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Diagnostics, Prognostics And Selection Methodologies For Uninterrupted Functionality Of K-Out-Of-N Systems

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***Abstract*—The present paper discusses techniques for k-out-of-n redundant systems based on condition assessment by diagnostics. Key is to assess the time development of the hazard rate, particularly for wear processes. This enables remaining useful life prognostics. Knowledge of acceleration due to stress enhancement enable prognostics for various scenarios. The paper discusses the framework of diagnostics and hazard rate, the associated predictability of failure as well as the impact of k-out-of-n redundancy. The paper concludes with a Markov analysis of a system with time varying transition rates.**

Keywords*—*Prognostics, k-out-of-n system, redundancy, hazard rate, diagnostics, Markov, time varying transition rate

I. Introduction

Strategic systems for power supply and drive control, preferably feature uninterrupted functionality. Redundancy is proven to increase the operational reliability and continuity (if minimum conditions are met). It can be implemented with multiple units to ensure the operation of at least one. E.g., a double cable circuit secures power supply in case of a cable fault provided each cable was rated for the full load. Redundancy offers a chance to repair a cable fault before also the second cable fails at which point the connection would fail.

So-called k-out-of-n (or k/n) systems form a redundancy category where an excess of n units aims to ensure that at least k units function. As an example, many cars are equipped with n=5 car tires to increase the availability of $k \geq 4$ for travel (albeit that even on-site tire change is interrupting).

The work reported here, is part of a research program that develops a framework and practices for optimizing the performance of systems under varying stresses. We consider failure of components that are critical for system functionality. In order to prevent failure, diagnostics are applied to substantiate functionality prognostics. This facilitates timely remedial interventions such as servicing and replacement of suspect components. Additionally, system redundancy allows to selectively reduce stress on components if the rest can take over to collectively provide continuous functionality.

We report on the conceptual work of component aging and diagnostics; system performance under component wear and under varying stress; and finally on Markov studies with time varying transitions rates followed by conclusions.

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II. Component Diagnostics

In our study, degradation processes are associated with hazard rates that can vary with ambient and load stresses (such as local temperature and generated heat) in addition to possible wear of the components. The component health or condition is monitored by diagnostics such as temperature sensing. Prognostics are used to signal need for intervention.

It may be noted that diagnostics cannot assess component health directly, but rather evaluates a side-effect. The relation between diagnostic output and true hazard rate must be substantiated by failure statistics and physical effects (Fig.1).

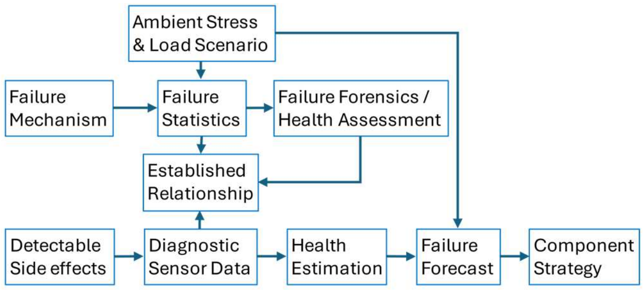

Fig. 1. Diagram for health estimation and component strategy based on a failure mechanism, ambient stress and load.

In this section, we study the relationships between component failure and diagnostics to predict (near) failure. Subsequently, we discuss the relevant statistical concepts of hazard rate, cumulative hazard and percentiles of failure times. Next, we study the effect of stress enhancements on aging and hazard rates. Lastly, we discuss diagnostics particularly for our case of thermal impact on component reliability and system performance.

A. Failure Statistics and Health

The establishment of a relationship between a diagnostic and a failure mechanism may be based on experiments, forensics and statistics in labs or operational experience. The health assessment follows from fitness to function and the hazard rate and/or Remaining Useful Life (RUL) until failure.

The starting point of our data analytics is Weibull statistics for failure data [1,2,3,4]. The Weibull cumulative function F (Fig. 2), hazard rate h, as functions of time t, with α and β the scale and shape parameter, in 2-parameter form are:

$$F(t) = 1 - R = 1 - e^{-(t/\alpha)^{\beta}} \quad (1)$$

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$$h(t) = \frac{\mathrm{d}F}{R\,\mathrm{d}t} = \frac{-\mathrm{d}R}{R\,\mathrm{d}t} = \frac{f}{R} = \frac{\beta}{\alpha^\beta} \cdot t^{\beta-1} \quad (2)$$

The cumulative hazard rate H on log-log scale yields the Weibull plot (cf. Fig. 3):

$$H(t) = \int_0^t h(x)\,\mathrm{d}x = -\ln\big(R(t)\big) = \left(\frac{t}{\alpha}\right)^\beta \quad (3)$$

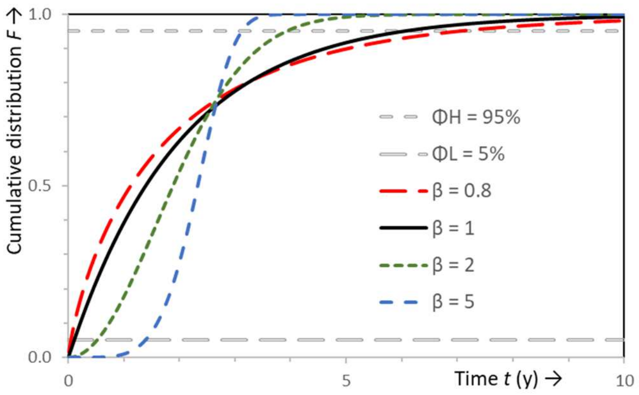

Fig. 2. Cumulative distribution functions F for various β values. For β>1, the function is S-shaped. All four cases have the same mean lifetime $\langle t \rangle$=2y.

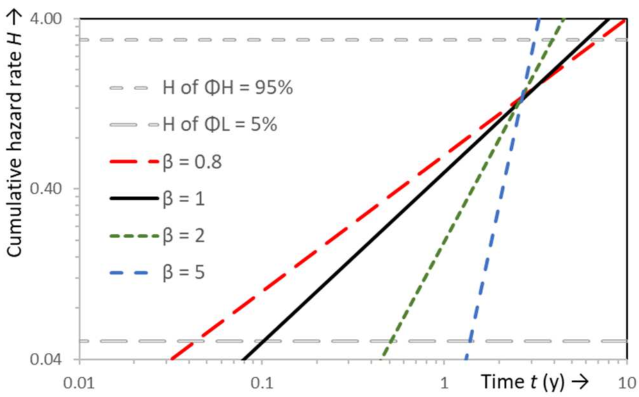

Fig. 3. The cumulative hazard functions $H(t)$ on log-log scale for the same β values as in Fig. 2. This is the well-known Weibull plot.

A confidence limit C_Φ is defined as the time at which a given failure probability Φ is reached. The difference between two confidence limits $C_{\Phi H}$ and $C_{\Phi L}$. is denoted the Φ_H - Φ_L confidence interval. A confidence limit C_Φ follows from (with F^{inv} the inverse of the cumulative function as in (1)):

$$C_\Phi = F^{inv}(\Phi) \quad (4)$$

As for the shape parameter: β<1 means a declining h as in child mortality, β =1 means a steady h as in random failure, and β>1 means an inclining h as in wear. The latter case, means that F is S-shaped (Fig. 2). Note, all cases in Fig. 2 have a $\langle RUL \rangle$=2y at t=0. The higher the β value, the narrower the Φ_H - Φ_L confidence intervals, i.e., the shorter the period in which the Φ_H - Φ_L fraction fails. In Fig.2, Φ_H - Φ_L=90% and 5% and 95% confidence limits intersect the curves. The impact of the β value on the widths of the intervals is evident. Similarly, Fig. 3 shows the intervals on log-scale.

The 3-parameter Weibull function adds a threshold parameter τ as starting point. One of the applications is when aging is triggered by an external event. The 3 parameter form is achieved if lifetime t is replaced by $(t$- $\tau)$ in (1), (2) & (3).

B. Dynamics in Degradation and Failure Processes

The component hazard rates can vary with load (generated heat) and ambient stress (local temperature). E.g., overheating may damage power electronics followed by failure or timely cool-down (while not all damage may be undone). Degradation may be triggered after a time t= τ and then raise the hazard rate. We discuss the dynamics of enhanced wear and random failure that may start from a trigger.

Fig. 4 shows a case of original random failure and two triggered processes: wear and random failure. Both have a zero h up to t=τ, after which (2) applies (replace t by t-τ). Triggered wear may due to another event (e.g., leak in cable jacket). Triggered random failure can be due to malfunction of a protection after which external random impact may cause failure that is unrelated to the component life time (so, random failure). The hazard rate jumps at t= τ to a constant h.

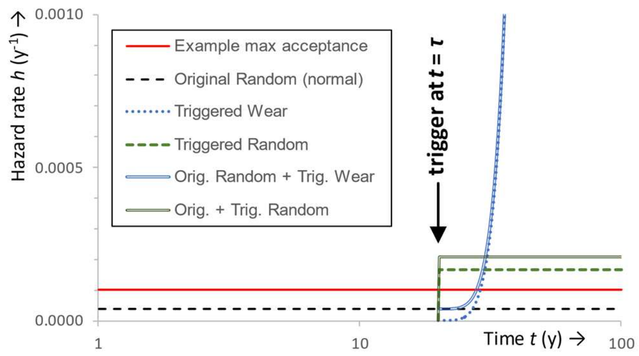

Fig. 4. Two example cases where triggered wear and triggered random failure add to the regular random failure. Both resulting hazard rates exceed the maximum acceptable hazard rate level here and intervention is needed.

If the aging process as such remains the same except for acceleration, then only its time scale changes. With a Weibull distribution α changes, but β stays the same. Conversely, this might be used to test the validity of an accelerated aging test. An Acceleration Factor AF relates the reference α_{ref} and the enhanced stress α_{enh} as $AF = \alpha_{ref} / \alpha_{enh}$. Lifetime passes faster at enhanced stresses. Clock periods Δt_i with associated AF_i can be converted into an equivalent $\Delta t_{eq,i}$ at reference stress. The resulting cumulative hazard rate H (3) can be expressed in terms of the reference stress and time t_{eq}=$\sum \Delta t_{eq,i}$. Then $H\big(t_{eq}\big)$ follows as:

$$H\big(t_{eq}\big) = \left(\frac{t_{eq}}{\alpha}\right)^\beta = \left(\frac{\sum_i \Delta t_i \cdot AF_i}{\alpha}\right)^\beta \quad (5)$$

This equation is valid for individual Weibull distributions provided β remains the same in all periods Δt_i.

C. Diagnostics

Components in II.A and II.B are indistinguishable batch items with statistics of (1)-(5). Whether an at random selected item belongs to the weaker or the stronger part of a batch, comes with the probability of (1). If diagnostics can successfully distinguish soon-failing items from the rest, the statistics change significantly. Components with a similar diagnostic outcome form a (sub)group with their own statistics. Conversely, a component with a given diagnostic can be regarded to represent the (sub)group and, although it is a single item, we still can assign a statistical function like a hazard rate to it (as randomly selected from that group).

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Condition assessment requires at least: a measurable side effect of the studied degradation, an adequate sensor system to measure the effect and, last but not least, intelligence to interpret the measurement output.

The intelligence may be built up by destructive testing or operational expertise until failure while keeping track of diagnostic output. However, it is noteworthy that hazard rates do not need to have a simple relationship with the amplitude of a sensor output. The interpretation of the diagnostic signals may concern characteristics such as phase shifts, the shape and multitude of peaks. Significant impact may also come from system impedance, a mix of sources or disturbing background noise, etc.. There may also be a critical level below which signals are not significant for diagnostics [5]. E.g., a clear wear phenomenon like electrical treeing along an insulator surface will have an increasing hazard rate, but may still produce a steady stream of partial discharge pulses [5].

We mainly focus on thermally accelerated aging in power electronics. Temperature is often a good indicator of the component health as both insulation reliability and junction functionality usually have a distinct temperature range for operation. Temperature monitoring of individual power electronics components may unambiguously identify near failure and the temperature rise can also be used to construct a hazard rate as a function of time and from that percentiles and the mean of the RUL. In the following we will assume that we are able to estimate $h(t)$ with sufficient accuracy.

III. System Performance

In comparison to single components above, redundant and reparable systems aim to increase resilience balancing:

1. Component hazard rate, constant λ or varying $h(t)$
2. Redundancy by configuration
3. Repair rate, constant μ or varying $\mu(t)$
4. System smartness enabling remedial intervention

As for the hazard rate, it was duly discussed above. What may be added, is that with given redundancy and repair options, component qualities are to be balanced with the system requirements. We consider both λ and $h(t)$ in this study. Both depend on stresses as in (2), (3) and (5).

The concept of redundancy by k-out-of-n systems is that n components are parallel and a switch selects k working items (Fig. 5). Whether or not the k/n switch is a discrete object, it is an essential system part that might fail on its own. At this stage, we ignore its vulnerability and assume ideal performance: correct, timely and uninterrupted.

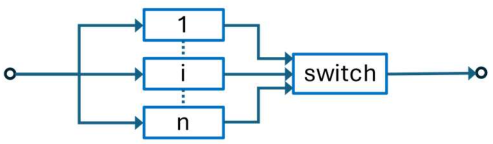

Fig. 5. The principle of k/n systems. The switch is to select a set of working k-out-of-n parallel components.

A fundamental design aspect is whether or not the system is reparable after component failure or near-failure. If it is, an equilibrium may develop between failure and repair rates. Occasionally the system may be down. The equilibrium is often quantified through the measures Availability and Mean Time between Failures.

If the system has one or more absorbing fault states, it reaches an end (of life) after n-k+1 failures ultimately. The system reliability $R_S(t)$ decays from 1 to 0. Still, redundancy can be very useful to extent the total system life depending on the hazard rates, redundancy configuration and repair rates.

IV. Experimental work

The framework aims at uninterrupted functioning of k/n redundant systems under dynamic stresses and timely deselect suspect items for recovery or replacement. Our primary goal is to build a framework with a chain of practices (Fig. 1). In the following we discuss our approach and some explorative results of a Markov model with time varying transition rates.

A. Approach

Redundant systems are often studied with Markov chains and constant transition rates. The differential equations can then be solved by Laplace transforms [6]. We also applied this to semi-constant rates, e.g., when the rates show little change within the prognostic horizon [7]. In our case, however, time varying load and ambient stress leads to transition rates that vary in time. Some other studies also discuss time variation in Markov models (cf. [8,9,10]).

In our approach, we assume that the relation between relevant processes and diagnostics are tested in labs and/or during operation. We also assume that diagnostics have an established relationship with $h(t)$ employing Weibull models [5]. In [7] we discussed Markov models for 1-out-of-n redundancy with constant transition rates, semi-constant transition rates with bathtub models and also involved defect sub-populations. At this stage, we focus on random and wear processes that may vary in time due to separate components. This results in acceleration factors (section II.B), that can vary and differ for the components that build the system.

The k/n redundant systems are studied with a Markov model, where the transition rates are time functions. The state probabilities are calculated by numerically solving the differential equations in Julia programs.

A specific case is studied that consists of n=3 components of which k=2 must work (Fig. 6). The initial, fully functional state is S_0. All three components C1, C2 and C3 endure a competition of two processes: random failure (α_r=λ= 10^{-4} y^{-1}, β_r= 1) and wear (α_w= 100 y^{-1}, β_w= 3).

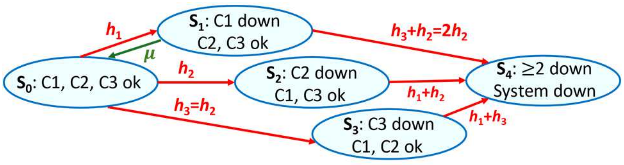

Fig. 6. Markov model used in this particular example case.

C1 suffers enhanced stresses (e.g., external heating) up to t=0.01 y. This is taken here to cause accelerated aging with a single (hazard rate) enhancement factor EF. From Section II.B follows that $EF= AF^{\beta}$. For a random process, β=1 and in our wear case, β=3. For convenience, both EF are 5000.

When C1 is deselected for high temperatures, it is considered failed (state S_1), switched off and recovers with rate μ. State S_2 and S_3 concern failure of C2 resp. C3. Any second failure means the system stops functioning, i.e., is down. This is malfunction and the system is out of active service. This state is taken to be the absorbing state S_4.

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The parameters are chosen to be in a typical range for power electronics, but the chosen failure scenarios are merely an example for working with time varying transitions rates. Except for the principles, the exercise is not meant to be characteristic in general. The configuration, scenarios and rates can be adjusted at will in future work.

The differential equations for the system in Fig. 6 are:

$$h_2(t) = h_3(t) = \left(\frac{\beta}{\alpha^\beta} \cdot t^{\beta-1} + \lambda\right) \quad (6)$$

$$h_1(t) = AF_w^\beta \cdot \frac{\beta}{\alpha^\beta} \cdot t^{\beta-1} + AF_r \cdot \lambda = EF\ h_2(t) \quad (7)$$

$$\frac{dP_0}{dt} = -(h_1 + h_2 + h_3) \cdot P_0 + \mu \cdot P_1 \quad (8)$$

$$\frac{dP_1}{dt} = h_1 \cdot P_0 - (\mu + 2 \cdot h_2) \cdot P_1 \quad (9)$$

$$\frac{dP_2}{dt} = h_2 \cdot P_0 - (h_1 + h_2) \cdot P_2 \quad (10)$$

$$\frac{dP_3}{dt} = h_3 \cdot P_0 - (h_1 + h_3) \cdot P_3 \quad (11)$$

$$\frac{dP_4}{dt} = 2 \cdot h_2 \cdot P_1 + (h_1 + h_2) \cdot (P_2 + P_3) \quad (12)$$

It may be noted that not only h_1, h_2 and h_3 vary in time, but also AF_w and AF_r. Also μ is taken a constant, but will probably also be taken a function of time in follow-up work.

B. Results

For EF=5000 compared to no acceleration, various repair rates μ were simulated. Fig. 7 shows the probabilities P_1 (C1 failure while C2 and C3 keep the system up) and P_4 (system down). The graph shows that the lifetime of the system is impacted by the enhanced wear that builds up damage, but that fast repair counteracts this. The random component returns to the original level, but wear only partly, as some damage always remains due to wear. The findings are in agreement with the expectations. The built numeric solver appeared to fulfill the requirements for the time varying transition rates.

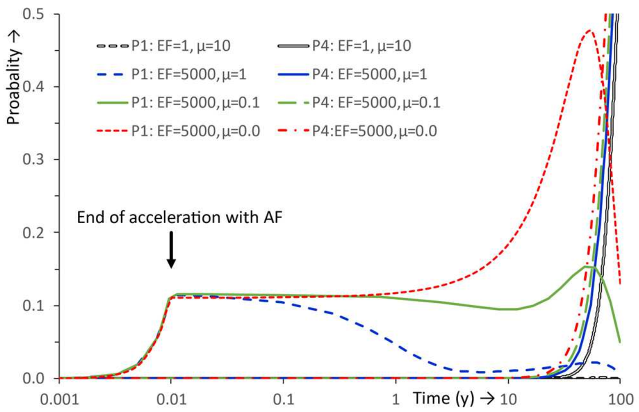

Fig. 7. State probabilities P1 and P4 for having Component 1 at deselection level respectively having the system down. Component 1 suffered enhanced stress causing an acceleration factor AF until t=0.01 y. The repair rate for Component 1 is μ (y^{-1}). Normally μ will be much faster, lowering P1 and P4.

Additionally, the cumulative hazard rate H of the system is shown in Fig. 8 for the cases in Fig. 7. This representation is useful for studying the quality requirements of the total system and the impact of its history.

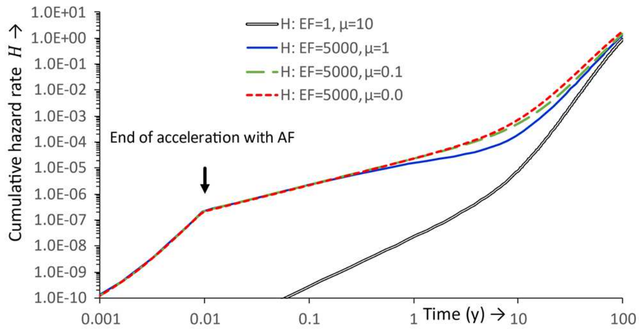

Fig. 8. The cumulative hazard rate for various repair rate and compared to non accelerated degradation

V. Conclusions

Establishing the relation between diagnostics and deterioration, can be very challenging. Various wear phenomena (like PD) regularly do not allow a firm RUL prediction, because the hazard rate as a time function remains uncertain [5]. This impacts Health Index models [11,12]. Still, such diagnostics are very useful for alerts and identifying PD. This study focuses on preventing overheating. Temperature sensors seem to be better at forecasting $h(t)$, but, e.g., their precise positioning can have a significant impact on the prognostics effectivity.

The differential equation solver completes the framework and chain of data analytics practices that were (re)developed in the past years. Further study will focus on models like digital twins for power electronics in the electrical energy supply and drivers for automotive applications.

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