SimSPRT-II: Monte Carlo Simulation of Sequential Probability Ratio Test Algorithms for Optimal Prognostic Performance

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***Abstract*— New prognostic AI innovations are being developed, optimized, and productized for enhancing the reliability, availability, and serviceability of enterprise servers and data centers, known as Electronic Prognostics (EP). EP prognostic innovations are now being spun off for prognostic cyber-security applications, and for Internet-of-Things (IoT) prognostic applications in the industrial sectors of manufacturing, transportation, and utilities. For these applications, the function of prognostic anomaly detection is achieved by predicting what each monitored signal "should be" via highly accurate empirical nonlinear nonparametric (NLNP) regression algorithms, and then differencing the optimal signal estimates from the real measured signals to produce "residuals". The residuals are then monitored with a Sequential Probability Ratio Test (SPRT). The advantage of the SPRT, when tuned properly, is that it provides the earliest mathematically possible annunciation of anomalies growing into time series signals for a wide range of complex engineering applications. SimSPRT-II is a comprehensive parametric monte-carlo simulation framework for tuning, optimization, and performance evaluation of SPRT algorithms for any types of digitized time-series signals. SimSPRT-II enables users to systematically optimize SPRT performance as a multivariate function of Type-I and Type-II errors, Variance, Sampling Density, and System Disturbance Magnitude, and then quickly evaluate what we believe to be the most important overall prognostic performance metrics for real-time applications: Empirical False and Missed-alarm Probabilities (FAPs and MAPs), SPRT Tripping Frequency as a function of anomaly severity, and Overhead Compute Cost as a function of sampling density. SimSPRT-II has become a vital tool for tuning, optimization, and formal validation of SPRT based AI algorithms for applications in a broad range of engineering and security prognostic applications.

Keywords—prognostic cyber security, internet-of-things real time prognostic AI

I. INTRODUCTION

A random stochastic process whose statistical moments are independent of time is said to be *stationary*. Some signals in computing systems and in mechanical and electromechanical industrial assets are always stationary (at least during undegraded operation). The majority of time series signals in executing enterprise computing assets and associated networks, as well as in machines, motors, pumps, propulsion systems, and other assets used in transportation, manufacturing, and utilities can be very dynamic during routine operation. For dynamic time series signals, AI-based advanced pattern recognition techniques learn the patterns of correlation between/among correlated signals and produce stationary time series signals, called residuals, that are monitored with "anomaly detection" algorithms for detection of anomalies in the servers, networks, or engineering assets. For both cases (univariate signals that are nominally stationary throughout operation, and dynamic signals that are analyzed by AI pattern recognition to produce stationary residuals), the degree of stationarity, as well as the statistical distributions for the signals, may be influenced by a change in operating conditions of the monitored assets (environmental or workload).

Because nonstationary considerations caused by these environmental or workload changes complicate the problem of monitoring time-series signals for anomaly detection, this paper will first summarize an approach for an idealized case: monitoring strictly stationary Gaussian process signals. The approach employs a sequential detection technique that has proven popular in many practical engineering applications in which the time-to-detection must be minimized while guaranteeing a prespecified rate of false and missed alarms. The approach is sequential in that a decision is made following a sequence of observations; the number of observations needed to reach a decision varies according to the learned statistical quality of the signal. We then show how the detection technique is made robust to deviations in stationarity as well as distribution moments for the monitored signals, and provide a comprehensive methodology for evaluation, tuning, optimization, and validation of advanced AI pattern recognition systems that combine empirical nonlinear modeling to produce residuals, with SPRT-based "detectors" that then monitor the residuals in real time for sensitive detection of the incipience or onset of subtle anomalies in noisy process variables, whether the original measured signals are stationary or contain dynamic components.

I.1 Sequential Probability Ratio Test (SPRT)

The Sequential Probability Ratio Test (SPRT) developed by Wald [Refs 1-3] provides the basis for detecting subtle statistical changes in a stationary noisy sequence of observations at the earliest possible time. For purposes of exposing the details of the SPRT, assume for now that the monitored process signal **Y** is normally distributed with mean zero and standard deviation σ (processes with nonzero mean μ can be transformed into a zero-mean process by subtracting μ from each observation). Process signal **Y** is said to be *degraded* if the observations made on **Y** appear to be distributed about mean M or with altered distribution moments (skewness, kurtosis), versus normal distribution moments centered at mean zero, where M is a predetermined *system anomaly/disturbance magnitude*. The SPRT provides a quantitative framework for deciding, with each new incoming observation (in realtime streaming mode) between two hypotheses related to this concept of signal degradation:

- H_0 : observations of **Y** are drawn from a normal distribution with mean zero and standard deviation σ.
- H_1 : observations of **Y** are drawn from a normal distribution with mean M and standard deviation σ.

The SPRT is a parametric test, meaning that the probability density function and associated parameters must be known prior to applying the SPRT. Wald's original SPRT was derived for normally distributed observations of process signal Y. One can derive expressions for other distributions (e.g., exponential, Poisson, binomial) as well. In practical IoT prognostic AI applications, however, it may be difficult to assume that:

1. The distribution of a process signal is known in advance.
2. The distribution of a process signal does not change over time.
3. The parameters of the distribution do not change over time.

Nonparametric sequential detection tests do exist, but the mathematics behind them are considerably more complex than for the parametric Gaussian SPRT. Even if the *a priori* distribution is known, the third assumption is often violated in practical industrial IoT systems. A nominally stationary Gaussian random process may enter a new operating regime (characterized by a different mean value or different 2nd and 3rd moments) upon influence from stimuli. In computing systems, for example, a sudden workload change may cause a monitored voltage or current signal to have an upward or downward step change in its nominal value. In this case a simple Gaussian SPRT would flag such a step change as a degraded signal, since the observations no longer appear to be drawn from a distribution conforming to the original H_0 hypothesis.

A better solution than going to nonparametric SPRTs is to combine the SPRT with a good nonparametric AI prognostic machine learning (ML) algorithm that effectively learns and then "filters" the dynamics that are inherent in the monitored systems or processes. In this paper we present a novel extension of Oracle's proven EP prognostic innovations into the realm of prognostic cyber security [Refs 4,5] and IoT streaming prognostics [Refs 6,7] through a combination of an excellent ML algorithm integrated with a simple parametric SPRT (and hence low compute cost for real time streaming applications), that yields the same prognostic ROI as the traditional Wald SPRT (low FAP/MAP, fastest anomaly detection), with good robustness to non-Gaussian artifacts, and without having to go to (complex and costly) nonparametric SPRT implementations.

I.2 Nonparametric ML Monitoring of Correlated Random Processes

Instead of attempting to adjust the SPRT's H_0 and H_1 distribution parameters to compensate for statistical changes in the process signal, one can employ a similarity-based modeling (SBM) approach [Ref 8] that exploits learned correlations among subsets of system signals. The SBM approach described in this section estimates the operational state of the system (i.e., the value that each signal is expected to take at time t) and compares the estimated operational state with the actual operating state (i.e., the actual values of the signals observed at time t). It is then determined if the difference between the estimated and actual states is due to normal statistical fluctuations in the signals, or if the difference is due to a bona fide disturbance or anomaly in one or more of the time series under surveillance. Such an approach, embodied in the Multivariate State Estimation Technique (MSET) [Refs 9,10] or similar nonlinear nonparametric pattern recognition algorithms, has been used effectively for monitoring instrumentation in safety-critical Nasa and military applications [Refs 10-15], and by Oracle for monitoring the health of business critical IT assets in data centers [Refs 16-19]. For enterprise computing prognostic applications, MSET has also been applied to proactive identification of complex resource-contention issues in large data base applications [16] and memory leaks in software systems [20]. MSET and other nonlinear nonparametric techniques are now being combined with SPRT "detector" algorithms for Internet-of-Things (IoT) prognostics in the manufacturing, transportation, and utilities industrial sectors [Refs 6,7,21].

II. 2-Dimensional Analyses with SimSPRT-II

The SPRT is an outstanding "detector" algorithm when combined with prognostic AI algorithms for rapid annunciation of the incipience or onset of anomalous patterns in digitized time series signals under surveillance. The SPRT is optimal in the sense that it gives the fastest mathematically possible annunciation of subtle disturbances in noisy process variables, and allows the AI experts setting up prognostics algorithms to independently specify the false- and missed-alarm probabilities (FAPs and MAPs). This is in sharp contrast to conventional prognostic algorithms that are based upon threshold-limit tests.

Many industrial processes have embedded diagnostic systems and online statistical process control techniques that perform real-time analysis of process variables with sophisticated pattern recognition, but then employ threshold-based tests (e.g. mean value + three-sigma, SPC control-chart thresholds, etc.) that are sensitive only to gross changes in the process mean, or to high step changes or spikes that exceed some threshold-limit test to determine whether or not a failure has occurred or a process is drifting out of control. These conventional methods suffer from either large false-alarm rates (if thresholds are set too close) or high missed (or delayed) alarm rates (if the thresholds are set too wide).

For typical IoT industrial surveillance applications, false alarms are very costly in terms of plant or physical-asset down time. Missed alarms can be even more costly when incipient problems are not identified and expensive assets fail catastrophically.

Coupling the AI pattern recognition method with a SPRT provides a superior surveillance tool because it is sensitive not only to disturbances in signal mean, but also to very subtle changes in the statistical moments of the monitored signals and the patterns of correlation between/among multiple types of signals. MSET or similar NLNP pattern recognition coupled with a SPRT provides the basis for detecting very subtle statistical anomalies in noisy process signals at the earliest mathematically possible time, thereby providing actionable warning-alert information on the type and the exact time of onset of the disturbance. Instead of simple threshold limits that trigger faults when a signal increases beyond some threshold value, the SPRT technique is based on user-specified false-alarm and missed-alarm probabilities, allowing the end user to control the likelihood of missed detection or false alarms. For sudden, gross failures of sensors or system components the SPRT annunciates the disturbance as fast as a conventional threshold limit check. However, for slow degradation that evolves over a long time period (gradual decalibration bias in a sensor; very subtle voltage drift from the variety of aging mechanisms that cause resistances to change very slowly with age; bearing degradation, lubrication dryout, or buildup of a radial rub in all types of rotating machinery; the gradual appearance of new vibration spectral components in the presence of noisy background signals, etc), the SPRT raises a warning of the incipience or onset of the disturbance long before it would be apparent to any conventional threshold based rules.

In spite of the outstanding features and performance of a SPRT based "detector" algorithm, there is still a great deal of latitude in adjustment and optimization of SPRT input parameters (alpha, beta, and M), and in "adjustment" of empirical signal attributes μ and V, all of which affect overall SPRT prognostic performance, and often in non-intuitive ways. It is important to note at this point what is meant by "adjustment" of empirical attributes μ and V for the signals under surveillance. Recall that for AI anomaly-detection prognostics, the signals being processed by SPRT detector algorithms are "residuals" computed by differencing the predicted signals from the corresponding measured signals. The parameter μ refers to the bias in the residuals, and V to the variance of the residuals. When μ and V are computed with the fastest-sampling rate raw signals from the transducers, it is often the case that μ and V computed with these high-frequency raw digitized observations result in sub-optimal SPRT performance (in terms of empirical alpha, empirical beta, and/or "time-to-detection", meaning the lead time to detect that degradation is starting to occur). When this is the case, it is very easy to improve μ and/or V. Improvement to the bias μ is achieved through enhancement of the AI prognostic algorithm (albeit with an increased compute cost) so that the predictions reflect the patterns in the measurements with higher fidelity, while V can be diminished by simple filtering (moving ensemble averages, or more sophisticated moving filters when warranted).

SimSPRT-II is designed to make systematic adjustments of the five input parameters affecting SPRT performance straightforward and in fact allows very rapid optimization of the SPRT algorithm in terms of achieving fastest decision time while still meeting prognostic functional requirements (PFRs) on FAP and MAP.

To illustrate we begin in Fig. 1 with a typical analysis with a time series signal that is reasonably Gaussian and white (top subplot). The SPRT in this case is set up with an alpha and beta of 5%. This alpha and beta are much larger than we use for production implementations of AI prognostics, and are set this high just to illustrate "false" alerts in the SPRT output results (2^{nd} and 3^{rd} subplots).

There is no degradation in the data monitored by the SPRT in Fig. 1. The SPRT alerts are normal and expected from the Wald theorem. Only when the frequency of SPRT alerts exceeds the prespecified value of alpha will a real Alarm be triggered. For normal Gaussian processes, The SPRT cumulative tripping frequency, which we call empirical alpha, will always be conservatively lower than alpha. In the example in Fig. 1 empirical alpha is 0.013, which is well below the design alpha of .05, as expected for Gaussian normal processes.

The challenge that arises for many types of industrial AI surveillance applications is that the monitored processes can be contaminated by non-Gaussian artifacts (including bias, skewness, kurtosis, or the presence of serial correlation). When this happens, unless one adjusts the SPRT parameters, a naively tuned SPRT algorithm can give empirical alphas that are greater than the specified alpha. Such a case is illustrated in Fig. 2, where the monitored data contains a small bias of 0.65 in the units of the monitored signal. Note the increasing frequency of SPRT alerts in the 2^{nd} subplot. This SPRT is set up with an alpha of 1%, but we see in the bottom subplot that the empirical alpha is higher than alpha (the cumulative tripping frequency is .0136. This is undesirable because when empirical alpha exceeds alpha, false SPRT alarms are issued.

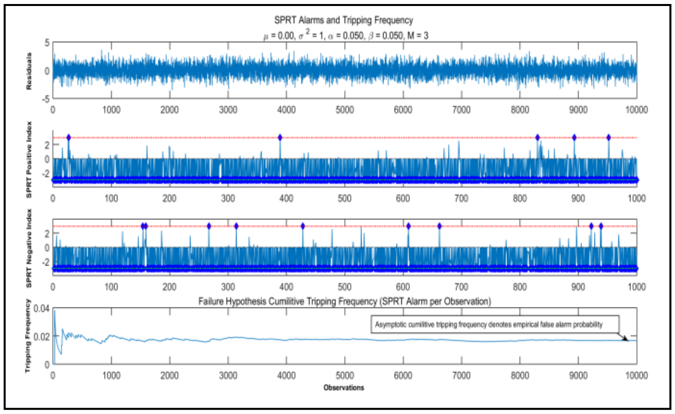


Fig. 1 Example SPRT Behavior for Fault-Free Signals

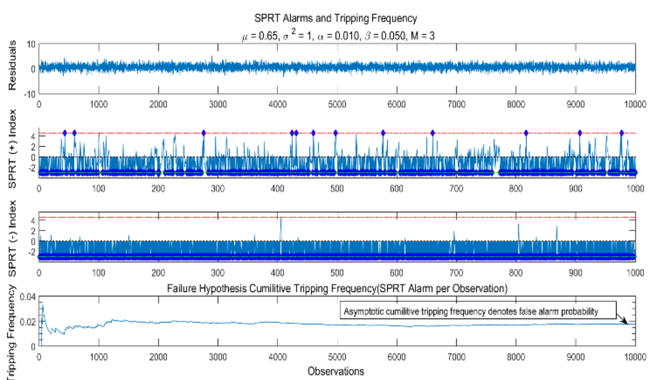


Fig 2. Example SPRT Behavior for Fault Free Data with Non-Gaussian Artifacts (Elevated Empirical Alpha)

SimSPRT-II allows systematic tuning and optimization of SPRT input parameters so that for any signal characteristics possessing a reasonable degree of non-normality and/or non-whiteness, SimSPRT-II enables the data scientist to be assured that empirical alpha will always be lower than the pre-specified alpha. Moreover, when empirical alpha is lower than alpha, SimSPRT-II will (for the first time, known to the authors) additionally identify parameters that lower the "decision time" to the smallest attainable. This is through minimization of a parameter we call the Average Sample Number (ASN), which is the average number of observations processed before the SPRT reaches a "fault" hypothesis alert when anomalous data are present. SPRT Detector algorithms optimized in pre-deployment analysis with SimSPRT-II provide the dual prognostic benefit of assuring minimal false-alarm probabilities while making a decision with the lowest achievable ASN, even for signals contaminated with nonGaussian artifacts, as we demonstrate with parametric 3D results from SimSPRT-II computations in the following section.

III. 3D Parametric Monte Carlo Simulation Results

SimSPRT-II leverages monte carlo simulation [Refs 21-23] and performs parametric multi-parameter simulations for any signal characteristics by permuting the adjustable SPRT parameters (alpha, beta, M, and μ) in a nested-loop structure to compute the asymptotic SPRT tripping frequency (i.e. the empirical alpha) and the "time to detection" through the Average Sample Number (ASN), and then allows the AI data scientist to view empirical alpha and ASN using 3D response surface methodology as bivariate pair-wise combinations of the five SPRT tuning parameters.

Fig. 3 illustrates, for example, the very large range of ASNs that result from allowable combinations of μ and M. It can be readily observed in Fig. 3 that one can get drastically different SPRT performance, in terms of "time-to-detection" for anomalies, depending upon the spatial region in the {μ,M} plane.

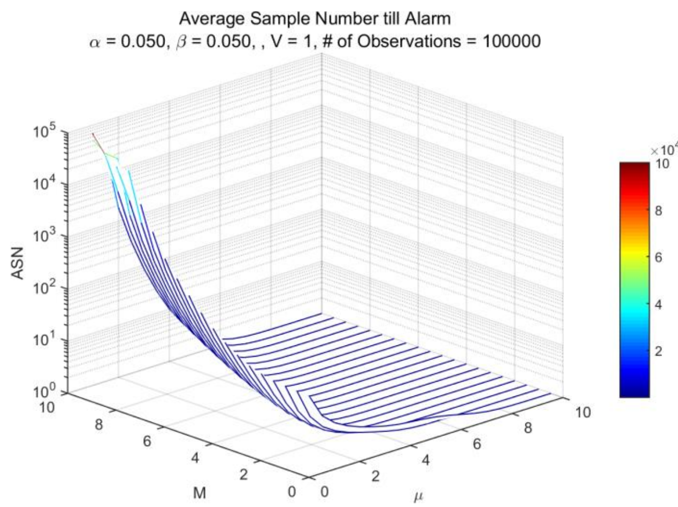


Fig 3. Avg Sample Number (ASN) as Function of M and μ

Moreover, for any given values of μ and M, both ASN and Empirical Alpha also vary with the input values of alpha and beta. This is illustrated for ASN in Fig. 4, showing how the "time-to-detection" metric varies significantly with pair-wise combinations of {alpha,beta}. Although it is desirable to minimize ASN to assure very rapid annunciation of the incipience of disturbances, it must be kept in mind that it is equally important (or for some use case more important) to assure that Empirical Alpha stays below the design value of alpha. SimSPRT-II has been designed with a new AI combinatorial optimization procedure to achieve both of these goals simultaneously.

Fig. 5 shows how the Empirical Alpha varies with combinations of {alpha,V}. Examining constant-alpha contours on this surface reveals that for this application, Empirical Alpha never exceeds alpha. For use cases such as this, AI-optimization algorithms are not necessary because one can just pick values of the SPRT design parameters that result in a low ASN (Fig.

4), and the application will simultaneously achieve low false alarm rates when there is no degradation present, and extremely rapid detection of subtle faults when degradation starts to appear. This capability is mathematically intractable with conventional threshold-based prognostic "detectors".

Fig. 4. ASN vs Alpha and Beta

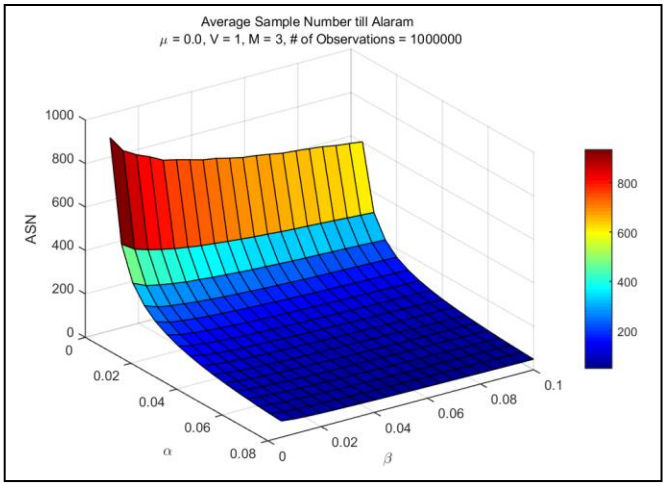


Fig. 6 shows Empirical Alpha as a function of {V,M} permutations. As was the case for Fig. 5, we see that for signals that are substantially Gaussian and white, per Wald's proof, empirical alpha is again always smaller than pre-specified alpha, as expected. However, for signal characteristics that possess some degree of non-normality, Fig. 7 demonstrates the danger of arbitrarily selecting alpha, beta, and M values when setting up a SPRT Detection algorithm. Note that for the red region in Fig. 7 at the top of the 3D surface, Empirical Alpha is greater than design alpha. Combinations of M and V in that region will yield prognostic Detector algorithms that do not meet prognostic functional requirements and will have excessive false alarms.

FIG. 5. EMPIRICAL ALPHA VS ALPHA AND V

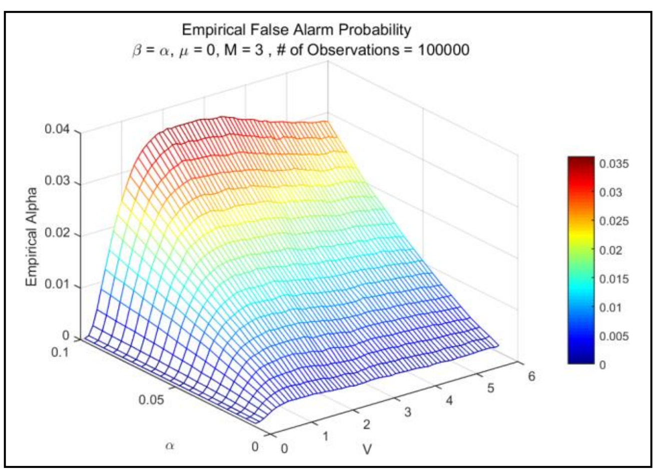
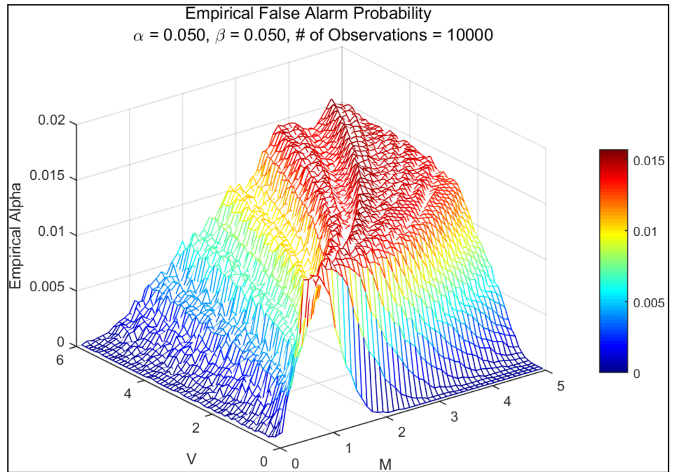


FIG. 6. GAUSSIAN SIGNALS: EMPIRICAL ALPHA VS V AND M



To avoid this undesirable outcome we have integrated SimSPRT-II with an automated AI algorithm that simultaneously assures that Empirical Alpha will always be lower than alpha, while the ASN (and hence the "Time-to-Detection" for subtle anomalies) will be minimal, even for IoT signals that may be contaminated with nonGaussian artifacts. Moreover, the new (proprietary) technique embodied in SimSPRT-II does this optimization with a minimal number of computations of ASN before the algorithm converges to a global minimum in the {M,V} space.

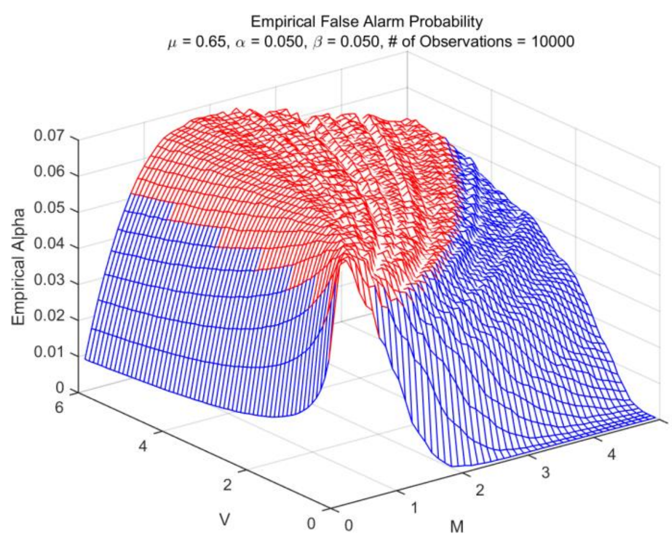


Fig 7. NonGaussian Signals: Empirical Alpha can Exceed Pre-Specified Alpha (Red Region), Creating Excessive False Alarms from Prognostic Algorithms

A brute force approach to identifying the lowest ASN in the acceptable blue region in Fig. 8 would be to just compute the ASN for all possible {M,V} pairs and select the pair achieving the lowest ASN. However, this could get quite compute costly. Instead, AI-approach for simultaneously optimizing Empirical False Alarm Probably and Time-to-Detection in SimSPRT-II is able to very rapidly achieve an optimal solution…usually with less than 15 evaluations of ASN during the optimization, as opposed to thousands of evaluations of ASN by the "brute force" approach.

CONCLUSIONS

SimSPRT-II is a comprehensive parametric monte-carlo simulation framework for tuning, optimization, and performance evaluation of SPRT algorithms for any types of digitized time-series signals. SimSPRT-II enables users to systematically optimize SPRT performance as a multivariate function of Type-I error, Type-II error, Variance, Sample Density, and Sample Histogram, and then to quickly evaluate the important performance metrics for prognostic solutions: False and Missed-alarm Probabilities (FAPs and MAPs), SPRT Tripping Frequency as a function of anomaly severity, and Overhead Compute Cost as a function of sampling density. SimSPRT-II has been architected with a novel multiparameter optimization technique that for the first time (known to the authors) allows advanced SPRT-based prognostics application to IoT and other time series that may be contaminated by nongaussian artifacts (without having to employ complex nonparametric SPRTs), and to simultaneously ensure that prognostic functional requirements (PFRs) are rigorously met for FAP, while attaining the lowest possible ASN (and hence fastest decision time for new anomalies appearing in noisy process variables). SimSPRT-II has become a vital adjunct in Oracle's ongoing developments of prognostic cyber security and for dense-sensor IoT streaming prognostics.

REFERENCES

[1] A. Wald, *A Sequential Analysis*, New York: Wiley, 1947.

[2] K. C. Gross and K. K. Hoyer "SIMSPRT: A SAS Code for Simulation of Sequential Probability Ratio Tests,", ***Proc. 18th SAS Users Group Intnl. Conf.,*** pp 909-914, New York, NY (May 9-12, 1993).

[3] K. C. Gross and K. Mishra, "Improved Methods for Early Fault Detection in Enterprise Computing Servers Using SAS Tools," ***2004 SAS Users Group International*** *(SUGI 29)*, Montreal, Canada. (May 9 – 12, 2004).

[4] B. A. Jeffries, J. W, Hines, and K. C. Gross, "Intrusion Detection of a Simulated SCADA System using Data-Driven Modeling," 38th IEEE Symposium on Security and Privacy (SP2017), San Jose, CA, (May 22-24, 2017).

[5] Hines, J.W., Yang, D. and Usynin, A., "SCADA System Monitoring and Diagnostics Using Empirical Models", Final Report, Battelle Energy Contract # 00050837, September 2007.

[6] K. C. Gross, K. Vaidyanathan, A. Bougaev, and A. Urmanov, "Round-Robin Staggered-Imputation (RRSI) Algorithm for Enhanced Real-Time Prognostics for Dense-Sensor IoT Applications," ***International Conference on Internet Computing and Internet of Things (ICOMP'16)***, Las Vegas, NV (July 25-28, 2016).

[7] K. C. Gross, K. Vaidyanathan, and M. Valiollahzadeh, "Advanced Pattern Recognition for Optimal Bandwidth and Power Utilization for Intelligent Wireless Motes for IoT Applications," ***17th International Conference on Wireless Networks (ICWN'16)***, Las Vegas, NV (July 25-28, 2016).

[8] S. Wegerich, A. Wilks and R. Pipke, "Nonparametric modeling of vibration signal features for equipment health monitoring," *Proceedings of the IEEE Aerospace Conference,"* March 8-15, 2003.

[9] R. Singer, K. C. Gross, J. Herzog, R. King, S. Wegerich, "Model-based nuclear power plant monitoring and fault detection: Theoretical foundations," in *Proceedings from the Intelligent System Application to Power Systems Conference*, pp. 60-65, July 1997.

[10] K. C. Gross, R. M. Singer, S. W. Wegerich, J. P. Herzog, R. VanAlstine, and F. Bockhorst, "Application of a Model-based Fault Detection System to Nuclear Plant Signals," Proc. 9th Intnl. Conf. On Intelligent Systems Applications to Power Systems, pp. 66-70, Seoul, Korea (July 6-10, 1997).

[11] K. C. Gross, S. Wegerich, and R. M. Singer, "New Artificial Intelligence Technique Detects Instrument Faults Early," *Power Magazine*, vol. 42, no. 6, pp. 89-95, 1998.

[12] R. L. Bickford, et al., "MSET signal validation system for space shuttle main engine," Final Report, *NASA Contract NAS8-98027*, August 2000.

[13] "Prognostics of Electronic Components: Health Monitoring, Failure Prediction, Time To Failure," K. G. Gross, K. W. Whisnant and A. M. Urmanov, Proc. New Challenges in Aerospace Technology and Maintenance Conf. 2006, Suntec City, Singapore (Feb 2006).

[14] "Electronic Prognostics Techniques for Mission Critical Electronic Components and Subsystems," K. C. Gross, K. W. Whisnant and A. M. Urmanov, Proc. 2006 Components for Military and Space Electronics Symposium, Los Angeles, CA, (Feb 2006).

[15] "Proactive Detection of Software Aging Mechanisms in Performance-Critical Computers," K. C. Gross, V. Bhardwaj, and R. L. Bickford, Proc. 27th Annual IEEE/NASA Software Engineering Symposium, Greenbelt, MD (Dec 4-6, 2002).

[16] K. J. Cassidy, K. C. Gross, and A. Malekpour, "Advanced pattern recognition for detection of complex software aging phenomena in online transaction processing servers," in *Proc. Intnl. Performance and Dependability Symposium*, Washington, D.C., June 23 - 26, 2002.

[17] "Integration of Electronic Prognostics with Software Aging and Rejuvenation for Business-Critical Enterprise Servers," K. C. Gross, 4th IEEE Intn'l Workshop on Software Aging and Rejuvenation, Dallas, TX (Dec 2012).

[18] "Proactive Fault Monitoring in Enterprise Servers," K. Whisnant, K. C. Gross and N. Lingurovska, Proc. 2005 IEEE Intn'l Multiconference in Computer Science & Computer Eng., Las Vegas, NV (June 2005).

[19] "Failure Avoidance in Computer Systems," A. Urmanov and K. C. Gross, Proc. 59th Meeting of the Society for Machinery Failure Prevention Technology, Virginia Beach, VA (Apr 18-21, 2005).

[20] K. Vaidyanathan and K. C. Gross, "Proactive detection of software anomalies through MSET," *Proc. IEEE Workshop on Predictive Software Models (PSM-2004)*, Chicago, Sept 17-19, 2004.

[21] A. More and K. C. Gross, "SimML Framework: Monte Carlo Simulation of Statistical Machine Learning Algorithms for IoT Prognostic Applications," 2016 Intn'l Symposium on Internet of Things & Internet of Everything (CSCI-ISOT), Las Vegas, NV (Dec 15-17, 2016).

[22] "Monte Carlo Simulation of Telemetric Signals for Enhanced Proactive Fault Monitoring of Computer Servers," K. Vaidyanathan and K. C. Gross, ***Proc. 2005 Simulation Multiconference***, Philadelphia, PA (July 2005).

[23] "Monte Carlo Simulation for Optimized Sensitivity of Online Proactive Fault Monitoring Schemes," K. Vaidyanathan and K. C. Gross, ***Proc. 2005 Intn'l Conf. on Computer Design***, Las Vegas, NV (June 20).