many of the rules are shown in more than one category, therefore, based on the above information the ability of classifying a case to one category is weak. That is the reason why genetic algorithm is important in order to reduce the replications of the rules and make rules more exclusive to one class. Equation (24) is the key of the algorithm so that the number of rules decreases while each of the remaining rules is able to cover all of the cases in a category. In the algorithm, the accuracy of the result and the efficiency of eliminating fuzzy rules depend on the value of the parameters. In the experiment, the value of w_{NCP} is 10, the value of w_{NCP_WRONG} is 50 and the value of w_S is 60.

Table 3 shows the result of the algorithm in terms of the rules for each category and the accuracy of identifying the cases. The result is acquired at the 500th generation of the genetic algorithm.

Table 3 Fuzzy rules defined in each of the category after running the genetic algorithm

Category	Applicable fuzzy rules that defined in the category	Number of fuzzy rules	Number of correct cases identified	Number of incorrect cases identified	Accuracy
Category 1 (Spring constant: less than 20000 N)	18,78,98,131,219,162,130	7	8	0	100%
Category 2 (Spring constant: between 20000 N and 40000 N)	100,105,162,125,164	5	7	2	77.8%
Category 3 (Spring constant: between 40000 N and 80000 N)	99,101,131,194	4	10	0	100%
Category 4 (Spring constant: between 80000 N and 100000 N)	10,21,100	3	4	1	80%
Overall Accuracy					**90.6%**

Table 3 shows that the number of rules decreases once genetic algorithm is applied to optimized the number of fuzzy rules. The overall accuracy is based on the number of cases that are correctly located in one category and the number of cases that are incorrectly located in this category. It is found that the overall accuracy of the classification system is 90.6%. When a vibration signal is given with unknown condition of the spring, there is a high probability for the algorithm to classify the case into a correct category by using the fuzzy rules in Table 3 so that the diagnostic personnel will know if the spring needs immediate replacement (category 1) or cautious attention (category 2 and category 3).

Figure 39 shows the relationship between number of generations of the genetic algorithm and the number of fuzzy IF-THEN rules for classifying the four categories. It shows that as the number of generations increases, GA eliminates the fuzzy rules as more optimization training of the data is involved, and the number of output fuzzy rules decreases.

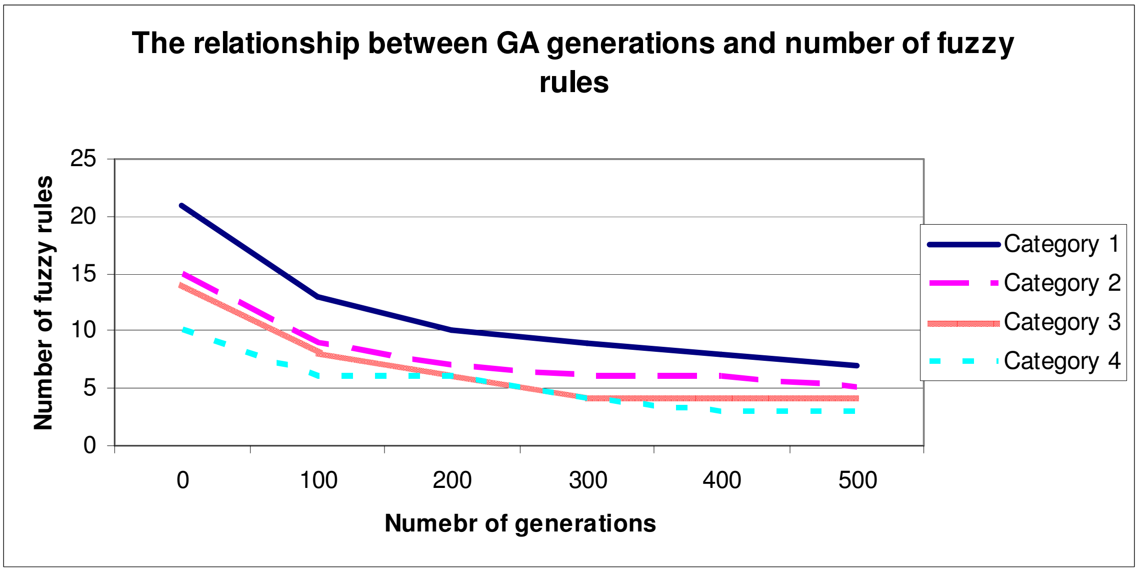

Figure 39 The relationship between number of GA generations and number of fuzzy rules

6.3 Discussion of different solving methodologies

In this chapter, two methods of analysing vibration signatures from circuit breakers are implemented. The cases are drawn based on the change of spring constant, representing the performance of the spring in the operating mechanism. In the first part of the chapter, Dynamic Time Warping [DWT] is used to identify the faulty cases from the normal cases by looking at the deviation of the vibration signature frequency content. When the deviation is significantly larger than a specified range as shown in the examples of category 1, 2, and 3 in figure 27, 28, and 29, the case is irregular. This algorithm is easy and simple and it requires not much computation power. However, it is not capable of identifying the severity of the breaker failure from looking at the frequency variation. On the other hand, in the second part of the chapter when multi-resolution analysis [MRA], fuzzy rules, and genetic algorithm are used, the algorithm was capable of not only distinguishing the abnormal cases from the normal cases, but also classifying the vibration signatures into different category so that the spring condition is known immediately. Fuzzy rules is capable of classify a new case to a category and genetic algorithm is an effective tool to minimize the applicable fuzzy rules. The accuracy of the identification was over 90%.

As the theory and implementation of the conventional algorithm and proposed algorithm are discussed, in the next chapter some suggestions are provided for future improvements of the project. Also, the conclusion of the thesis is provided too.

Chapter 7
Contribution, Future Prospects and Conclusion

The main contribution of this research in solving the problem of predictive maintenance of circuit breaker is to propose new method of analyzing circuit breaker vibration signals as these signals contain useful information for diagnostic purpose such as the source of the fault in a breaker and the degree of the fault so that diagnostic technician can use this information for decision making in breaker maintenance. In this thesis, spring problem is demonstrated as an example of how signal processing technique is applied with the task of analyzing vibration signals. Selection of the best signal processing technique is accomplished so that the technique is accurate, user-friendly, and clear and easily understood. However, there are a number of research areas requiring further investigation in order to provide more information to power engineers on how to statistically anticipate circuit breaker problems.

Yet, a number of insights were provided. Instead of capturing vibration data from a circuit breaker model, researchers may capture data from a genuinely operating circuit breaker. Section 3.1 describes several examples how this may be set up. For example, the circuit breaker needs to be locked on the ground to make sure it will not slide when it opens or closes. Accelerometers are attached on the surface on the operating mechanism and arcing chamber. Accelerometers are connected to DC source and oscilloscope to capture and save or print out the vibration waveforms. Researchers must be aware of qualifying conditions: each circuit breaker has its unique vibration signature, so when comparing vibration signature between different circuit breakers, signal calculation adjustments are required.

This analysis used a change of spring constant protocol to monitor the performance of how the spring provides kinetic energy to the breaker. In the future, different parameters may be monitored and the researchers may examine the condition of circuit breakers based on new data. For example, valve position in trip and close coils, acceleration parameters in the changeover valve, damping in hydraulic cylinders and mechanical linkages, gas pressure in primary contacts, and breaker resistance in line systems. When performance is measured with these parameters, power engineers may have a clearer picture of how each component of a breaker is working together.

A by-product of this thesis is the realization that test procedures must be standardized so that when a breaker is operated, the signatures from different parts of a breaker are stored in a database. As this database builds up, more data would be available and power engineers would be able to apply different data mining techniques for analysis. This takes time and it may even take years to obtain data on most possible outcomes from breaker events, but once this database is maturely established, breakers could be remotely monitored ultra-efficiently.

Finally, the data can be useful to other types of circuit breakers since different kinds of circuit breaker may have similar problems in operation and their vibration signatures may look very similar. This database model may serve as a prototype for finding problems even though other models use different components.

In this thesis, the importance of circuit breakers as mechanical switching devices that carry and disrupt electrical current in a circuit is discussed. Circuit breakers must function in normal and abnormal conditions, and must accommodate short circuits and outages. When there is a fault, the circuit breakers isolates the problem area so that extremely high currents do not flow into the whole power grid network thereby damaging related electrical devices including generators, transformers, and the loads. The importance of the circuit breaker function provides incentive for utility companies to spend money and manpower to utilize and maintain circuit breakers so that the reliability of the power supply can be more secure and the chance of damaging devices due to extremely high current exposure decreases. Traditionally, circuit breakers are monitored manually. Technicians rarely use measuring instrumentation to assist them in finding a problem nor do they use measuring instrumentation for troubleshooting. Instead, they use eyes to accomplish professional inspection. This way of doing maintenance is insufficiently accurate and results in possible overlooking of breakers faults. Moreover, there is a fundamental paradox involved in traditional circuit diagnostic techniques. Examining and inspecting circuit breakers involves disassembly. For example, the technician examines the lubrication of the mechanical parts, the dielectric strength of the contacts, and the pressure of the SF_6 gas. This part, inspection, is done manually; it is simple and the usage of special equipment is minimized; however, the process may be very time-consuming. More significantly, the deconstructing and reassembly of breakers may introduce new faults that affect the reliability of the load's power supply.

As CIGRE discovered that majority of the failure of a breaker comes from operating mechanism, the goal of this study is to make the task of monitoring problems in operating mechanism more accessible. This study demonstrates how vibration signatures may be used in the predictive maintenance context. There are three advantages of monitoring circuit breakers using vibration signatures. First, this method does not involve contact, travel and technician time. Second, those most familiar with breaker performance will have historical benchmark for comparison purposes. Third, vibration monitoring techniques are applicable for any kind of circuit breakers, regardless the structure of the breakers and the rated voltage.

There are many parameters that are available for monitoring the condition of a circuit breaker. The confirmed hypotheses was that vibration signatures obtained on operating mechanisms and arcing chambers and that vibration signatures are reliable sources for evaluating circuit breaker operational integrity. Although further research is suggested, this thesis applied digital signal processing techniques on the vibration signature to retrieve useful information about breakers.

There are different algorithms available for vibration analysis. From the literature review, dynamic time warping [DTW], Resolution Ratio [RR], Discrete Envelope Statistics [DES] and extract time extraction, Chi-square based shape methods, and fractal theory are applied by different researchers. This research applied multi-resolution analysis to decomposed and differential signal levels. Data mining techniques were used to draw useful information from these waves. From the variation of the data point allocations in different cases, classification became available. In this research, optimizing fuzzy rules using GA is analyzed.

The vibration data is obtained from a circuit breaker Simulink model. The circuit breaker model used in thesis is a modification and an extension of the model proposed by Michael Stanek. The model demonstrates the operation of a modern live-tank SF_6 self-blast breaker with a spring-hydraulic operating mechanism. The model visualizes the breaker components by using systems that consist of inputs, outputs, and processing unit. The processing unit functions are represented by blocks of equations, logic expression, and inequalities in Simulink. Modifications have been made to Michael Stanek's circuit breaker model in order to improve the accuracy of the output signal of a breaker, including the calculation of withstand voltage, implementation of the arc model, and the addition of vibration sensing model. The vibration sensing model is the module where vibration signals are generated. In this model, a silicon micromachined accelerometer is simulated. This model reflects the dynamic performance of the sensing element and the control strategy (closed loop), and electrostatic force. As the state of the breaker changes, the sensing element oscillates due to change of electrostatic force and vibration signal is captured.

In the simulation part of the thesis, spring performance was chosen as an example of how vibration signature analysis may be implemented since spring is one of the major sources of energy in a breaker. Two methods of analysing vibration signatures from circuit breakers are studied. Dynamic Time Warping [DWT] is competent to identify the faulty cases from the normal cases from looking at the deviation of the vibration signature frequency content. When the deviation is significantly larger than a specified range, the case is faulty. In contrast, the method was not capable to identify the degree of how bad it performs from looking at the frequency variation. In the second method, when multi-resolution analysis [MRA], fuzzy rules, and genetic algorithm are used, the method was capable of not only distinguishing the abnormal cases from the normal cases, but also the classifying of the vibration signatures into different categories so that the spring condition can be retrieved immediately. Fuzzy rules is capable of classify a new case to category and the genetic algorithm is an effective tool to minimize the applicable fuzzy rules. The accuracy of the identification is very satisfactory, which is over 90%.

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