ADVANCED PROGNOSTICS FOR FCS EQUIPMENT

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Problem – The Future Combat Systems (FCS) requirement 3.2.1.8.6.8 (page 68 of S786-52000, System of Systems Objective Capabilities Specification for FCS) calls for an accurate and timely "Future System State Forecast." Such prognostication requires continuous real-time assessment of mission-critical systems and equipment to avoid failures via prompt predictive maintenance. Typical failures include (but are not limited to) cracking, misalignment, imbalance, short-circuits, broken gears, bearing faults, dust clogging, and wear from wind-blown dirt and sand. Maintenance personnel cannot track the huge volume of continuous, real-time data from hundreds of platforms in the Unit of Action, so the monitoring system must include a capability for (quasi)-autonomous real-time analysis and assessment of the data.

Prognostics Solution – The Oak Ridge National Laboratory (ORNL) has developed an advanced statistical methodology that forewarns of equipment failures from process indicative data, x_i. The analysis steps follow. (1) Check the data for quality. (2) Remove confounding artifacts (e.g., fundamental electrical sinusoid) by fitting a parabola in the least-squares sense over a moving window of length $2w+1$, with w data points on each side of the current central point, and taking the central point of the fit as the best estimate of the low-frequency artifact, f_i. The residue, $g_i = x_i - f_i$ is essentially artifact-free. Removal of a known low-frequency artifact uses a filter window width, $w = F_S/(4.4\ F_N)$, where F_S and F_N are the frequency values of the data sampling and the high-pass cutoff of the artifact, respectively. Removal of an unknown artifact involves a search over values of w to determine the best sensitivity for the measures of condition change, as described below. (3) Discretize the artifact-free signal, g_i, into one of S integer symbols, $0 \le s_i \le S$-1. (4) Create a d-dimensional vector, $y(i) = [s_i, s_{i+\lambda}, \ldots, s_{i+(d-1)\lambda}]$, using an appropriate time lag, λ. (5) Tabulate the occurrences of this vector in the discretized (binned) d-dimensional phase space to obtain an approximate distribution function (DF). The location and visitation frequency of the phase-space bins capture the essence of the equipment dynamics. In particular, (un)altered parameters/dynamics result in an (un)changed DF. (6) Repeat (5) for each contiguous, non-overlapping data segment to form DFs for the nominal (baseline) and sequel unknown (test) states, in which the bin populations are denoted by Q_i and R_i, respectively. (7) Compare the baseline and test DFs via phase-space dissimilarity measures (PSDM) defined as:

$$\chi^2 = \sum_i (Q_i - R_i)^2/(Q_i + R_i), \text{ and } L = \sum_i |Q_i - R_i|,$$

where the sums run over the populated cells of the phase space. (8) Define a set of renormalized dissimilarity measures (RDMs), as the number of standard deviations from the baseline average. This approach allows assessment of the power of the PSDM as detectors of condition change, in comparison with traditional nonlinear measures (TNM), such as correlation dimension, Lyapunov exponents, Kolmogorov entropy, or mutual information. This method allows a meaningful comparison of the TNM and PSDM in the face of the disparities in range and variability. Distant (nearby) states have large (small) RDM, which we interpret as forewarning of departure from (closeness to) nominal operation. (9) Indicate condition change (failure forewarning) after a specific number of sequential RDM occurrences above a certain threshold.

Results – For all the applications to date, PSDM provide consistently better discrimination of condition change than TNM. Indeed, while TNM distinguish fairly well between regular and chaotic dynamics, they cannot discriminate between *slightly different* chaotic regimes, especially for limited, noisy data. The reason for this enhanced performance is clear from the definitions: the PSDM compare the two quantities by first subtracting them locally and then summing these differences over the whole phase space; in TNM, the quantities are first averaged over the whole phase space and the averages are then compared. Applications to date (all successful) include: (a) imbalance and misalignment seeded-faults in a motor-driven pump; (b) seeded faults in electric motors (air-gap offset, broken rotor, turn-to-turn short, and imbalance); (c) progressively larger drill bit wear; (d) distinction between different states for (un)balanced centrifugal pump; (e) progressively larger seeded crack in a rotating blade; (f) motor-driven gear failure (accelerated test); (g) motor-driven bearing failure (accelerated test); and (h) structural failure by cracking. Timely forewarning for such diverse applications lends strong credibility to the robustness of this advanced prognostics paradigm.

Status – The method involves high-fidelity laboratory integration of the basic technological elements into software that analyzes archival data on a desktop computer for forewarning of failure in a simulated environment. The methodology handles limited, noisy, time-serial data (e.g., electrical power, current, voltage; mechanical vibration and torque; stress and strain) and provides the equipment health status in a “traffic-signal-inspired mode:” green for “go” (nominal operation), yellow “caution” (forewarning of failure), orange for “alert” (impending failure), and red for “stop” (must shutdown immediately to avoid imminent failure). The analysis is much faster than real-time, and can handle multiple data streams for prognostication at the component level. No special hardware is required, and the software adds no additional weight or bulk. ORNL has been granted six U.S. patents on the approach (with two additional patents pending). Consequently, the technology readiness level is 5 (TRL5).

Prototype – Ongoing development includes a graphical user interface for the operator, robust software for the prognostication analysis, and implementation on a hand-held device (e.g., personal digital assistant) for on-line analysis of real-time data. We expect to complete these improvements in 2004, which would allow qualification for TRL6. Developments needed for TRL7 (suitable for field testing) involve primarily: (i) extensive statistical validation for specific equipment fault(s) in an appropriate operational environment (measures of success include true-positive and true-negative rates, and the forewarning time distribution); and (ii) quasi-automatic determination of robust sets of parameters for analyst-independence.

Conclusion – Our innovative method combines several original advances to achieve sensitivity that is at least one order of magnitude larger than that of competing methods. This paper will present methodology details, results to date, status of the technology, a roadmap for technology deployment, and specific suggestions for near-term FCS prognostication applications.

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