Evaluation of Feeder Monitoring Parameters for Incipient Fault Detection Using Laplace Trend Statistic

Charles J. Kim, *Member, IEEE*, Seung-Jae Lee, *Member, IEEE*, and Sang-Hee Kang, *Member, IEEE*

***Abstract*—This paper focuses on a systematic and cumulative statistical approach for identifying symptom parameters of incipient faults in distribution feeders. The proposed method aims at providing a tool for evaluating and identifying the best and highly correlated parameters to the faults so that they could be used for incipient fault detection and feeder condition monitoring. The Laplace test statistic is adopted for trend analysis of the event log of candidate parameters and applied to actual feeder event data for online detection and monitoring purposes.**

***Index Terms*—Condition monitoring, hazard function, incipient fault, Laplace test statistic, trend analysis.**

I. Introduction

OVERHEAD power distribution systems use a variety of components to deliver power to customers. Various types of insulating devices such as insulators, fused cutouts, and lightning arrestors are used to mechanically connect energized conductors to poles while keeping these conductors electrically isolated, or insulated, from the poles. The failure of equipment in power distribution systems can have direct or indirect impact on the reliable delivery of electricity. Also, certain failures can result in loss of service.

Even though the majority of the distribution equipment failures are caused by natural degradation, distribution systems experience faults for a variety of reasons. Some faults are precipitous, and others gradual. The faults that are caused by accidents or severe weather are random and unpredictable, so they are called "unpredictable faults." Others, however, occur when damage or contamination progressively weakens the distribution equipment of its integrity over time. These faults, called "incipient faults," are caused by degradation of equipment, and, theoretically, are predictable or avoidable if the degradation process and the means to monitor it are known. The incipient faults are less acceptable to customers because the faults occur when the public does not expect interruptions in service. Hence, a strategic and well-organized method to detect incipient faults would be of great importance for maintaining a reliable system.

To meet the high expectation of customers on feeder reliability, utility companies have investigated and invested in detecting incipient faults and monitoring feeder status so that they can alert repair crews before an imminent fault causes customer service interruption [1], [2]. Several studies have focused on the condition monitoring of various pieces of equipment such as circuit breakers, transformers, underground power cables, and insulators [3]–[11]. Most of such efforts are centered on the "single-cause" scheme that, with known symptoms of a type of failure, attempts to sort out the fault by analyzing the monitored data. Considering, however, that there are hundreds of different pieces of equipment in different statuses undergoing different failures and faults in a distribution feeder, it is not very surprising that studies of the single-cause scheme on distribution incipient fault detection have reported only limited performance. A project sponsored by the Electric Power Research Institute (EPRI) concerning a distribution fault anticipator/locator, launched with objects to reduce labor costs and crew time through faster identification of faults and to decrease outages through detection of incipient faults, has yet to isolate the symptom parameters [12].

Substation-based monitoring could be better utilized if a "multicause" scheme is applied in which a cumulative feeder condition is extracted from the monitored data. However, even this scheme poses one fundamental question: how can the decisive parameter be extracted or selected from the monitored data that cumulatively reflects the feeder status and incipient faults? This task is challenging, especially when there is no history or knowledge of the parameter–cause relationship of a feeder and when there are too many candidate parameters to be considered.

The objective of this paper is to propose a multicause, trend statistic method which, by analyzing the parameters of monitored data and the Supervisory-and-Control-and-Data-Acquisition (SCADA)-based fault log of a feeder, evaluates the parameters and identifies the optimal one for a feeder condition indicator and incipient fault anticipator.

In the next section, we discuss the rationale of incipient fault detection and the parameter evaluation. Section III compares a few statistical trend analysis methods. The lengthy Section IV

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reports the application of the Laplace statistic on actual monitored data for parameter evaluation. Section V concludes the paper and briefly discusses the impact of the proposed approach in other science and engineering areas.

II. Incipient Fault Detection and Parameter Evaluation

Detection of faults before they actually occur is a critical element of securing high reliability of a distribution system. However, prediction of an imminent fault has been a challenge for engineers and scientists in the field of diagnosis and analysis of failure trends. When some distribution equipment begins to deteriorate, intermittent incipient faults persist in the system from as short a time as several days to as long as several months. In this scenario, the characteristic behavior would manifest itself progressively during the incipient phase, leading to a fault condition.

The main principle of failure prediction and incipient fault detection, therefore, centers on monitoring the distribution line and discriminating the signatures (or symptoms) of faults in a feeder before breakdown or breakout.

When the symptom parameters are known and measurable, and their correlation with actual failure is determined, the failure prediction problem reduces to simple parameter monitoring. However, since an exact failure process of equipment or a system is usually not completely known, most failure prediction problems are in either or in between the following two cases: partially known symptom parameters with a fragment of actual failure history data and totally unknown symptom parameters with no available failure history data.

Hence, it would be the first step to monitor and analyze the trend of the partially known parameters with actual faults. In this scenario, as depicted in Fig. 1, the feeder condition monitoring and incipient fault detection executes a closed-loop operation that involves parameter processing, SCADA-generated fault log analysis, and the characteristic parameter identification by matching the "event" log of the parameter with the fault log. The term "event" here indicates some abnormal activity or value that, when occurring repeatedly, eventually leads to a fault.

The whole process of parameter evaluation and identification parallels the incipient fault detection activity, which monitors the parameter identified by the "evaluation and identification" process. When a new and different parameter is found that better matches the trend of the event/fault log, then the new parameter would replace the previous parameter, and the detection activity resumes with the substitute. This feedback process assures that the incipient fault detection and feeder condition monitoring can run, even under changed environment of loads and terrains, with the most relevant, cumulative characteristic parameter.

The scope of the investigation of this paper is focused on the parameter evaluation and identification of the closed-loop process. As depicted in Fig. 2, the paper proposes an approach of "timed event" trend statistic concept to provide a systematic tool for evaluating and identifying detection parameters so that the best and highly correlated parameter(s) of a feeder could be used for incipient faults and condition monitoring.

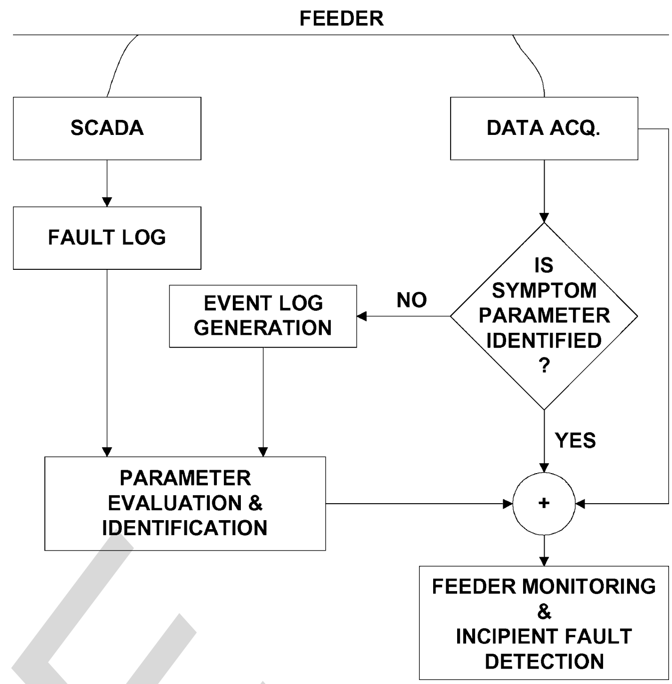

Fig. 1. Continuous loop for incipient fault detection by parameter evaluation and identification.

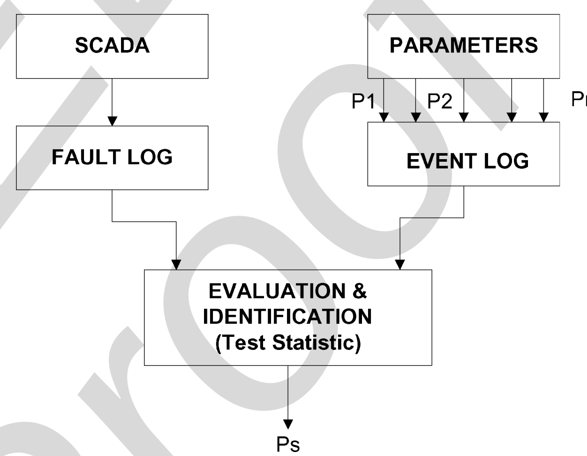

Fig. 2. Optimal detection parameter identification using event log and trend statistic.

Unlike regular trend analysis that relies on "time-averaged" events over a period of time, the "timed event" statistic focuses on the rate of the occurrence of the event. In fault anticipation, when the events occurred in a given period of time is more important than what the average number of events is: the trend of the event occurrence is more meaningful since repeated events lead to a catastrophic fault [13]. The next section discusses statistical trend analysis methods of events.

III. Trend Analysis Methods of Event Log

Observing the behavior of several candidate parameters and finding which one shares the failure trend and can be used to monitor is not an easy task. When a statistical method for relating the behavior of parameters and imminent fault fails, it is mainly because of the unknown or incompletely known parameters. With partially known or totally unknown symptom parameters, even a sound approach achieves only partial success. Another cause for partial success in the statistical approach could be found in the inappropriate application of statistical measures. For example, using such measures of symptom parameters as the number of activities ("event") or the time-averaged events over a time period does not always successfully indicate the trend of the system under investigation.

A better measure for indicating an increasing or decreasing trend is "inter-arrival" times over a period of time, and one of the better-known approaches is the Weibull distribution and hazard function model [13]. The inter-arrival event analysis on candidate parameters, by fitting the events to the model, can determine which parameters are the precursors of the faults.

On the other hand, a new method of trend analysis, timed-event analysis, highlights the time location of the event occurrence. The information of the time location of the event occurrence eliminates certain candidate parameters: if the time location of the parameter is the same for a period of time, the event is caused by random acts, therefore, the parameter is eliminated from the symptom parameter candidates.

A brief discussion on the Weibull hazard model and the time-event Laplace test statistic follows.

A. Inter-Arrival Event and Weibull Hazard Function

Failure distribution mathematically characterizes the probability of system failures as a function of time. The Weibull function is well known in failure analysis, and is defined by

$$W(t) = e^{-(t/a)^b}, \qquad \text{with } b > 0 \text{ and } a > 0 \tag{1}$$

where b is the shape parameter and a is the scale parameter.

On the other hand, the Weibull hazard function indicates a time-varying failure rate and is defined by

$$H(t) = \frac{b}{a}\left(\frac{t}{a}\right)^{b-1}. \tag{2}$$

The shape parameter b directly controls the hazard function and indicates the trend of the failure. The interpretation of the shape parameter is as follows [14]:

- $b > 1$, the failure rate is increasing with time;
- $b = 1$, the failure rate is constant with time;
- $b < 1$, the failure rate is decreasing with time.

The application of the Weibull hazard function for parameter selection begins with the analysis of the inter-arrival times of the events of the parameters. The "event," again, could be any change in magnitude of the parameters distinguishable from nominal behavior of the parameters, but not a fault or failure. The inter-arrival time stamps are marked by calculating the difference between the occurrence of each event and the time interval of two successive events, and by formulating the hazard function.

To estimate b and a, nonlinear fitting technique or regression analysis is usually applied with selected initial values. In the nonlinear curve-fitting case, the chi-square (χ^2) goodness of fit is measured to evaluate the fit of the hazard function to the observed inter-arrival data. Usually, 95% confidence of the fit requires that χ^2 be less than 0.05. However, there is a practical problem in the hazard function approach: sometimes, the χ^2 is not reduced to the critical value of 0.05, no matter how many rounds of iterations are performed [14]. The disadvantage of the hazard function approach is illustrated in the actual event log analysis in Section IV.

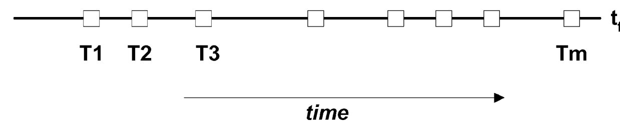

Fig. 3. Arrival time illustration of m events.

B. Timed-Event and Laplace Trend Test

If an event is caused by unpredictable incident such as accident or lightning, such event will occur at a constant or random rate., or, it will never reoccur. On the other hand, if an event is a precursor of an incipient fault, then such event by nature will occur more frequently, and the time to the next occurrence will likely be shorter. The Laplace trend statistic is a simple and powerful tool for distinguishing between a constant rate at which events are occurring and an increasing rate of occurrence of such events.

Consider a situation where a fault occurred at time t_f and m events have been observed over an interval of length t_f, where the origin is designated as time zero (0). The total m events are indistinguishable, caused by unpredictable or incipient faults, and their arrival times are designated as $T_1, T_2, \ldots, T_m$ as illustrated in Fig. 3.

Then, the Laplace test statistic (U_L) is defined by

$$U_L = \frac{\frac{1}{m}\sum_{i=1}^{m} T_i - \frac{t_f}{2}}{t_f \cdot \sqrt{\frac{1}{12 \cdot m}}}. \tag{3}$$

The Laplace test statistic has the following very simple interpretation. Under the assumption of constant rate of occurrence, the arrival times to faults, i.e., T_i's would be uniformly distributed over the interval (0, t_f), or randomly scattered around the midpoint of the interval $t_f/2$. Therefore, the sample mean of the T_i's would be approximately equal to $t_f/2$, and U_L would approximately become a normal distribution with mean 0 and variance 1 [14], [15].

When the events are occurring more frequently toward the end of the interval t_f, however, the sample mean becomes bigger. Therefore, a test statistic of events that exceeds a certain threshold could be interpreted to foretell that there is a trend supporting that the events are the precursors of the (incipient) fault. The threshold for supporting trend of fault is determined in terms of the z value of the standardized normal distribution for a chosen level of confidence (α), $z_{\alpha/2}$. The z value of the standardized normal distribution for 95% confidence level ($\alpha = 0.05$) is 1.96. The Laplace test statistic above the positive threshold value then indicates an increasing possibility of imminent fault, and one below the threshold, no positive trend to a fault. Therefore, a parameter for which events are measured and the Laplace trend results in higher than the threshold value of 1.96 could be selected as a precursor, symptom parameter of a fault.

To improve the test statistic performance for a small sample size of events, an adjusted Laplace test statistic was suggested in [16] which is also approximately standard Gaussian distribution. The adjusted test statistic (U_{AL}) is obtained by multiplying the mean (μ) by the original test statistic (U_L) and by dividing the result by the standard deviation (σ) of the timed event

$$U_{\mathrm{AL}} = \frac{U_L \cdot \mu}{\sigma}. \tag{4}$$

The threshold value based on the z value applies to both the original and the adjusted Laplace trend statistics.

Overall, the Laplace trend test is very useful for pinpointing which parameter of event has a positive trend with an actual fault. Since most distribution faults are due to incipient failure of the distribution equipment, the use of the Laplace test statistic helps to decide which parameters to monitor for predictive distribution maintenance.

IV. A Case Study for Parameter Identification

We applied the approach of the Laplace test statistic to the feeder event logs recorded in July and August 1996 and December 1996–February 1997. The data were originally acquired at an unmanned substation of Korea Electric Power Corporation (KEPCO) for a rural 12-kV feeder [17]. A summary of the "event" and the event log follows.

A. Feeder Log

1) Feeder Monitoring: The rural feeder in the substation had registered more faults than others and that was the reason it was selected as a test feeder for KEPCO's long-term research on feeder health monitoring. Feeder data were monitored for all three-phase voltages and currents and the neutral current using a data acquisition module with sampling rate of 3840 samples per second.

The difficulties in frequent access to the remotely located substation and the limited size of memory of the data acquisition workstation forced the recording crew to adopt a rather risky but sound monitoring practice: they decided to record twice a day for only 1 min at each time. The first recording time of day was set at 5:00 A.M.. The theory behind this was that most of the faults in the feeder had been involved with failures of insulators, and the early morning time roughly fitted the dew point hour at which the surfaces or connections of the distribution equipment were finely moisturized and believed to be accelerated in the failure process, so this would increase the chances of detecting abnormal activities of failing devices in the feeder [18]. The second recording time, 5:00 P.M., was selected to see the behaviors under full loading conditions.

Actually, the monitoring turned out to be quite successful as long as this investigation of failure trend is concerned: the data were good enough to show and connect the events with actual faults.

2) Feeder Fault Log: Tables I and II report the fault occurrences for the July and August 1996 and December 1996–February 1997 periods, respectively. These logs are drawn from SCADA-generated data with the following fault classification: a fault whose cause is known and involved with a device is classified as an "incipient fault," and all other faults as "unpredictable faults." For purposes of this investigation, the reported faults of the periods are numbered. The "Arrival Time" indicates the fault occurrence day counted from the start day of each monitoring period.

TABLE I
FAULT LOG OF JULY 1–AUGUST 4, 1996 PERIOD

No.	Fault Date	Arrival Time	Fault Class
F1	July 5, 1996	5	Incipient Fault
F2	July 18, 1996	18	Incipient Fault
F3	July 31, 1996	31	Incipient Fault
F4	August 2, 1996	33	Incipient Fault
F5	August 4, 1996	35	Incipient Fault

TABLE II
FAULT LOG OF DECEMBER 26,1996–FEBRUARY 22, 1997 PERIOD

No.	Fault Date	Arrival Time	Fault Class
F1	January 1, 1997	7	Unpredictable Fault
F2	January 9, 1997	15	Unpredictable Fault
F3	January 27, 1997	33	Unpredictable Fault
F4	February 10, 1997	47	Incipient Fault
F5	February 22, 1997	59	Incipient Fault

3) Parameter Extraction: The initial screening, after the processing of the acquired data in time and frequency domains and the elimination of the unchanging (or not responding to faults) parameters over the monitoring period, reduced the candidate parameters to four. The four candidate parameters were named as follows:

- AN—nonharmonic component of neutral current collected at 5:00 A.M.;
- AH—high-frequency (above 1 kHz) component of neutral current collected at 5:00 A.M.;
- PN—nonharmonic component of neutral current collected at 5:00 P.M.;
- PH—high-frequency (above 1 kHz) component of neutral current collected at 5:00 P.M..

Because of data acquisition problems, the "AH" and "PH" parameters were not collected for the first several days of the first observation period and for the last 30 days of the second period.

4) Event Log: The "event" of the parameters is specified as follows. A symptom parameter is believed to show a relatively high degree of random variation in magnitude when a failure process is accelerated, therefore, the degree of magnitude variation over a period of time could be used to indicate feeder activity or condition. In this context, the index of variation in magnitude over a daily average determines if there were an "event" or not: an "event" occurred if the index were above a certain threshold, and "no event," if below the threshold.

The event logs, shown in Tables III and IV, report the "event" occurrence dates (in terms of arrival times from the start of each monitoring period) for each parameter for each monitoring period. The last rows of the tables combine the fault logs of Tables I and II by the fault class: "IF" for incipient fault and "UF" for unpredictable fault.

TABLE III
EVENT LOG OF JULY 1–AUGUST 4, 1996 PERIOD

		EVENT/FAULT Arrival Times
Events	AN	1, 5, 9, 11, 13, 14, 17, 20, 25, 26, 30
	AH	14, 15, 17, 20, 25, 26, 30, 31, 32, 35
	PN	2, 6, 8, 15, 17, 19, 20, 21, 23, 24, 25
	PH	22, 24, 30, 31, 33, 34, 35
Faults	IF	5(F1), 18(F2), 31(F3), 33(F4), 35(F5)
	UF	NONE

TABLE IV
EVENT LOG OF DECEMBER 26,1996–FEBRUARY 22, 1997 PERIOD

		EVENT/FAULT Arrival Times
Events	AN	2, 6, 11, 13, 15, 19, 27, 31, 37, 40, 41, 42, 45, 47, 51, 56, 59
	AH	4, 5, 6, 11, 13, 15, 19, 21, 27
	PN	1, 2, 3, 4, 7, 11, 13, 14, 20, 21, 27, 30, 31, 43, 44, 55, 56
	PH	22, 24, 30, 31, 33, 34, 35
Faults	IF	47(F9), 59(F10)
	UF	7(F6), 15(F7), 33(F8)

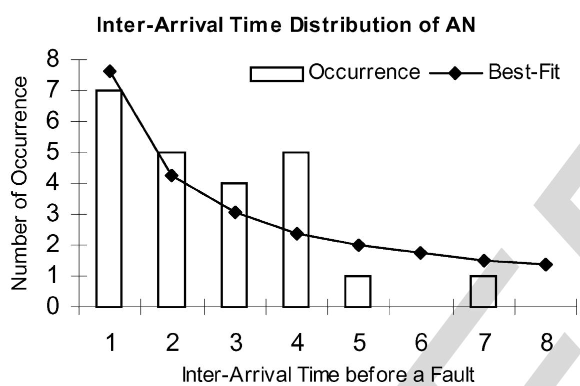

Fig. 4. Inter-arrival distribution and nonlinear fit for AN parameter.

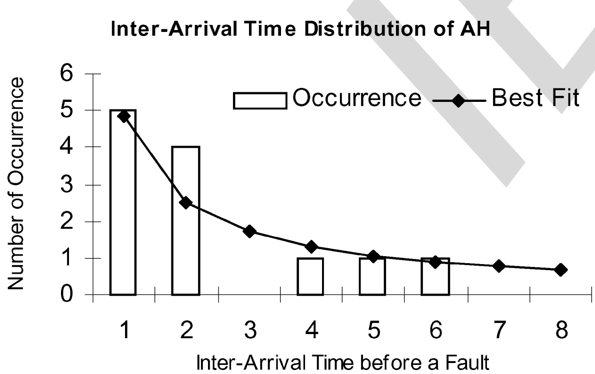

Fig. 5. Inter-arrival distribution and nonlinear fit for AH parameter.

B. Weibull Hazard Function Application

To apply the Weibull hazard function application to the event log, we first convert the "events" to the "inter-arrival events," i.e., average time between two events before a fault. The result is a distribution (or histogram) of the number of occurrences of the inter-arrival times. The x axis divides the inter-arrival times into 1-day bins, while the y axis shows the number of occurrences. Figs. 4 and 5 display the histograms for AN and AH parameters, respectively.

Then, a nonlinear parametric fit is applied to find the shape and scale for the distribution. In Fig. 4, along with the histogram, the best-fit Weibull hazard function is plotted which approximates $b = 0.17$ and the chi-square goodness-of-fit $\chi^2 = 2.42$. The shape with 0.17 shows the negative trend of the distribution and, further, the χ^2 of 2.42 is far away from 0.05 to give enough confidence of the fitting.

Similarly, AH's best fit curve in Fig. 5, with $b = 0.04$ and $\chi^2 = 1.04$, does not give enough confidence to believe the shape and the hazard function are right for the "fitted" hazard function.

Conclusively, particularly when samples are small, the Weibull hazard function is not appropriate for the trend analysis of events for parameter evaluation.

C. Application of Laplace Test Statistic

In the application of the Laplace test statistic, we analyze the event log, along with the fault log, in two different perspectives. The first one is to analyze the event log in a way that each fault recorded is an independent fault, i.e., a fault is caused by a specific cause and, thus, it can be cleared by removing the cause. In this perspective, once the fault-causing device is replaced by a healthy one, the distribution feeder is supposed to return to normal status. We call this a "single-cause repairable system." Under the single-cause repairable system approach, we focus only on the events reported before a fault, and, thus, the analysis of the trend of the events tells only of that specific fault. Similarly, any events reported before a fault should not be included in the trend analysis of the events for another fault.

The other point of view is to consider faults as being not independent: faults are caused by multiple causes from numerous pieces of distribution equipment that are undergoing failure processes. The events then contain more than one cause. In this second view, even after a fault is reported and a faulty device is replaced or corrected, the distribution system is not clear of the failure processes of other devices. We call this a "multicause repairable system." In the multicause repairable approach, all the events before any fault are included in the trend analysis of the fault. Therefore, the trend analysis for the first fault in the monitoring period includes only the events before the fault; however, that for the last fault includes all the events of the period.

1) Single-Cause Repairable System Approach: In this approach, only the events occurring before a fault are used for a trend analysis for the fault. This approach generates a Laplace test statistic for each fault of the periods. However, since the faults F3, F4, and F5 are adjacent, and, moreover, since F4 and F5 do not have enough event recordings, F4 and F5 are not included in the analysis of the Laplace test statistic. The unpredictable faults (F6, F7, and F8) also are omitted from this analysis. In addition, not all parameters are analyzed for the test statistic since some parameters could not be extracted for a certain segment of the monitoring periods. Prominently, high-frequency parameters (AH and PH) were not sampled, particularly, before the faults F9 and F10.

The following illustrates in detail the derivation of the Laplace test statistics. First, for each fault, we derive the number of events (m), the time interval between the first event and the last event before a fault (t_f), and the arrival time of each event ($T_i, i = 1, 2, \ldots, m$), for each parameter. Then, applying

TABLE V
ELEMENTS FOR LAPLACE TEST STATISTICS CALCULATION FOR THE FAULTS OF THE FIRST PERIOD

Faults/Statistics		AN	AH	PN	PH
F1 (at 3)	m	1		1	
	t_f	3		3	
	T_i	1		2	
	U_l	-0.577		-0.577	
F2 (at 15 after F1)	m	6	3	5	
	t_f	15	15	15	
	T_i	2,6,8,9,11,14	11, 12, 14	3, 4, 12, 13, 14	
	U_l	0.566	1.933	0.981	
F3 (at 13 after F2)	m	6	5	6	4
	t_f	13	13	13	13
	T_i	2, 3, 4, 7, 8, 12	2, 7, 8, 12, 13	1, 2, 3, 5, 6, 7	4, 6, 12, 13
	U_l	-0.326	1.132	-1.632	1.199

TABLE VI
LAPLACE TEST STATISTICS FOR THE INCIPIENT FAULTS

First Period						
Faults	F1 (at 3)		F2 (at 15 after F1)		F3 (at 13 after F2)	
Statistics	U_l	U_{Al}	U_l	U_{Al}	U_l	U_{Al}
AN	-0.577		0.566	1.149	-0.326	-0.523
AH			1.933	1.561	-1.132	2.165
PN	-0.577		0.981	1.834	-1.632	-2.758
PH					1.199	2.371

Second Period				
Faults	F9 (at 14)		F10 (at 12 after F9)	
Statistics	U_l	U_{Al}	U_l	U_{Al}
AN	-0.577		-0.326	-0.523
AH			-1.132	2.165
PN	-0.577		-1.632	-2.758
PH			1.199	2.371

the statistic equation, we find the U_L for each parameter for the faults. The elements for the three faults of the first period are displayed along with the Laplace test statistics in Table V.

A similar process for F9 and F10 produces the Laplace statistics for the faults of the second period. Finally, we have the Laplace statistics for five incipient faults as shown in Table VI. Since the number of events is comparatively small, the adjusted statistics (U_{AL}) are also calculated.

The Laplace statistic table reveals that there is no single parameter that has a higher statistic value (U_L) than the cutoff line for a positive trend (i.e., 1.96) for any of the five incipient faults. In other words, there is no parameter positively related to the faults. The adjusted statistic (U_{AL}), however, picks the AH as one of the better symptom parameters. This poor result, caused partly by the small event size, leads to the second approach.

2) Multicause Repairable System in Expanded-Window Approach: A typical distribution feeder has hundreds of pieces of equipment. Since they have been in service for varying periods of time, they are in various states of health or integrity. At any one point in time, dozens or scores of them are at some stage of incipient failure and one or a few of them reach the point of flashover and fault. However, soon after, others will reach the point of failure in due course. Therefore, even after the source of a particular fault is located and repaired, the measurable characteristic (the "event") may persist in the system.

TABLE VII
LAPLACE TEST STATISTICS FOR THE INCIPIENT FAULTS UNDER MULTICAUSE REPARABLE SYSTEM APPROACH.

Period	First Period					Second Period	
Faults	F1	F2	F3	F4	F5	F9	F10
AN	1.732	0.809	0.608			0.926	0.577
AH		2.412	2.133	2.382	2.191		
PN	1.732	1.081	1.840			-1.190	-1.410
PH			2.514	2.699	3.236		

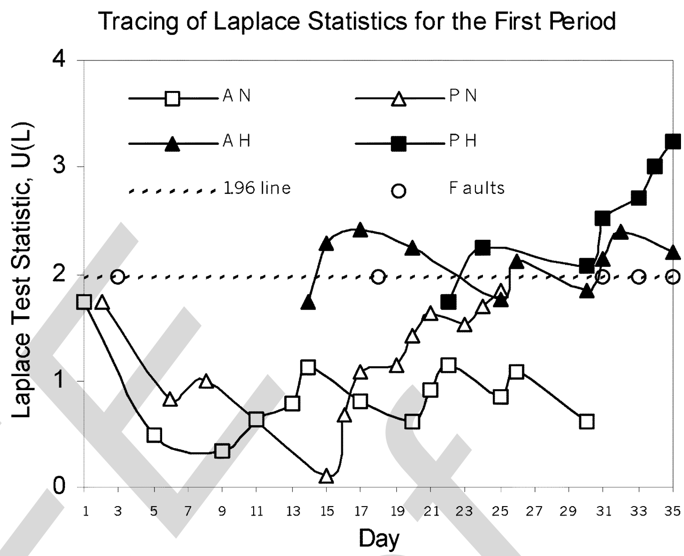

Fig. 6. Tracings of the Laplace statistics for the first period.

Hence, an event occurring just before a fault may be a precursor of a fault that will come much later. The multicause repairable system approach for a fault, therefore, includes all the events occurring before the fault. The investigation of the approach leads to the following recalculation of the statistics.

Under this scheme, the faults F4 and F4 can be included. However, in the second monitoring period, parameters AH and PH are not considered, mainly by the lack of event points. Since there are enough numbers of events for most faults, the adjusted statistics are not calculated. Table VII summarizes the test statistics under the multicause reparable system approach.

The parameters with higher Laplace statistics than the 1.96 cutoff line finally emerge from the multicause approach: they are AH and PH. The other two parameters, which report more events during the monitoring periods, show no positive trend with the incipient faults.

In addition to the parameter identification by the "offline" approach using the event log of a period, we try to expand the scheme of the multicause reparable system approach to a daily reporting of the statistic as an index for online feeder health conditions. In this scenario, unlike in the regular multicause approach where statistics are calculated only when faults are reported, they are calculated at each event, using all the previous events reported. The statistics generated from this online scheme could be used to alert the crew to an imminent fault.

Fig. 6 shows the tracing of the Laplace statistics of the parameters for the first period. All five faults are also indicated on the 1.96 cutoff line. The statistic traces of parameters AH and PH show that they climb up above the 1.96 line a few days before the actual faults.

This expansion further illustrates that the approach of using the Laplace test statistics, in addition to being a great potential as a symptom parameter identifier for incipient fault detection, could be used as an anticipator for feeder status and imminent faults.

V. Conclusion

A Laplace trend analysis was applied to isolate parameters for incipient faults in a distribution system. Four parameters of actual event logs of two separate monitoring periods, along with SCADA-generated fault log, were examined using the Laplace test statistic. The investigation reported the effectiveness of the statistic as a symptom parameter identifier for incipient fault detection, and illustrated that the approach of the Laplace test statistics could be used as an online anticipator for feeder status and imminent faults. The methodology proposed in the paper without any modification can be applied to many other failure-physics-related area such as material failure prediction, lifetime prediction, failure anticipation of computing devices, and other mission-critical applications.

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