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Arc Fault Detection Through Model Reference Estimation

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ABSTRACT

In most arc fault circuit breakers, arc detection is accomplished through the signature analysis of remotely sensed branch currents, with high frequency spectral components being indicative of arcing. This paper presents an alternative approach based upon system identification. A model is assumed for the load on the distribution bus. This model is updated continuously by comparing measured voltages and/or currents to the values predicted by the model. The resulting prediction errors are used to adjust the model in real time. In aviation loads, even in nonlinear loads that are rapidly and repetitively engaged and disengaged, we find that the model successfully adapts to give a good description of the load. However, when an arcing fault is present, its chaotic nature prevents a successful model identification and the prediction errors remain large. The large, continuous prediction errors provide a means of fault identification in a short time and with a high level of confidence.

1.0 INTRODUCTION

An arc fault is a luminous discharge between two electrical conductors and is objectionable because heat is produced as a byproduct of this unintentional electrical path. If not immediately detected and interrupted, an arcing fault can quickly lead to high heat electrical fires that can involve other wires, compromising the function of multiple electrical control and/or power circuits. The heat of an electrical arc can cause the ignition of combustible materials and is a leading cause of electrical fires.

Arc faults in electrical systems are a significant source of damage that cannot be addressed by conventional circuit breaker technology. In a home, arcing faults can occur when insulation ages, when insulation is damaged by insects or rodents, or a variety of other causes. In an aircraft, such faults can arise from causes as diverse as combat damage, insulation aging, loose connections or damage to electrical wires that can occur during routine maintenance.

The quick and reliable detection of arcing in aircraft electrical distribution networks is of great importance in order to interrupt the arc in a timely manner and thereby minimize collateral damage. As aviation technology migrates to more electric aircraft, arc fault management technology is likely to become an integral part of an aircraft's electrical system.

Arcs are chaotic and, as such, may display different features. When an arcing path is struck, this causes a discontinuity in the current flow in power conductors. For alternating current, this arc strike can occur each half cycle as the voltage builds until it reaches a value high enough to support current flow across an air gap. When an arc strikes, it may cause a "chaotic" current flow across a heat generated plasma path which can be detected in the frequency domain as an event having broadband frequency content. So, periodic strikes are one characteristic of arcs in an AC system and broadband frequency content is characteristic of both AC and DC system arcs. The majority of the technologies that have been proposed for arc fault management are based upon an electrical signal analysis of signals taken from power delivery conductors and rely upon the detection of one or more of: (1) the characteristic broadband frequency content of an arcing fault; (2) the rapid change in currents (di/dt) characteristic of sudden arc current flow; (3) repetitive strikes during characteristic times in the AC waveform; and/or (4) changes in the electrical current profiles in successive half cycles in search of a pattern characteristic of arcing [1-4].

Unlike the above approaches which are directed at identifying what ***is*** an arc, we propose modeling what ***is not*** an arc by assuming a linear model and then updating that model in real time. Arcing does not lend itself to successful modeling (at least, not with a linear model). As such, when our model is unable to explain the underlying system, this can indicate either that the load has changed or that an arc is present. If, after an interval of time, the model proves unable to tune to describe the system, this is an indication of arcing. We find the technique to be particularly helpful for relatively low level faults that are masked by legitimate loads. An examination of the estimation errors (residuals) provides an important source of information, that, in combination with other arcing indicators, can lead to a robust and reliable arc detection technique.

2.0 MODELS FOR AN ELECTRICAL LOAD

Figure 1 depicts the elements needed for the identification of a load on an electrical branch. A power source of known electrical characteristics delivers electrical power to a load having arbitrary electrical characteristics. There are many ways to model a load. For the general case, a load may be defined by a time record of the voltage across the load and the current through the load, with these measurements obtained using a voltmeter and ammeter as shown in Figure 1. If the voltmeter and ammeter are located physically adjacent to the power source, then the source voltage is the same as that recorded by the voltmeter and any line impedance due to the connection between source and load may be lumped into the load model.

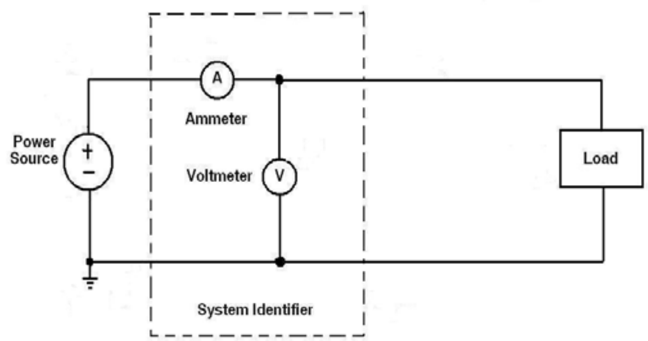

Figure 1 – Load Measurements Allow a System Model

2.1 Autoregressive Modeling

Electrical loads exhibit a wide ranging set of behaviors. For example, in a constant resistance load, the voltage across the load will be proportional to the current through the load. The equation describing such a system is known as a zeroeth order equation. In more complicated loads having one or more energy storage elements such as inductors or capacitors, the circuit behavior can usually be described by first or second order differential equations. Even if the system is of relatively high order, its transient response is generally dominated by elements having first or second order dynamics. An example of such loads is a switching power supply. Loads such as an incandescent light have a variable resistance. Initially, the bulb filament is cold and has a relatively low resistance. This causes high current inrush when the lamp is first turned on. As the filament heats up, its resistance goes up to a steady state value and the initial high voltage transient dies out to leave a zero order, constant resistance, steady state response. Dimmer circuits that operate by controlling the phase of a lamp use solid state switching elements and are highly nonlinear. However, in steady state, the overall load characteristic of these devices is largely second order with frequency components that are multiples of the fundamental forcing function.

Electrical loads are continuous in nature but may be modeled by a discrete model that operates on sampled voltage and current data. We have chosen to use a linear autoregressive model:

$$y_k = a_1 y_{k-1} + a_2 y_{k-2} + \ldots + a_m y_{k-m} + b_1 u_{k-1} + \ldots + b_l u_{k-l} + c_1 e_{k-1} + \ldots + c_n e_{k-n} \quad (1)$$

where y_k and u_k are the sampled data output and input sequences respectively. So, y_k would be the present output sample, y_{k-1} would be the immediately preceeding sample, and y_{k-m} would be the output that was acquired m sample periods ago. The sequence $e_{k-1} \ldots e_{k-n}$ represents a residual sequence that is made up of estimation errors. This is discussed below. An equation having the form of equation (1) is known as an ARMAX(m,n,l) model since it has m autoregressive terms, n moving average terms and l exogeneous (or input) terms.

An ARMAX(m,n,l) model is completely defined by the knowledge of the constant coefficients $(a_1,a_2,\ldots a_m,b_1,\ldots b_l,c_1,\ldots c_n)$ When these coefficients are not known, they must be estimated. Define a vector of model coefficients as

$$\Theta = col\ (a_1,\ldots a_m, b_1,\ldots b_l, c_1,\ldots c_n) \quad (2)$$

and a vector of measurements as

$$M_k = col(y_{k-1}, y_{k-2},\ldots y_{k-m}, u_{k-1},\ldots u_{k-l}, e_{k-1},\ldots e_{k-n}). \quad (3)$$

Then equation (1) can be written in vector form as

$$y_k = M_k^T \Theta \quad (4)$$

Figure 2 portrays the way in which an ARMAX model may be developed for an electrical load in a distribution network. In this figure, the system (load) consists of an arbitrary number, n, of subsystems, each of which may be engaged or disengaged at independent and arbitrary times through switches Sw_1 – Sw_n. In an aircraft, these loads might be motors, pumps, lights, heaters or avionics. When a load is engaged/disengaged, the overall nature of the system is changed and the system model must be adjusted by the system identifier. Voltage measurements u and y are made at discrete intervals and digitized by an A/D converter. Measurements of u are proportional to system voltage (ignoring voltage drops across a low valued shunt resistor). Measurements of the difference y-u are proportional to system current. All measurements are fed to a parameter identification block which assumes an ARMAX model of known order and identifies the parameters in that model.

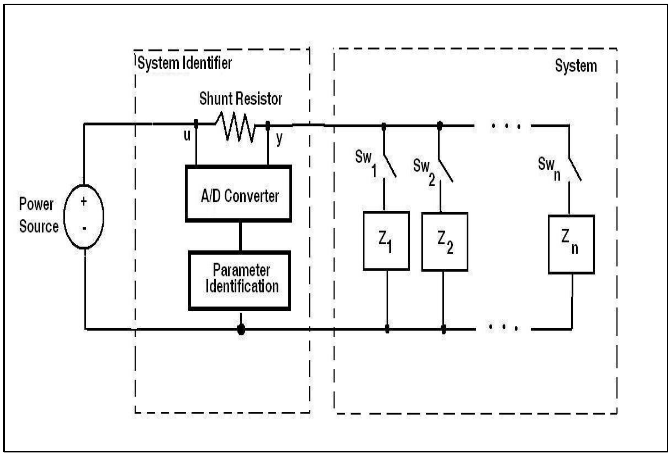

Figure 2 – System Identification for a Time Varying Load

Even if the system is continuous, time varying and nonlinear, it may often be modeled by a discrete, time invariant, linear model as long as that model is frequently adjusted. An arcing scenario is depicted topologically in Figure 3. Here a series arc or a parallel arc would function in the system as a chaotic series or parallel load. When an arc occurs, it impacts the voltage and/or current measurements that are taken on the conductors connecting source and load. However, an arcing fault results in a relationship between current and voltage that is highly nonlinear and time varying and that defies satisfactory modeling. This is the basis for our arc fault identification approach.

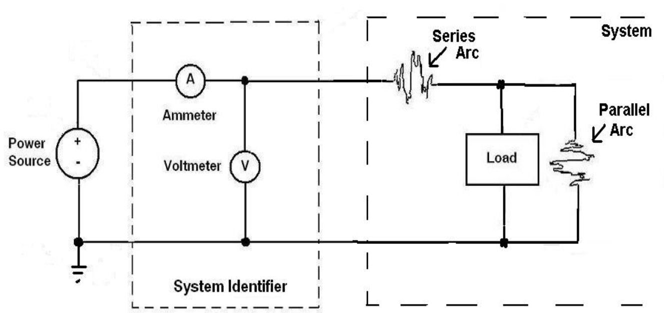

Figure 3 – To the Identifier, an Arc Can Look Like a Variable Load

3.0 PARAMETER ESTIMATION

For a given system, if the order of an ARMAX model is assumed, then the task of identifying the best model that fits the system is one of identifying the parameter set Θ. When the goal is to carry out real time parameter identification, that is, updating the parameter estimate each time that a new measurement set is obtained, then a recursive technique is preferred. Many techniques have been proposed, with various optimality characteristics. Two of the most common are least squares and stochastic approximation. Recursive least squares is optimal in the sense of minimizing the sum of the squared estimation errors. As each set of data points is acquired, this algorithm proceeds in two steps [5]. First, a covariance matrix is updated as

$$P_k = \left[P_{k-1} - P_{k-1}M_k\left(M_k^T P_{k-1} M_k + 1\right)^{-1} M_k^T P_{k-1}\right] \quad (5)$$

where P_k is a square matrix of dimension m+l and the initial value of this matrix is $P_0=1000\mathrm{I}$ where I is the identity matrix (note that the choice of P_0 will depend upon relative magnitudes of the data but should generally be chosen to be a large number). Then the estimate of the parameters for sample k is generated as

$$\hat{\Theta}_k = \hat{\Theta}_{k-1} + P_k M_k \left[y_k - M_k^T \hat{\Theta}_{k-1}\right], \quad (6)$$

Where the initial estimate, Θ_0 equals zero. For a time varying system, more recent data is more meaningful for constructing a model than older data and a forgetting factor may be used to downweigh older measurements. Alternatively, the covariance matrix P_k may be periodically reset to a high multiple of the identity matrix (eg: 1000I). Equation (6) has a standard form known as a differential corrector. The parameter estimate at time k is calculated as the previous estimate plus a correction term which is proportional to the error in the estimate which is the bracketed term in equation (6). This bracketed term is a scalar quantity which is also referred to as the residual and which will be discussed subsequently as the sequence e_k. The residual represents that portion of the measured data that is unexplained by the model.

An alternative algorithm for parameter estimation is the stochastic approximation algorithm in which the parameter estimate is updated with each new measurement set according to

$$\hat{\Theta}_k = \hat{\Theta}_{k-1} + \mu M_k \left[y_k - M_k^T \hat{\Theta}_{k-1}\right] \quad (7)$$

where μ is a constant and, as before, the term in brackets represents the residual or estimate error [6]. The advantage to the stochastic approximation approach over standard least squares is that it is simple to implement, can be used for a high order system with little additional overhead, and can adapt to a time varying system. However, the choice of μ is critical. If μ is chosen to be too large, the parameter estimates will vary widely from sample to sample. If it is too small, the convergence to an acceptable model will be slow.

3.1 Model Reference Estimation

As described above, once an ARMAX model of known order is chosen, parameter estimation may be applied to a data stream to determine the model parameters. At a given sample, k, the ARMAX model may be used to make an estimate of what the output y_k should be based upon past samples of u and y and estimate errors, e. This estimate is calculated as

$$\hat{y}_k = M_k^T \hat{\Theta}_{k-1} \quad (8)$$

and the difference between the estimate and the actual measurement that is obtained is the residual

$$e_k = y_k - \hat{y}_k \quad (9)$$

Our approach is to use this residual as an indicator of arcing. So, system current and/or voltage data is continuously acquired and a linear ARMAX model for the system is continuously adjusted to best explain the system. Even when the system load is dramatically changed, for example, when a motor or switching power supply is engaged, the model adjusts and the residual sequence, although temporarily large in magnitude, reduces to small magnitudes, reflecting a successfully tuned model. On the other hand, if an arcing fault occurs, it results in a residual sequence that grows large and stays large. This is because a linear ARMAX model cannot accurately describe the chaotic behavior of an arc fault. Accordingly, we can use the residual as an arc indicator.

A block diagram for this approach is depicted in Figure 4. Voltage and current data is acquired from the bus by an A/D converter. The digital readings are taken at a periodic sampling time and then used by a parameter estimator to tune the parameters in an ARMAX model. The residual sequence, e_k, is processed and if it exceeds a certain threshold then it is identified as resulting from an arc fault and the circuit breaker is tripped.

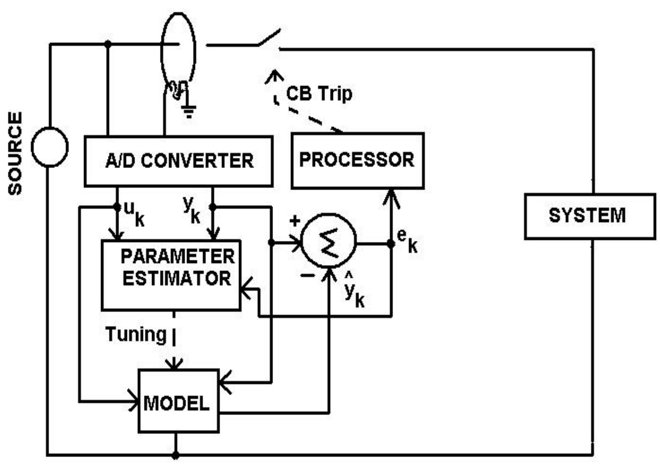

Figure 4 – Model Reference Estimation for Arc Detection

3.2 Choosing a Parametric Model

Although there have been schemes for arc detection wherein the sense means is collocated with the cabling, most approaches assume that arc fault detection occurs remote from the actual location of the fault and fault detection is generally located within a power controller or circuit breaker. In an electrical distribution system, although many loads are discontinuous (eg: an avionics switching power supply or a household lamp dimmer), they will often lend themselves to a low order linear model. That is, even though the actual load may be nonlinear or of high order, the dominant dynamics are generally described by a relatively low order linear model. The sensing means also may contain dynamics. For example, if current is being sensed by means of a current sense transformer (CT), the CT will generally act as a bandpass amplifier. Determining what portion of the measurement is due to the load, what portion is a consequence of sensing dynamics and what portion is unexplained and thus a candidate for arcing, is a key question. By using a parameter estimation scheme that allows for model tuning, a low order linear model may be used to successfully capture complicated system and sensor dynamics.

4.0 ARC RECOGNITION IN AN AC NETWORK

In order to validate the arc recognition approach, experiments were carried out using a published standard for arc recognition in 60 Hz alternating current systems, U.L. 1699 [7]. In our experiments, current data was collected using a 1000:1 current sense transformer, model number CT-000, manufactured by Coilws.com, Inc. Samples of current information were acquired at 50 KHz using a 12 bit A/D converter. Two benchmark cases were developed that correspond to what are generally very difficult cases to analyze for a fault. The first such case is an 800 watt dimmer circuit that is highly nonlinear and that exhibits many of the behaviors typical of arcing but that is not a fault load and should not be identified as such. The second case is a low level carbonized path fault which is masked by a legitimate load. A successful arc detection procedure should always recognize the latter situation as a fault and should never recognize the former.

4.1 Benchmark Case – an 800W Dimmer

Figure 5 shows data acquired from a benchmark test case as described in the U.L. 1699 standard for 120 VAC, 60 Hz arc fault interrupt devices [7]. The load is an 800 watt tungsten lamp load that is controlled by a phase control dimmer set to 90°. This is a highly nonlinear load. Sampling occurs at a rate of 50 KHz with 12 bit resolution. As seen by the envelope in Figure 5, when the load is first turned on, high inrush currents occur due to cold bulb filaments. At each zero crossing, a triac turns off power until phase voltage reaches a setpoint, at which time the triac turns on, switching the load (a lamp) into a relatively high voltage with no soft start. Figure 5 portrays a six second record and represents 360 cycles of 60 Hz AC.

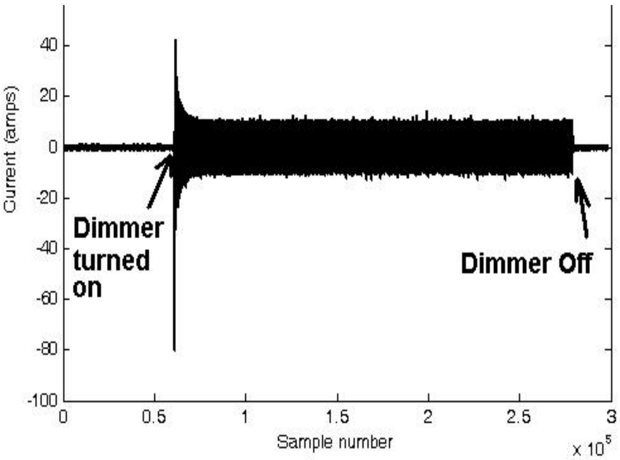

Figure 5 – Current Signature from a 60 Hz, 800W Dimmer

Figure 6 shows a detail of the current signature from the 800W dimmer and illustrates why this is a good candidate load for contrast when evaluating both system identification and nuisance tripping during arc fault recognition. A dimmer load is both time varying and nonlinear. During each half cycle of the AC waveform, current is inhibited from flowing from the zero crossing (a soft start) and instead is engaged discontinuously halfway through the cycle. While the load is a resistance, it is time varying and increases in resistance as the filament heats. A dimmer load is ideal for examining nuisance trip issues because it exhibits the "shoulder" that is often seen in AC arcs, occurring when fault current across a plasma path is extinguished during a zero crossing of current and then restriking when voltage increases beyond a certain point. So, even though a dimmer load is not a fault, it can look "arcy" and result in a false recognition and so it represents an important benchmark against which to contrast arc detection algorithms.

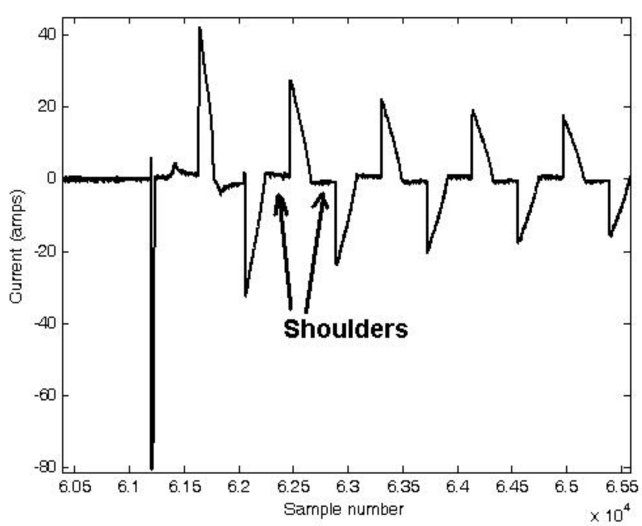

Figure 6 – Detail of Current Signature from 800W Dimmer

We modeled the dimmer by assuming an autoregressive moving average ARMA(4,4) model that regresses on the past three samples plus the 835th oldest sample. This is done for both past currents as well as past residuals. A full period of 60 Hz, AC is 833 samples, so by regressing slightly farther back than one full cycle, our model can incorporate memory and a degree of pattern matching. Figure 7 portrays a detail of the actual current and the current predicted by our model. The model estimate is depicted by a dashed line. The residual, representing the difference between the actual measurement and the estimate, is shown in the lower plot. It may be seen that the estimate lags the actual current measurement for this initial cycle, resulting in large residuals (estimate errors) that are on the order of the actual current. This is due in large measure to the sudden imposition of a previously unmodeled load. As the model adapts, the estimate more closely tracks the measurements and the residuals reduce in magnitude.

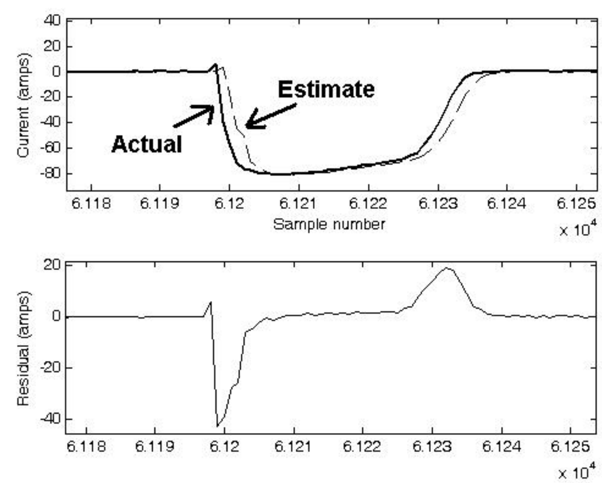

Figure 7 – Estimation Error for the First Half Cycle

4.2 Leakage Across a Carbonized Path

Perhaps the hardest type of arcing behavior to detect is that which starts as a low level leakage. Low level faults are simulated by the SAE 5692 wet arc tests [9]. Underwriters Laboratories uses carbonized samples that are prepared from PVC jacketed wire that is subjected to a prescribed series of processing steps [7]. By introducing a known resistance in series with the carbonized sample, arcing faults are limited in magnitude. An example test set-up as prescribed in U.L. section 42.2 is depicted in Figure 8. A masking load of 24 ohms represents a 5 ampere rms current draw that is continuous. When the switch is closed, a carbonized fault is applied. A load limiting resistor of 24 ohms ensures that the arcing fault will be less than 5 amperes. This represents one of the more difficult arc detection cases since the arc magnitude is limited to less than the level of a masking load.

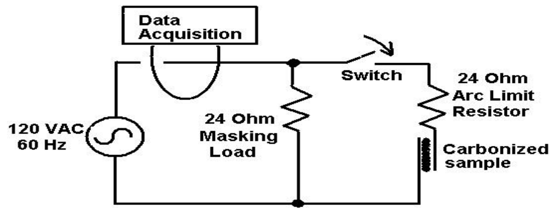

Figure 8 – Data Acquisition of an Arc Signature with Masking Load

With the test set-up depicted in Figure 8, data was collected from a carbonized arc. Using a sampling rate of 50 KHz, a six second record corresponding to 360 cycles of AC were collected as shown in Figure 9. Initially, the only load present was the masking load. Then the switch was closed to apply a current limited carbonized fault. This can be seen on the data trace as an increase in current with a rather ragged appearance on the current envelope. Figure 10 depicts the current record acquired for a few cycles before and after the switch closure.

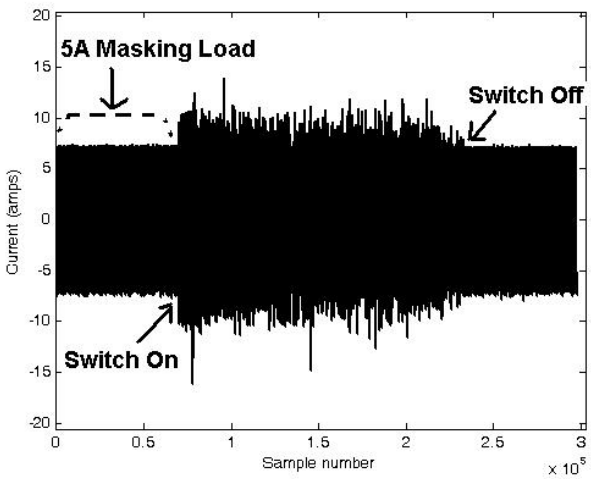

Figure 9 – Application of a Carbonized Fault

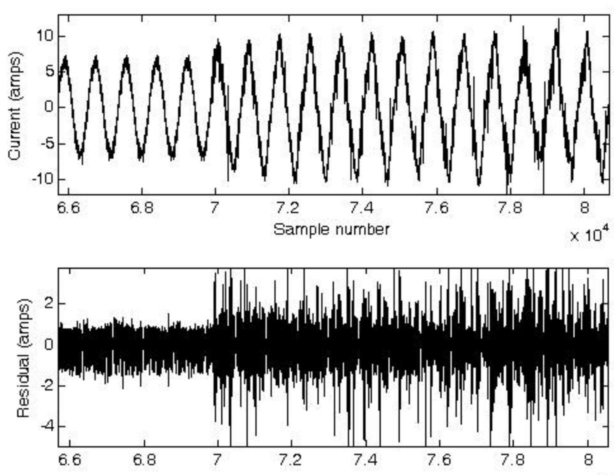

Figure 10 – Detail of Initial cycles After Arc Imposition, Plus Residuals

4.3 Processing the Residuals to Detect an Arc

The residual sequence that arises from a model estimation yields an indication of the quality of the model in describing the underlying system. So what is left is to process the residuals to see if we can extract the information that is important to arc identification. Furthermore, this must be carried out in real time, since upon the occurrence of an arc, we need to detect and interrupt quickly in order to minimize damage to collateral conductors. When a comparison is made between the residuals that result from identification of the 800 watt dimmer and the residuals that result from a carbonized fault that is limited to 5 amperes, it is noted that the dimmer residual sequences are quite large in magnitude for the one or two points that correspond to the discontinuous application of current and then they quickly die out. In contrast, the residuals for the carbonized arc experiment tend to be smaller but do not die out. We propose a performance index which is derived from the residuals by using the equation:

$$J_k = \alpha J_{k-1} + 1 \quad \text{for e(k)> 2 amperes} \tag{10a}$$

and

$$J_k = \alpha J_{k-1}, \quad \text{for e(k)<2 amperes} \tag{10b}$$

where J_k is the performance index at the k^{th} sample, e(k) is the residual that is calculated at the k^{th} sample, and α is a positive multiplier that is less than one and that serves to discount old data.

A record of the dimmer and the carbonized fault currents showing the respective residuals and performance indexes are shown in Figures 11 and 12. The current records, residual sequence and performance index are shown on the same scales to show relative magnitudes. The surprising feature is that while the dimmer appears to have the larger residuals, for the most part they are short in duration and occur each time the dimmer turns on as the model tries to accommodate the discontinuous jump in current. The maximum cost for the dimmer is J=20. In contrast, the carbonized fault has residuals that are "denser" in the sense that they exhibit an overall larger amplitude. This results in a higher performance index. Using the cost, J, as an arc fault indicator, the final task is to determine what value of J to use as an indicator of a faulted electrical distribution system. Lower values allow quicker arc detection but with a greater possibility of nuisance trip. Higher values may result in delayed trip times.

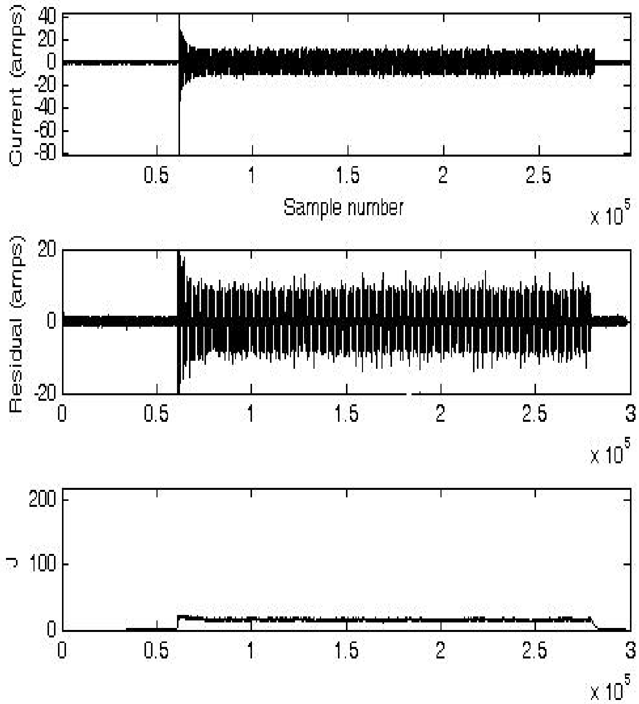

Figure 11 – Sampled Data, Residuals and Cost for Dimmer

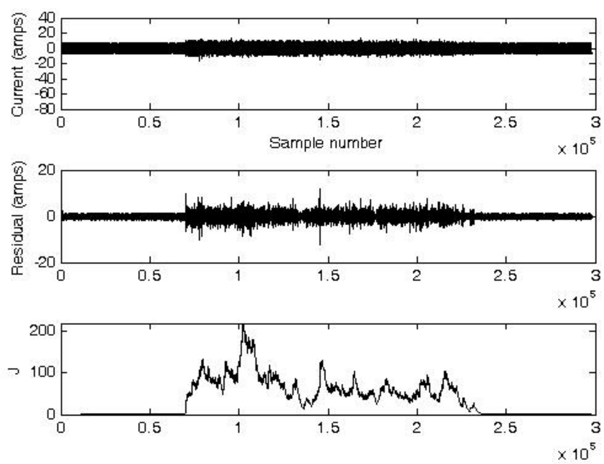

Figure 12 – Sampled Data, Residuals and Cost for 5A Carbonized Fault with 5A Masking Load

5.0 DISCUSSION

In an arc fault management system, samples must be processed in real time and we have implemented this real time arc detection using a system based upon a Xilinx field programmable gate array (FPGA) running at 50 MHz. The proposed algorithm has the advantage that it is recursive and an update to the system model and an arc detection signal can be made as each new sample is acquired, while having minimal storage and processing needs. In particular, there is no need to compute a spectral distribution via discrete fourier transform. The proposed technique has elements that are common to other proposed techniques. In particular, by using samples in the regression that are a full cycle or half cycle back from the present sample, past patterns of signals can be incorporated into the algorithm with deviations being indicative of a fault.

In a direct current system, the system dynamics are not excited by the source except when a load is engaged. This complicates the distinction between an arc and a legitimate load and lengthens the arc recognition time. We are presently investigating ways in which a power management system may play a role in enhancing real time system identification by introducing small, well-known, variable impedances in series with the load and using load current measurements to tune parametric models. If successful, model reference arc identification may represent an important addition to the DC arc management toolbox.

6.0 CONCLUSION

An autoregressive time domain model is assumed for a branch in an electrical distribution system. By continually updating this model in real time, an estimate for the behavior of the load on the electrical branch may be determined. Typical loads are well characterized by such models. However, if an electrical arcing fault occurs, this is complicated behavior that is difficult to describe and the model will not adequately predict the behavior of the load. The mismatch between expected and measured load behavior is recognized as an arc fault and a circuit interrupter can then be used to remove power from the faulted electrical branch. This paper has described the approach as applied to two limiting cases: a dimmer that is not faulted but that exhibits very "arcy" behavior, and a low level carbonized fault in the presence of a masking load. The approach in this paper may be used alone or in conjunction with other approaches to yield an arc fault detection that is robust to nuisance tripping.

ACKNOWLEDGEMENTS

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