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# A LEARNING METHOD FOR USE IN INTELLIGENT COMPUTER RELAYS FOR HIGH IMPEDANCE FAULTS

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Abstract—The physical variables and environmental parameters which influence the behavior of a high impedance fault are quite large in number and difficult to quantify. While several techniques to detect high impedance faults have been proposed, and much progress has been made, a complete and flexible solution has not been perfected. Texas A&M University(TAMU) research has concentrated on designing an intelligent relay system which utilizes multiple detection parameters and a learning ability to provide a more effective solution for detecting low current faults. An intelligent system is characterized by an effective analysis and synthesis of information and a learning ability which makes the system's reactions appropriate to each situation. To classify system status, inductive reasoning has been used. However, for a detection system using the inductive reasoning process, only the induced detection rule will be applied to classify and detect faults. This detection system has a problem: an unreliable teacher. To solve this problem, a learning detection system is proposed which synthesizes the status output of the decision rule and an event detector to identify the system status. This learning detection system improves its performance over time. The learning detection system has been successfully tested with a complex set of sampled fault data from staged faults.

Keywords: High impedance fault, intelligent system, computer relay, learning system, induction process, decision rule.

## INTRODUCTION

The clearing of distribution line faults is usually accomplished by devices that can sense the overcurrent produced by a fault and quickly react to disconnect the faulted section of the feeder from the healthy system. Such devices usually include overcurrent relay and circuit breaker combinations, reclosers, and fuses. In addition to providing overcurrent protection, these devices must be capable of carrying an acceptable increase in the level of load current and transient overcurrents. The current which flows during a fault depends on a number of variables, one of which is the fault impedance. A high impedance at the fault point can limit the fault current to levels that are well below the threshold of operation of conventional fault clearing devices. In such circumstances, the existence of a fault cannot be detected by overcurrent devices and will persist until some external event signals its presence.

The physical variables and environmental parameters which can influence the behavior of a high impedance fault have been known to be quite large in number and difficult to quantify in a deterministic manner. Quite a few efforts have been made to investigate, in a statistical manner, specific behavior characteristics such as arc burst duration, arc repetition rate, and the dependency of frequency spectral magnitude on the arc burst duration and surface condition[1, 2].

Several techniques to detect high impedance faults have been proposed, and much progress has been made [3, 4, 5, 6, 7]. However, a reliable and flexible solution has not been found. Most fault detection techniques have considered and focused only on one parameter for the detection of a fault under given set of conditions. However, the behavior of high impedance faults is affected by many physical and environmental variables such as feeder configuration, load level and type, surface condition, and weather. It was noted that, while each technique may offer a partial solution, none to date has proven to be totally acceptable under all conditions. In addition, the behavior of the parameters of high impedance faults is very random and, in most cases, unpredictable; therefore, the result of each technique is not always certain. Moreover, even though each technique has at least one weakness with respect to environmental parameters, it does not give any means to provide adaptability to the environment.

TAMU research has concentrated on finding an intelligent detection system which uses multiple detection parameters and utilizes a learning ability. This will provide an automatic performance improvement with experience, and thus a more effective solution for high impedance fault detection. Automatic adaptability to physical and environmental factors is a major research concern. In developing this intelligent system, the reasoning method

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has been the backbone of the whole system structure. We will examine the inductive reasoning method in the next section.

## INDUCTIVE REASONING

Inductive reasoning for pattern classification is based on entropy minimization. Entropy is a measure of the disorder in classifying data. Entropy minimization is an ordering principle by which it is determined which past events are more like future events in ways that are sufficient for predicting the outcome. If one wishes to classify a set of samples into a more ordered state, he attempts to lower the entropy. Therefore, by minimizing entropy, a decision rule for classification can be induced. By this rule, the concept of each class, fault and non-fault, is learned from sample events. This rule indicates the knowledge of the classes of a given situation.

The end of induction is to discover a law having objective validity and universal application. However, the conclusions of a process of inductive reasoning are merely to attach one new particular to those particulars taken in the beginning. Thus, beginning with the particular "all high impedance faults observed to date show high frequency current bursts," it might be concluded with the universal "all high impedance faults show high frequency current bursts" or with the less general "all high impedance faults observed to date show high frequency current bursts and it is highly probable that the next high impedance fault to be observed shows high frequency current bursts."

The essential principle of induction for classification is: the induced rule is that rule consistent with all available information for which the entropy is minimum.

The entropy of a rule is defined as below[8]:

$$S = -k \sum_{i=1}^{m} x_i p_i \ln p_i$$

where,
$m$ is the number of total steps in a rule,
$i$ is the step,
$x_i$ is the number of samples of either Fault class or Non-Fault at step $i$,
$p_i$ is a mean probability of the $i^{th}$ step for either Fault class or Non-Fault,
and $k$ is a constant.

For simplifying the procedure in rule induction, a simplified entropy minimization formula was derived[9]:

1) Find a best variable (so called maximum digit index) which can classify the samples into most orderly state.
2) Separate two classes using the chosen variable, then find a step or a rule.
3) Eliminate those samples in both classes which are the subsets of the above step.
4) From remainders, do steps 1 - 3 until there is no more remainder.

With above induction process and its derived rule, a detection system can be developed. The next is the discussion of the procedural behavior of the detection system using the induction process. First, the detection system initializes the induction process with the parameters of sampled data. The parameters and corresponding class of samples are given by a human expert or historical data with experience of actual operation or staged fault tests. For a better induction process, as many variables as possible are necessary to fully describe each class. The electrical parameters are chosen by experience. The chosen electrical parameters must positively identify high impedance faults and at the same time, possess an ability to discriminate transients associated with normal system events.

Harmonic currents are the major electrical parameters. They are total odd harmonic current, total even harmonic current, subharmonic current, high frequency current, second, third, and fifth harmonic currents. With these parameters, it is necessary to find a statistical measure which can indicate the activities of each parameter for each class, and thus indicate the high impedance fault. Mean, standard deviation, and mean absolute value were chosen for this purpose. The variables which are used for the induction process are a combination of parameters and statistical measures. The length of data for measuring these variable values is limited to, for convenience, 30 cycles. This makes a sample value.

Secondly, we start the induction process calculating the threshold values of each variable. With threshold values the variables of each sample data are converted into binary values. From these binary values, the simplified minimum entropy process follows. The final decision rule is derived with an induction process. This rule is applied to find the final status about a distribution feeder.

Thirdly, we update a decision rule when experimental sample data are provided as operational experiences. The same induction process is used with new data to obtain a new decision rule.

The rule is based on no more than the available information and on all of the available information. Therefore, the detection rule might be changed in different cases. An investigation was done to find how the detection rule changes, or does not change, as the high impedance fault case changes.

As was mentioned, the behavior of high impedance faults is random, transitory, and thus unpredictable. However, it is possible to categorize behavior in terms of the fault current amplitude increase and the arc burst duration. Five different cases were studied. The first and second cases were high impedance faults and non-faults on wet soil. The third, fourth, and fifth cases were on dry soil. High frequency currents as a electrical parameter was not included in this investigation. However, it has been found that the behavior of high frequency current is very similar to that of sub-harmonic current in most fault cases. The result of this study is summarized in Table I. From this investigation, the following were found.

1. No one general rule is found, therefore, different rules are necessary at different sites.
2. Even harmonics and sub-harmonics are generally important parameters to classify the activities of high impedance faults and non-faults.
3. If amplitude increase is small and arc burst duration is short, then the sub-harmonic is the best parameter for classification.
4. If amplitude increase is large and arc burst duration is long, then any harmonic parameters can be selected for classification.

Therefore, we need a system which is intelligent enough to adapt itself to outside environment. An intelligent device, including man, can be thought of as a system capable of adjusting to its environment. To make such adjustments, the device must continually classify a slightly different status of the environment as equivalent or not equivalent[10]. It has been shown that inductive reasoning can improve the classification of faults and switching events and, combined with other information such as an event detector output and operator interaction, can be used as an intelligent system to adapt a detection device to its environments with an induced rule[9]. In the next two sections, we will examine the intelligent systems at large and the upgrade of a detection system with inductive reasoning to a learning detection system.

Table I. Rules for Different Fault Cases.

| Examples | Faulted Signal Description | | Harmonic Parameters | | | | Remarks |
|---|---|---|---|---|---|---|---|
| | Mag. | Burst | Rule 1 | Rule 2 | Rule 3 | Rule 4 | |
| 1 (site 1) | Large<br>Medium | Long<br>Medium<br>Short | Even | ANY | | | Even |
| 2 (site 1) | Medium<br>Small | Medium<br>Short | Sub | ANY<br>EXCEPT<br>EVEN | | | Sub |
| 3 (site 2) | Medium | Long<br>Medium | Sub | Sub<br>3rd | | | Sub |
| 4 (site 2) | Large | Long | ANY | ANY | | | |
| 5 (site 2) | Medium<br>Small | Medium<br>Short | Sub | Odd<br>3rd | | | Sub<br>Odd |
| 1 + 2<br>(site 1) | Large<br>Medium<br>Small | Long<br>Medium<br>Short | Even | Even | | | Even |
| 3 + 4+ 5<br>(site 2) | Large<br>Medium<br>Small | Long<br>Medium<br>Short | Sub | Odd<br>3rd | | | Sub<br>Odd |
| 1+2+3+4+5<br>(site 1+2) | Large<br>Medium<br>Small | Long<br>Medium<br>Short | Even | Even | 2nd | Sub | Even<br>Sub |

## INTELLIGENT SYSTEMS

A system that possesses and acquires knowledge and reasons with that knowledge, like a human, seems the most desirable intelligent system. An intelligent system is characterized mostly by a learning ability which makes the system's reactions appropriate to each situation [11]. When a system improves its performance at a given task over a period of time, without amending programs or structures, it can be said to have learned something. Our main concern in learning is to attempt to provide a more reliable and adaptive solution for high impedance fault detection.

A typical learning system consists of four major components: Critic, Learner, Rule, and Performer[12]. This system contains a feedback loop. Essentially this is the general frame work of a pattern classifier which learns to associate input descriptions with output categories or classes. The Critic compares the system status with the actual status. In practice this job is done by a human expert, or teacher. The function of the Critic is known as confirmation/unconfirmation assignment. The Learner is the heart of the system. This is the module that has responsibility for updating the knowledge base or decision rule to be adaptive to the varying physical variables and environmental parameters. The Rule is the data structure or modularized procedure that encodes the systems' current level of expertise. It guides the activity of the Performer. It can be updated by the actions of the modules in a feedback loop. The Performer is the part of the system which carries the task. This action is guided by the Rule in some way, and thus when the Rule is updated, the behavior of the system as a whole changes.

To improve the analysis and synthesis of information from a distribution system, and thus to improve overall detection and discrimination under a wide variety of conditions, a multiple variable approach with inductive reasoning is proposed. If adaptability is added to this scheme, it is felt that most high impedance fault cases can be detected and classified. Conclusively, an intelligent detection system consists of multiple variable inductive reasoning incorporated with other supporting elements. This intelligent detection system, as a whole, works as a learning detection system: the detection system which learns the varying and unknown information during operation and the learned information is, in turn, used as an experience for future decisions and detections.

In an intelligent detection system for high impedance faults, a learner and a rule can be provided by an inductive reasoning process. Inductive reasoning is to classify and learn about the system by receiving knowledge of system status under a variety of conditions. An operator and an event detector will act as a critic to confirm or unconfirm what the induced rule decided about the system status. The next section examines a learning detection system. The rule will be combined with the critic to learn about the system and to be updated by the learned knowledge.

## A LEARNING DETECTION SYSTEM

We have discussed inducing a rule from received information about electrical parameters from the distribution line. The outputs from this decision rule, when applied to a distribution system to detect faults, make a final decision on system status. This final decision activates a performer, i.e., relay, to trip or not to trip. However, when there is any discrepancy between the final decision and the actual status, the decision rule needs to be changed and updated. This is the reason why we have a closed feedback loop inside a typical learning system.

For the induction process to learn about the system status and thus to update a rule, data with a known classification is necessary. However, when the system is operated, there is not any way to confirm that the final system status decided upon by a decision rule is correct. In this circumstance, it is impossible to save the data and class as correct sample data to be used for learning in the induction process.

Because using incorrectly identified stored data is very dangerous and unreliable, the problem of the reliability of the final decision, which is also known as the problem of an unreliable teacher, should be minimized and ideally eliminated. This is to be done by a critic or a reliable teacher. The problems of an unreliable teacher are summarized below.

1. Type I error: The system is under a Fault status, but the final decision is "Non-Fault."
2. Type II error: The system is under a Non-Fault status, but the final decision is "Fault."
3. There is no way to indicate the actual system status with only the decision rule and induction process itself.

To meet these problems of an unreliable teacher, operator interaction and an event detector are assumed as a critic or a reliable teacher. Operator interaction provides confirmed or unconfirmed information on the final decision of a fault. When a final decision of "Fault" is made and the "TRIP" signal is issued and the power line disconnected, then an operator checks and replies if it is actually a fault or not. This information provides the actual system status (i.e., reliable teacher) and is very essential to eliminate Type II errors. By this confirmation/unconfirmation, the data class to be stored is correctly identified. However, this operator interaction still does not provide any useful information to eliminate Type I errors, because an operator interaction is activated only after a final decision of "Fault."

To minimize Type I errors, an almost perfect event detector is assumed. This event detector is a part of an existent fault detector which has a sensitivity problem. It detects any disturbance or event on the distribution line. High frequency current or subharmonic current, which are very sensitive to any kind of transient, is the best candidate for an event detector. If a disturbance or event is detected by this detector, a '1' output will be issued, otherwise, a '0' output will be issued.

Even though the final decision is not "Fault," there might be some numbers of consecutive events. Then it is suspected that a fault condition might be present and remain undetected. In this particular situation, a "WARNING" signal is issued to call an operator's attention to the feeder. Until there is a response from an operator, all the data which are involved in this particular decision will remain unclassified and thus not stored as valid data. When an operator response is entered, with confirmation or unconfirmation, then the correct system status is obtained and thereafter data classification can be achieved.

To perform these functions, a decision control block inside the learning detection system combines and synthesizes the status output from an induction process, an operator input, and an output from an event detector. Here, it is assumed that when the final combined decision from a learning detection system is a "Fault", then a "TRIP" signal is issued and it activates a performer to disconnect the distribution feeder. Then, an operator provides a confirmation or unconfirmation input to the system. Combining all these inputs, a learning detection system successfully learns about the system and parameters, identifies the data which makes the decision controller decide such results, and places the identified data into a fixed-size memory. This memory is later accessed by an induction process to update rules. The newly induced rule will replace the old one, and thus change the behavior of the detection system as a whole.

The structure of a learning detection system is shown in Figure 1. Data storage is in memory where classified data are stored. This data storage, which has a fault data section and a non-fault data section, is a fixed-size FIFO (First In First Out) memory. Therefore, when a new classified data comes in, the first data goes out.

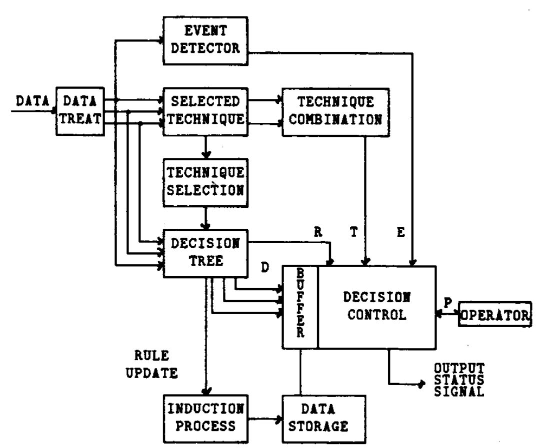


**Figure 1. Structure of a Learning Detection System.**

The signals inside a learning detection system are E, R, P, and D. E indicates an event output (1 for event, 0 for otherwise), R indicates a status output from a decision rule of an induction process (1 for fault, 0 for otherwise), P indicates an operator input (1 for confirmation, 0 for unconfirmation), and D indicates a data class to be stored as a valid data (1 for fault class, 0 for otherwise). These signals are combined and synthesized in the decision control block. The reasons that all the signals are used to get one final output are recapitulated below.

1. A decision rule from induction is based on no more than the available information, and on all of the available information. Therefore, it might miss some unexperienced and very unusual data.
2. An ideal match between the status output from a decision rule and an event detection is always expected. However, in this case, higher security against false decision making and more reliable and accurate detection can be highly guaranteed by combining all the signals.

A decision control block controls and decides a sequence to a final decision. If assuming 2 digit numbers and each number indicate the status of E and R. Then any uninterrupted 3 counts of {01, 11, 10, 11} will cause a "TRIP" signal, any uninterrupted 6 counts of {01, 00, 10} with less than 2 counts of any {01, 11, 10, 11} will cause a "WARNING" signal. In case of both "TRIP"" and "WARNING" signals, the data involved in the corresponding signal output is still pending until their is an operator input to get conformation/unconfirmation on the decision. When an operator input comes in, then the data is classified and stored as fault data (when P=1), or non-fault data (when P=0). Any counts of {00} will cause no output and the corresponding data is classified and stored as non-fault data (i.e., D=0). The numbers 3 and 6 are adjustable; we can lower the number to increase the detection sensitivity, or raise to provide a strong safety against false trip.

The time frame of the intelligent detection system is discussed here. When a "TRIP" signal is issued, a relay is tripped and the line is disconnected, then the operator input makes the detection system classify the data which are involved with this particular final decision and remained unclassified. The classified data are stored in the memory as valid experience data. With these new memory contents, a new rule is induced. This new rule will substitute an existing rule, and adjust the total performance and behavior of a detection system. A decision comes out of the detection system every 30 cycles. During this time, the amount of data which are pending and unclassified should be considered. Therefore, a data buffer is necessary in the decision control block. An example execution using this learning detection scheme is discussed in the next section.

## AN EXAMPLE EXECUTION

With sample data, an example execution with this learning detection system was performed. The training sample data consists of high impedance faults, capacitor bank operations, and load tap changer operations. Fortunately, the high impedance fault case is not frequent; therefore, for the number of data in the training case, it seems appropriate to provide more non-fault data than fault data. A total of 58 sample data sets were chosen where 17 of them were fault data and the rest were non-fault data. Figure 2 shows part of a high impedance fault waveform which was used for the knowledge acquisition purpose in a learning process. With these training sample data, an induction process can describe each class in terms of statistical measures. To calculate the statistical measures for each parameter, the waveforms were passed through a notch-filter to minimize the fundamental component. From this notched waveform, each electrical parameter is obtained through a corresponding filter. With these electrical parameters, means, standard deviations, and mean absolute values of parameters are obtained over a fixed window of 30 cycles. Table II shows first 25 sets of training samples with statistical measures of three electrical parameters:odd harmonics, even harmonics, and sub-harmonics. Then, the threshold value calculation follows. From the 1/0 table derived using the threshold values, the induction process starts to derive a rule. For more detailed procedure of rule induction, one can consult reference 9. In this example, the 6th digit has a maximum digit index, so the first step is on this 6th digit:

Step 1: If the 6th digit is 1 (that is, the standard deviation of even harmonic currents is higher than a threshold value, i.e, 0.614), then it is Fault.

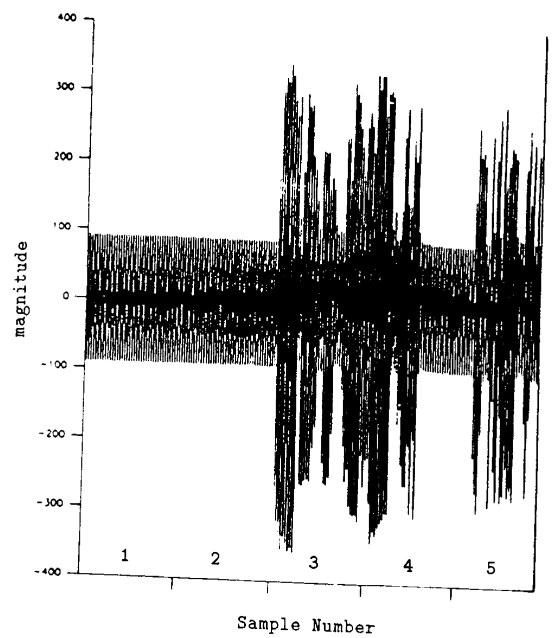


Figure 2. Training Sample Waveform.

Table II. First 25 Training Samples.

| # | ELECTRICAL PARAMETERS | | | | | | | | | CLASS |
|---|---|---|---|---|---|---|---|---|---|---|
| | ODD HARMONICS | | | EVEN HARMONICS | | | SUB-HARMONICS | | | |
| | MEAN | MEAN ABS | STD DEV | MEAN | MEAN ABS | STD DEV | MEAN | MEAN ABS | STD DEV | |
| 1 | -0.170 | 9.304 | 19.114 | 0.026 | 2.008 | 4.393 | -0.140 | 3.271 | 6.660 | F |
| 2 | 0.215 | 29.866 | 34.525 | -0.197 | 7.288 | 9.267 | 0.262 | 10.630 | 13.892 | F |
| 3 | 0.106 | 24.667 | 30.498 | -0.089 | 5.720 | 7.411 | 0.167 | 10.649 | 14.381 | F |
| 4 | 0.037 | 12.703 | 18.098 | 0.060 | 3.500 | 4.957 | 0.127 | 6.849 | 12.536 | F |
| 5 | 0.024 | 27.285 | 32.204 | -0.008 | 6.469 | 7.965 | -0.223 | 10.861 | 13.954 | F |
| 6 | -0.024 | 21.807 | 27.810 | -0.084 | 4.505 | 5.835 | 0.201 | 7.169 | 9.275 | F |
| 7 | -0.233 | 14.640 | 20.383 | 0.166 | 3.395 | 4.609 | -0.152 | 6.164 | 9.033 | F |
| 8 | 0.180 | 6.101 | 7.874 | -0.162 | 3.121 | 4.106 | 0.118 | 3.998 | 5.753 | F |
| 9 | 0.045 | 6.457 | 8.075 | -0.022 | 2.843 | 3.764 | 0.004 | 5.419 | 8.268 | F |
| 10 | 0.125 | 5.771 | 9.247 | -0.130 | 2.248 | 3.261 | 0.170 | 3.297 | 5.121 | F |
| 11 | 0.038 | 2.506 | 2.942 | -0.037 | 1.362 | 1.801 | 0.024 | 1.914 | 3.078 | F |
| 12 | 0.078 | 2.303 | 2.746 | -0.066 | 1.292 | 1.784 | 0.104 | 1.937 | 3.248 | F |
| 13 | 0.035 | 3.589 | 4.960 | -0.043 | 1.985 | 2.853 | 0.033 | 2.747 | 4.541 | F |
| 14 | 0.004 | 1.251 | 1.477 | -0.001 | 0.306 | 0.377 | -0.005 | 0.365 | 0.449 | F |
| 15 | -0.001 | 2.816 | 3.946 | 0.004 | 1.291 | 2.020 | 0.008 | 2.245 | 4.384 | F |
| 16 | 0.017 | 2.323 | 3.694 | -0.021 | 0.698 | 1.242 | 0.028 | 1.465 | 3.331 | F |
| 17 | 0.045 | 1.382 | 1.744 | -0.046 | 0.624 | 0.941 | 0.050 | 1.020 | 1.878 | F |
| 18 | 0.703 | 1.231 | 1.435 | -0.719 | 0.782 | 0.505 | 0.822 | 0.994 | 0.931 | NF |
| 19 | 0.672 | 3.365 | 4.011 | -0.682 | 0.743 | 0.571 | 0.803 | 0.985 | 0.975 | NF |
| 20 | 0.645 | 3.308 | 3.937 | -0.667 | 0.669 | 0.394 | 0.774 | 0.845 | 0.644 | NF |
| 21 | 0.637 | 3.230 | 3.829 | -0.653 | 0.655 | 0.368 | 0.759 | 0.817 | 0.603 | NF |
| 22 | 0.639 | 3.203 | 3.759 | -0.651 | 0.652 | 0.346 | 0.755 | 0.802 | 0.564 | NF |
| 23 | 0.640 | 2.171 | 2.776 | -0.653 | 0.699 | 0.441 | 0.760 | 0.990 | 0.980 | NF |
| 24 | 0.649 | 1.114 | 1.184 | -0.662 | 0.662 | 0.222 | 0.766 | 0.766 | 0.349 | NF |
| 25 | 0.647 | 1.089 | 1.154 | -0.660 | 0.660 | 0.218 | 0.767 | 0.767 | 0.336 | NF |

After this step, all the samples which have 1 in their 6th digit are eliminated. From the remaining samples, using a similar procedure, the second step is derived.

Step 2: If the 2nd digit is 0 (that is, the mean absolute of odd harmonic currents is less than a threshold value, i.e., 3.628), it is Non-Fault.

Testing sample data is somewhat complicated in the high impedance fault case. It has various kinds of bursts in terms of amplitude increase and of length. Some parts of this sample data have a few normal or event-looking data, but the conductor is still on the ground. Figure 3 shows a test sample waveform. The first four samples are apparently normal. At the fifth sample, a fault starts with a large amplitude increase, and long and medium length burst durations. Sample numbers 10 and 11 look normal, or at least like an event by observing the total current, but, the conductor is on the ground; they are actually a fault. Sample numbers 12 through 16 show apparent fault only by the total current. Sample numbers 17 and 18 show normal or event by observing total current; however, they are a fault. Sample 19 is fault data.

The status from the decision rule is obtained by passing variables through the rules. The first rule is on the standard deviation of even harmonic current and the second rule is on the mean absolute value odd harmonic current. The output status is shown in Table III.

The data of samples 1 through 4 has been automatically classified and stored as non-fault data. These data already replaced the first 4 data of the non-fault section of an existing memory. The data of sample 5 and 6 are pending unclassified. At the 7th sample, a "TRIP" signal is issued, and if a confirmation input from an operator arrives at the detection system, each data of sample 4 through 7 is classified as fault data. These data go to the memory and replace the first 3 existing fault data. The new

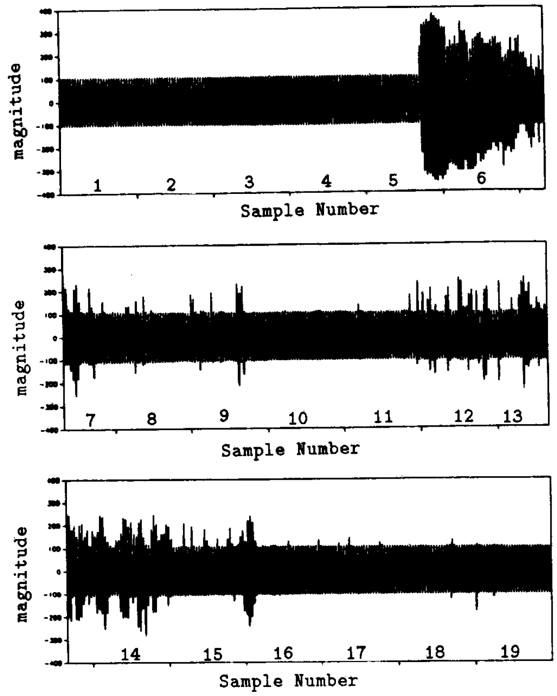


Figure 3. Test Sample Waveform.

rule says that:

Step 1: If the 6th digit 1 (that is, if the standard deviation is higher than a new threshold value, i.e.,0.609), then it is Fault.

Step 2: If the 7th digit is 1 (that is, if the mean value of sub-harmonic currents is greater than a new threshold value, i.e., 0.407), then it is Non-Fault.

Step 3: If the second digit is 0 (that is, if the mean absolute of odd harmonic currents is less than a new threshold value, i.e., 4.762), then it is Non-Fault.

As we see here, the new rule is slightly different from the existent rule.

Table III. Status Output from Test Samples.

| TEST SAMPLE NUMBER | ACTUAL STATUS | DECISION TREE STATUS | EVENT DETECTOR OUTPUT | DECISION CONTROL SIGNAL |
|---|---|---|---|---|
| 1 | NF | NF | 0 | N/A |
| 2 | NF | NF | 0 | N/A |
| 3 | NF | NF | 0 | N/A |
| 4 | NF | NF | 0 | N/A |
| 5 | F | F | 1 | N/A |
| 6 | F | F | 1 | N/A |
| 7 | F | F | 1 | TRIP |
| 8 | F | F | 1 | |
| 9 | F | F | 1 | |
| 10 | F | F | 1 | |
| 11 | F | F | 1 | |
| 12 | F | F | 1 | |
| 13 | F | F | 1 | |
| 14 | F | F | 1 | |
| 15 | F | F | 1 | |
| 16 | F | F | 1 | |
| 17 | F | F | 1 | |
| 18 | F | F | 1 | |
| 19 | F | F | 1 | |

It is not appropriate to draw any general and convincing conclusions by the execution of a detection system on this particular set of test samples. However, it is found that there is no false trip and no missed trip where most techniques usually miss low-level faults. The decision rule from an induction process shows very good performance. Both reliable detection and security against false trip could be acquired by multiple detection parameters and an induction process. By adding an event detector, which shows a perfect performance in indicating the occurrence of events, the intelligent system is getting experience and adapting itself to a variety of conditions.

## CONCLUSIONS

The objective of this research was to find an intelligent detection system. This intelligent system has two specific properties. First, it is capable of taking advantage of multiple detection parameters or variables. Secondly, it provides adaptability using inductive reasoning, incorporated with some critic modules in a detection system. Inductive reasoning which will minimize entropy was applied to acquire the knowledge of fault class and non-fault class. We applied this knowledge to make the intelligent system adaptive to surrounding environments.

A learning detection system was implemented with inductive reasoning and an event detector. An example execution was shown with a decision rule which was derived using training sample data consisting of high impedance faults, switching events, and normal status. A complicated set of test data was used to test the performance of the learning detection system. It was found that, even when it met very complicated situations, the learning detection system made smart decisions and evolved itself to a new situation with a newly derived decision rule.

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