A Statistical Method for the Detection of Power System Faults

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Abstract

Power systems are being operated closer to their limits than ever before. Faults on the power system have the potential to push the system operation beyond these limits and cause a system wide collapse. However, when the limits are exceeded, it is the duty of protection relays to ensure the system does not collapse. The detection of faults plays an important role in the correct operation of digital protection relays and the stability of the system. Most fault detection methods use variations of electrical quantities as the detection criteria but do not fully utilise this information. This paper presents an adaptive statistical estimator for the basis of detection and classification of power system faults. Results from simulation work on an Electromagnetic Transient Program (EMTP) are presented and the performance of this method is compared to the more traditional fault detection algorithms.

1 Introduction

Power system high voltage equipment is protected from potential damaging transients by protective relays. Analogue relaying devices have performed reliably for many years, however, they are being gradually replaced by digital relays.

Digital protection relays use a variety of different techniques to extract the power system frequency quantities of voltage and current on which to base a relaying decision [1]. However, in order to operate correctly in the minimum time, some type of fault detection and classification algorithm usually precedes this signal processing. Fig. 1 shows the major components that are included in a modern digital relaying subsystem. The fault detection (FD) algorithm is contained within the digital signal processor (DSP).

Traditional detection methods such as the sample-by-sample (SBS) and cycle-by-cycle (CBC) techniques require a detection threshold setting. This threshold must be low enough to detect faults but also high enough to avoid false detections; this usually results in setting compromises. These methods rely only on magnitude information and may incorrectly classify normal system events as faults, for example, the transients accompanying transformer tap changes and during motor starting. In particular, the SBS technique may have problems dealing with some transient conditions, for example, line energisation and circuit breaker reclosing. Furthermore, the CBC technique allows each transient to ripple through its data buffer, in effect, corrupting the data used to discriminate for faults in the present and the next few cycles. Other more sophisticated techniques, such as those based upon Kalman filtering may require up to fourteen separate Kalman filters all operating in real-time and in parallel [2], [3], [4]. These techniques require an enormous amount of processing power for such a small portion of the relaying task which may result in reduced sampling rates degrading their performance. Moreover, the initial covariances

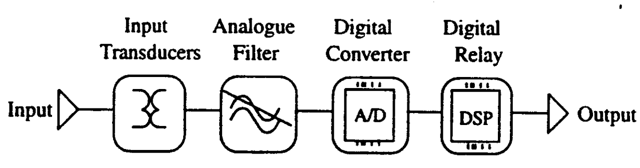

Fig. 1. A Block Diagram of Digital Protection Relaying System Components

determine the speed of solution, that is, only from extensive knowledge of the system noise statistics can maximum benefits be extracted from these techniques and this is often not readily available.

Several other techniques based on the magnitude change in the noise statistics from Kalman filters during the occurrence of faults have been proposed [5], [6]. The latter uses a fault detection method based upon Kalman filtering with hypothesis testing by testing for a sudden jump in the noise statistics. Once again the detection sensitivity is dependent upon the initial covariances.

Another similar technique is based on a non-linear adaptive fault detection filter for on-line fault detection and isolation of non-linear systems which combines an extended Kalman filter with a weighted sum-squared residual method to achieve fast fault-detection for non-linear systems [7].

This paper discusses some fundamental issues involved in the detection of faults on a power system, develops an adaptive median operator fault detector for the real-time implementation in a digital protective relay and presents the results of its performance against existing detection methodology.

2 Protection System Components

Although the detection of faults from a digital protection relay occurs in software, there are many analogue components preceding this which have a major influence on its accuracy. Therefore, in order to accurately model a protection relay on a computer, it is important that accurate models of all componentry affecting its outcome must also be included. The following section discusses some of the issues involved when simulating a power system protection relay on a computer in order to obtain results similar to those possible from field testing.

2.1 *Input Transducers*

Current transformers (CTs) and voltage transformers (VTs) are essential elements in the detection of faults on modern power systems. The primary voltage and current quantities from the power system must be transformed, in both magnitude and phase, from many thousands of amperes or volts to values which can be manipulated by digital components for relay protection purposes. In reality, this transformation never produces identical results and errors in both magnitude and phase will eventuate. Although protection CTs usually will accurately reproduce harmonics up to the fifteenth, saturation can produce significant current error [8]. CCVTs may also produce significant errors for near faults when the faulted phase voltage undergoes a sudden change of a relatively large magnitude and may produce undesired subsidence transients [9].

2.2 *Analogue Filtering*

Analogue filters serve a dual purpose in most modern digital protective relaying schemes, attenuating harmonic content and eliminating aliasing effects from the sampling process. The non-fundamental frequency components of the voltage and current waveforms provide useful fault information for the relay. Filtering these frequencies *before* processing by a FD routine reduces the effectiveness of most FD techniques. Fig. 2 shows the difficulty a FD technique may have when strict criteria is placed on the analogue filter to reduce harmonics. In this paper,

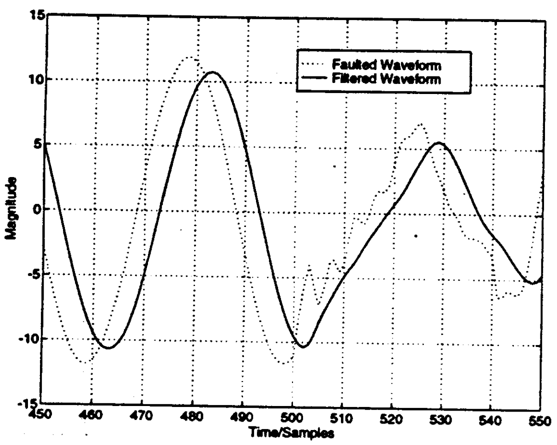

Fig. 2. The Effect of Strict Analogue Filtering Criteria on the Damping of Transients

the analogue filter is designed specifically to perform only one function, anti-aliasing. The cut-off frequency is such that many of the transients accompanying faults are not damped, thereby providing additional information for fault detection. Harmonic filtering can be performed using digital filters at a later stage. This also reduces the amount of noise injected by the analogue filter.

2.3 *Digital Conversion*

An Analogue-to-Digital (A/D) converter is required to convert the analogue signals of voltage and current into digital numbers for signal processing. Most digital converters only provide a limited range of numbers with which to represent any input quantity. Furthermore, the A/D converter must track accurately the extremely wide dynamic range encompassing normal and fault values that may be present. If the maximum dynamic range is not used to represent the voltage and current quantities, a dramatic reduction in numerical accuracy occurs. For example, a 16-bit A/D converter may be required to acquire data from a feeder rated at 1200 amperes and also accurately convert data for fault currents on this feeder that may be as high as 20,000 amperes. If dynamic conversion is not used, a severe loss in data accuracy results which should be represented in any A/D converter model.

2.4 *Signal Extraction*

Most commercially available digital protection relays have decision logic based upon the extraction of the fundamental power system components using Fourier transform techniques. Today, digital signal processors have enough processing power to solve such functions in real-time. The fast Fourier transform (FFT) is a highly efficient procedure for computing the the discrete Fourier transform (DFT) and is usually performed upon the voltage and current samples derived from voltage and current transformers. The FFT correlates these signals with sine and cosine functions over a finite interval and therefore has a finite impulse response (FIR).

Although FIR filters operate correctly during most situations, large errors may be induced when the input signal changes rapidly due to faults. Once a fault occurs, the voltage and current phasors rapidly change from pre-fault to post-fault values. During these conditions, both quantities will be included in the

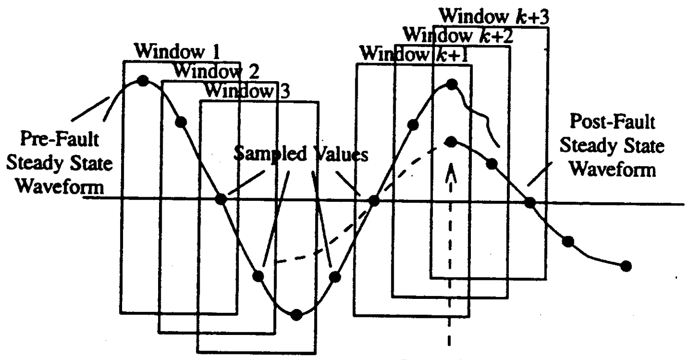

Fig. 3. The Transition From Pre-Fault to Post-Fault Steady-State Waveforms

FFT summation as shown in Fig. 3. Due to the FIR of the FFT, the output may contain large errors and the damping inherent in this technique may result in a rather slow convergence to an accurate phasor estimate when both transients and steady state quantities are included in the summation [10]. Therefore, a correct relaying decision may be difficult to achieve quickly when both pre-fault and post-fault data are included in the decision window due to these rapid changes.

In order to obtain an accurate estimate of voltage and current phasors in the minimum time, only post-fault quantities should be included in the FFT summation. Other estimation techniques, such as those based upon Kalman filtering, also require a trigger to identify the start of a fault. It is, therefore, very important to detect the instant of fault inception and to include only the post-fault quantities in the decision logic for a rapid relay response.

3 Fault Detection

The following section discusses two of the more traditional methods available for the detection of faults. Voltage samples, current samples or both may be used as the criterion for detecting faults.

3.1 Sample-by-Sample Check

A sample-by-sample fault checking routine compares the value of the present sample with that of the previous sample. If the difference between adjacent samples is outside a preset range, a transient disturbance is determined to have occurred and a counter is increased. The value added to this counter depends on the size of this difference. If this difference is small, the counter is incremented by a number proportional to the difference, that is, the counter is incremented by a small number for small differences. When the counter has reached a threshold value, a fault is determined to have occurred. This method of accumulating confidence in the decision has been widely used in applications where the output contains uncertainty. Fig. 4 illustrates a SBS method.

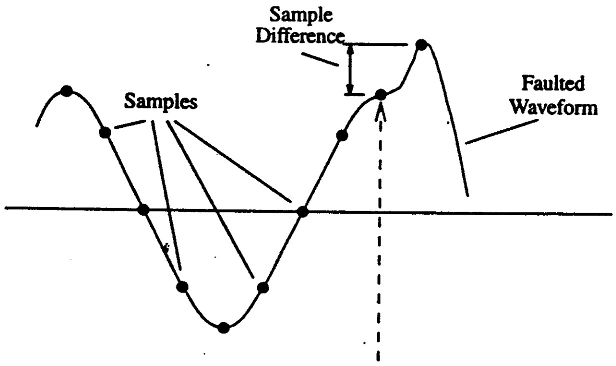

Fig. 4. A Sample-by-Sample Fault Detection Method

3.2 Cycle-by-Cycle Check

This method compares the present sample with the corresponding sample from the previous power system period and determines if the discrepancy existing between the two is sufficient to indicate the occurrence of a transient disturbance. Once again an accumulating confidence decision is made before a final decision is made. A CBC method is illustrated in Fig. 5. The major problem with this method is that each sample is used for discrimination one cycle later, even the post-fault samples. This results in corrupted samples being used for fault discrimination.

3.3 Discrimination

One of the most difficult tasks required of a fault detection algorithm is to discriminate between faults and normal system events. This discrimination determines the balance between security and dependability. During a fault the voltage and current waveforms will usually deviate from normal system operation. Most FD algorithms will prefer to use either one of these waveforms to extract information for their discrimination. To decrease the level of false detection both current and voltage

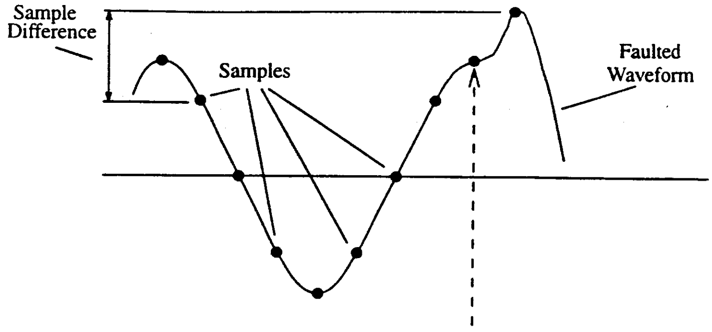

Fig. 5. A Cycle-by-Cycle Fault Detection Method

information can be utilised. Also, the probability of false fault detections is minimised by using an accumulating confidence decision, that is, to gain confidence in a fault detection decision, each fault is confirmed a number of times.

4 Fault Induced Transient Studies

The magnitude of the fault noise is affected by many factors such as fault location, fault resistance, fault inception angle and the source impedance ratios. In order to provide a robust FD method, a thorough understanding of the spectra of fault-induced transients is required.

There have been a number of studies conducted to investigate the properties of fault-induced transients [11], [12], [13], [14]. These studies have found that the mean value of the unfaulted phase quantities are approximately equal to their pre-fault phase values and the mean value of the current in the faulted phase quantities is approximately equal to the square root of twice the variance. Also, the mean value of the voltage in the faulted phase(s) was found to be, on average, less than 75% of that of the healthy phase(s).

These studies also concluded that for a given system configuration, the noise spectrum is independent of the type or location of the fault and that the dominant noise spectrum is centered around 240 Hz, irrespective of system configuration. Furthermore, all of the analogue components which precede the digital relay were found to produce their own noise and usually modify the fault waveforms in someway. A FD algorithm must be able to use these observations to provide a reliable detection methodology.

5 The Median Operator

The median operator uses the statistical information derived from sampled power system waveforms to discriminate between normal system events and faults. This operator is based on two filters commonly used in digital signal processing, the median and mean filters [15]. This section describes the operator.

5.1 The Median Filter

The median filter is a non-linear filter widely used in image processing applications because of its excellent noise rejection properties and its ability to preserve discontinuities. The median value of a set of sampled numbers is defined as the middle value after numerical sorting. The running median can be maintained by discarding the oldest sample and inserting the newest sample into an already sorted list before extracting the median value. The performance of the filter is determined by the set size and the sampling rate, both of which are usually fixed a-priori.

5.2 *The Mean Filter*

The mean filter is merely an averaging or smoothing type filter commonly used to track the average of a process. This type of filter is primarily used to stabilise the output when there is uncertainty in the input quantities. The mean of a set of sampled numbers is defined as the sum total over the set size. The running mean can maintained by subtracting the oldest sample from, and adding the newest sample to a running summation, and extracting the mean value. The performance of this filter is also determined by the set size and the sampling rate.

5.3 *The Algorithm*

The median operator uses the statistical quantities of mean and median to estimate the mode of an incoming signal in order to discriminate between normal system events and faults. The mode of a probability density function $p(x)$ is defined as the value of x where the function $p(x)$ is a maximum. Estimates of the mode must be used since there is no direct method available for its calculation. The most frequently used parameters for estimating the mode are the median and mean statistics [15].

Transients can be detected in a signal by monitoring the changes in the probability density function of the signal. These changes provide an good indication of the signal stationarity. The running mean and median estimates also provide a good estimate of the signal stationarity. Therefore, these two statistics can provide a method for detecting transient events.

The distance between these two estimates will provide a method for discriminating between faulted and unfaulted conditions. The type of transients contained in the signal will determine the distance between these two estimates since the median is a more robust estimate of the mode than the mean. In mathematical terms this process is described in Eqn. 1, where $e_L(k)$ represents the absolute distance between the two estimates.

$$e_L(k) = \left|\text{median}\left[x(k), L\right] - \text{mean}\left[x(k), L\right]\right| \qquad (1)$$

where $x(k)$ is the value of sample k and L is the length of the data window.

Median estimates using long data windows are biassed when transients are included in the window, the length of data window equalling the duration for the biassed estimates. For example, the values of the transient will migrate toward the extremes of the data window after sorting due to their departure from steady state values. The median value will therefore be biassed during these times. An unbiased median value will only appear at the output if the transient occupies more than 50% of the data window. Therefore, short data windows provide better response during the occurrence of transients.

Usually the length of the data window is fixed a-priori resulting in a compromise in filter performance. However, it is possible to control the size of the data window and therefore the size of the transients passed through the filter.

5.4 *The Adaptive Algorithm*

To improve the performance of this detection technique, a method of controlling the data window length is required. This is primarily to ensure that the minimum data window length is used during transients but it also allows unwanted transients to be filtered out by choosing a larger window.

As each transient event reaches the data window, the difference signal $e_L(k)$, will tend to increase as the front of the data window reaches the transient, grow until the middle point of the window is passed, then decrease. Therefore, to adjust the size of the data window one needs to know whether the difference is either increasing or decreasing, a differential operator $w_L(k)$, can be used for this purpose. This operation can be performed by subtracting the present sample difference from that of the previous sample,

$$w_L(k) = e_L(k) - e_L(k-1). \qquad (2)$$

A block diagram of the adaptive median operator is shown in Fig. 6. The feedback loop uses the difference $|\circ|$, differential operator $\nabla(\circ)$ and its sign, sgn($\circ$) to adjust the window length.

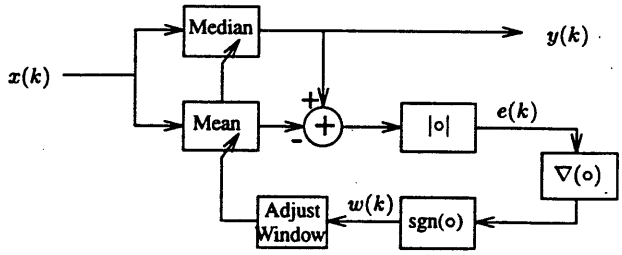

Fig. 6. Adaptive Median Filter Implementation [15]

6 Detection Criteria

A fault detection algorithm must discriminate between faults and normal system events. Most FD algorithms achieve this by including some kind of accumulating confidence decision (ACD) algorithm, that is, ensuring a correct decision is made by confirming the fault condition a number of times. An ACD method is necessary for both the SBS and the CBC methods of detection to ensure they do not produce false detections. The above algorithm, however, does not require an ACD algorithm as it incorporates a proven method for discrimination into the FD method. This property is illustrated in the next section.

7 Algorithm Assessment

To verify the ability of this algorithm to correctly detect faults, several AC systems were modelled on an EMTP [16]. The object of these studies were to demonstrate the problems related to traditional fault detection techniques and to illustrate the potential of the adaptive statistical method described in this paper. The second aim was to demonstrate the robustness of this method through extensive testing on the widest possible range of system conditions and system parameters that may occur in modern power systems. The results presented here focus on the last of these objectives.

The following figures are taken from fault studies of a 230 kV transmission network - a single phase fault occurs at sample number 1000, circuit breaker operation occurs at sample 1225. A sampling rate of 4 kHz was used to produce the following figures, however, similar results have been obtained from lower sampling rates. Fig. 7 shows the result of processing samples

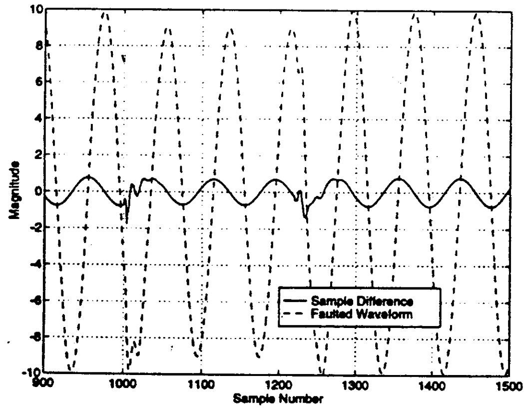

Fig. 7. Sample Differences Based on a Sample-by-Sample Algorithm

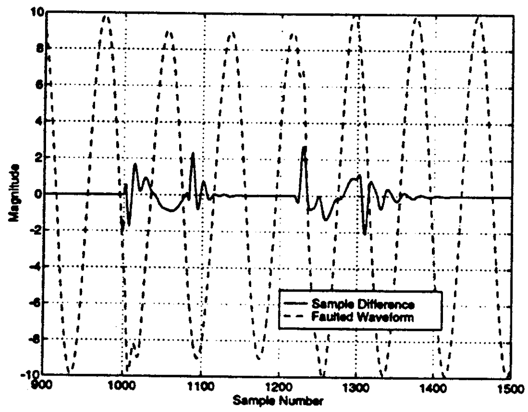

Fig. 8. Sample Differences Based on a Cycle-by-Cycle Algorithm

of the faulted waveform through a SBS difference algorithm while Fig. 8 shows the output from a CBC sample difference algorithm. These figures show the presence of transients due to the fault and circuit breaker operation but also contain some undesirable effects.

Fig. 7 displays the significant amount of background noise associated with the sample differences obtained from the SBS technique and Fig. 8 clearly illustrates the propagation of faulted samples affecting the output for the future samples. Also, note that in Fig. 8 the length of samples affected by circuit breaker action is approximated 50% more than those affected by the actual fault. Now compare these figures with that of the difference output from the median operator, Fig. 9. Fig. 9 clearly illustrates that the median operator difference output registers the fault as significant while circuit breaker action receives minor attention. Also observe that the length of the samples affected by the transient is small enabling the detection of faults to occur

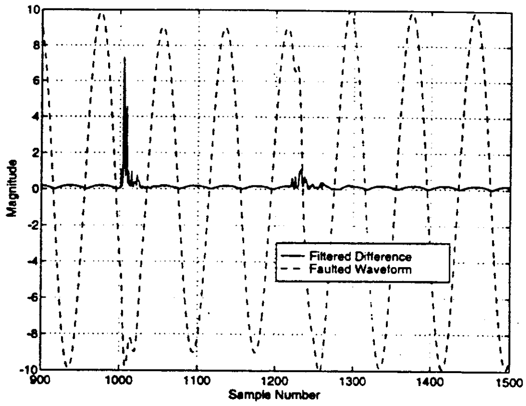

Fig. 9. Filter Differences Based on the Median Operator Algorithm

immediately following the end of this disturbance. This is in contrast to that of the CBC output. Also, this method reduces the amount of background noise that is superimposed on the SBS output. Fig. 10 shows the result of processing samples

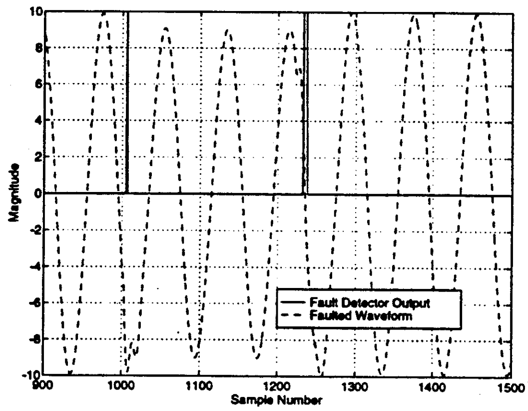

Fig. 10. The Output From a Sample-by-Sample Fault Detector After an ACD

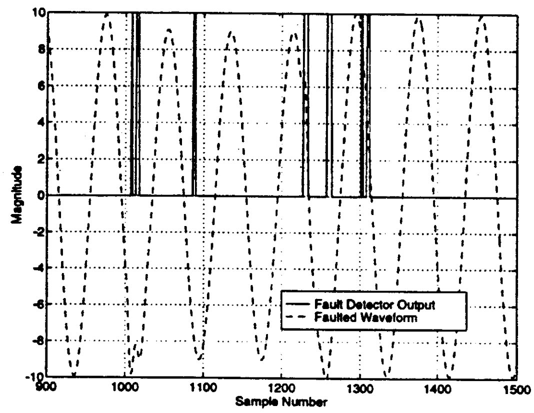

Fig. 11. The Output From a Cycle-by-Cycle Fault Detector After an ACD

of a faulted waveform through a SBS fault detection algorithm and a three sample ACD algorithm, while Fig. 11 shows the output from a CBC fault detection algorithm using a similar ACD method. While Fig. 10 manages to detect the fault, it also incorrectly identifies the circuit breaker action as a fault even *after* using an ACD technique.. Fig. 11 illustrates the amount of false detections occurring even with a high threshold setting and an ACD, due mainly to the aforementioned rippling effect. Contrast the output from the two traditional methods with that

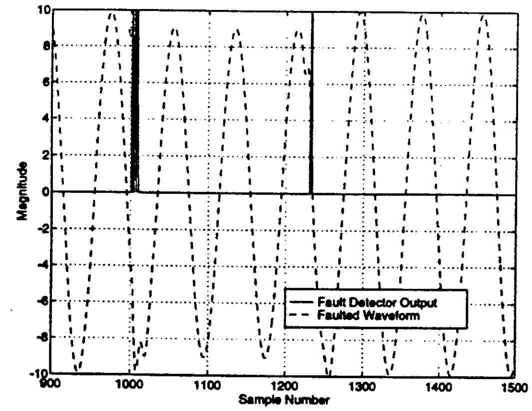

Fig. 12. The Output From the Median Operator Fault Detector Before an ACD

from the median operator fault detector *without* an ACD algorithm, shown in Fig. 12. This figure highlights the ability of the median operator to discriminate correctly without the need for extra filtering techniques such as an ACD algorithm; this increases the relay sensitivity while reducing the time delay.

8 CONCLUSION

A simple, robust fault detection technique requiring minimum computational burden and utilising statistical information about the transient signals has been presented. This method uses the mean and median statistics to estimate the mode from a set a sampled numbers. Discrimination is provided by monitoring the distance between these two estimates. Furthermore, a simple extension to this method to enable the length of the sample window to adjust automatically to provide the maximum sensitivity is discussed.

A discussion of the requirements for modelling protective relaying equipment on a computer is also presented. The ability of the analogue filter to reduce the performance of a fault detection algorithm has been illustrated and the effects of restructuring this filter specifically for anti-aliasing enables higher sampling rates and therefore higher a cut-off frequency, minimising these effects.

The adaptive statistical based fault detector presented herein has been applied to power system relay computer modelling conducted on an electromagnetic transient program in order to examine its potential. The performance of the algorithm was tested against both the SBS and the CBC methods and results show that correct discrimination is achievable without an ACD algorithm. These results included in this paper confirm the potential for this type of FD methodology.

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