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APPLICATION OF CROW-AMSAA ANALYSIS TO NUCLEAR POWER PLANT EQUIPMENT PERFORMANCE

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ABSTRACT

The importance of equipment reliability growth measurement and prediction in the commercial nuclear power plant is presented along with applicable governmental and industry organization requirements. Equipment reliability analysis difficulties the nuclear utility engineer faces are described and related to organizational requirements. Opportunities for application of Crow-AMSAA (CA) analysis in the nuclear power plant are described.

1. INTRODUCTION

The South Texas Project (STP) plant consists of two Westinghouse pressurized water reactor (PWR) nuclear steam supply systems (NSSSs) each of them providing roughly 1250 MW of commercial electric power to the Texas grid. High levels of nuclear safety and electrical production reliability are primary plant owner and plant management business objectives.

NSSS nuclear safety goals traditionally have been promoted by high reliability in the engineered safety features (ESF) equipment supplied with the reactor plant to mitigate the effects of reactor accidents. However, electrical production reliability and reliability of electrical production equipment also promotes nuclear safety by reducing demands on ESF equipment and plant operator interaction. That is, there is a synergism between nuclear safety and electrical production reliability. For the reasons described above, reliability of ESF systems and equipment as well as electrical production equipment in a nuclear power plant is the concern of the US nuclear regulatory commission (NRC) (NRC, 2005). As a consequence, the performance of certain equipment and plant systems is required to be monitored and reported on.

2. CROW-AMSAA BACKGROUND

Obtaining and processing data to calculate and trend the reliability of certain equipment has been a constant problem at STP. Often times, the date of failure is unknown, the failure mode is difficult to identify, data is missing, or there simply isn't enough failure data. Using CA reliability growth model allows for "dirty" data since it models the process, not the system. It allows for small data sets, missing data, and mixed failure modes. Duane-AMSAA was first developed by James T. Duane at General Electric. Larry Crow from Army Material Systems Analysis

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Activity (AMSAA) later described the same concept but provided statistical analysis by establishing the relationship between the CA model and the Weibull distribution (DOD, 1981) (Broemm, 2000). For that reason, CA is sometimes referred to as a "Weibull Power Process."

3. CROW-AMSAA CALCULATION

CA plots events on cumulative time (t) versus cumulative events (n(t)) with a best fit line. There are three methods to calculate the line of best fit; rank regression (RGR), maximum likelihood equations (MLE), and the International Electrotechnical Commission (IEC) (International Standard, 2000). For the purpose of this paper, IEC will not be discussed since it is not used in applications at STPNOC.

For RGR, λ, the y-intercept or scale parameter, and β, the slope parameter, are solved using the following equations:

$$\beta = \ln\left(\frac{n\sum n(t)t - \sum n(t)\sum t}{n\sum t^2 - \left(\sum t\right)^2}\right) \qquad \text{Eq. 1}$$

where n = total number of events
t = cumulative time, and
n(t) = cumulative events at t.

$$\lambda = \ln\left(n(t) - t\beta\right) \qquad \text{Eq. 2}$$

For MLE, the λ and β are solved using the following equations:

For failure terminated tests:

$$\beta = \frac{n}{(n-1)\ln t_n - \sum_{i=1}^{n-1} \ln t_i} \qquad \text{Eq. 3}$$

$$\lambda = n / t_n{}^{\beta} \qquad \text{Eq. 4}$$

For time terminated tests:

$$\beta = \frac{n}{n\ln T - \sum_{i=1}^{n} \ln t_i} \qquad \text{Eq. 5}$$

$$\lambda = n / T^{\beta} \qquad \text{Eq. 6}$$

where T = total test time.

The equation of the line can be defined by the following equation:

$$\ln n(t) = \ln\lambda + \beta \ln t\,. \qquad \text{Eq. 7}$$

Knowing the λ and β values, the instantaneous (ρ(t)) and cumulative (C(t)) failure rate can be solved :

$$\rho(t) = t^{\beta-1}\lambda\beta \qquad \text{Eq. 8}$$

$$C(t) = t^{\beta-1}\lambda \qquad \text{Eq. 9}$$

4. CROW-AMSAA APPLICATIONS

For the purpose of performance monitoring from the perspective of STP plant management, the NRC, and industry standards bodies, see NEI (1996), Kee (1996), and INPO (2005). The failure mechanism leading to equipment or system unreliability is not as important as the unreliability itself. In general, identifying all failure mechanisms is not possible for a typical plant system that incorporates several different types of equipment.

Monitoring and reporting on equipment reliability has been exhaustively explored in the commercial nuclear power industry. However, none of the monitoring and reporting methods in the nuclear power industry has taken advantage of the CA technique which is a robust method for analyzing "dirty data" as recommended by Abernethy (2000). In here, we explore the use of the CA technique for monitoring and reporting on safety and non-safety related equipment. Also shown is an example of an economic analysis using CA.

4.1 ECONOMIC PERFORMANCE

Since CA relates cumulative events versus cumulative time, economic decision-making performance relative to maintenance policies can be evaluated and shown using the method.

In particular, the effect of a change in maintenance policy in terms of reduction in events can both be measured and forecasted. Forecasting would be effected by calculating the expected number of future events, n,

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given the existing policy derived from equation 2:

$$n = t_n{}^{\beta}\lambda \qquad \text{Eq. 10}$$

and, based on performance estimates of the new maintenance policy model, the events expected:

ΔN = n – actual number of failures Eq. 11

An example is shown in Figure 1 where STP experienced a phenomenon in the rod control system (RS) called incomplete rod insertion (IRI). In response, STP worked with the fuel vendor to redesign the nuclear fuel assemblies to eliminate interference with the control rods. As a consequence, scheduled inspections and IRI events were significantly reduced.

Table 1. Comparison of actual and avoided events.

Year	Total additional events predicted (as of year) N_e	Total additional events measured (as of year) N_p	Total events avoided (as of year)
1998	1	1	0
1999	2	1	1
2000	5	1	4
2001	8	2	6
2002	13	2	11
2003	20	2	18
2004	28	2	26

Knowing the net cash flow (CF) and discount rate (DR) associated with each event (in this case, primarily revenue loss) the net present value (*NPVc*) from discounted cash flow for the current maintenance policy, based on the CF and failure rate (as calculated from the CA approximation) can be calculated:

$$NPV_c = \lambda_c CF \sum_i \left[\frac{(t_i - t_0)^{\beta_c}}{(1+DR)^i} - \frac{(t_{i-1} - t_0)^{\beta_c}}{(1+DR)^i} \right], \qquad \text{Eq. 12}$$

where i refers to the year the cash flow occurs and the subscript *c* refers to the current maintenance policy. A similar calculation can be made for the new maintenance policy:

$$NPV_n = \lambda_n CF \sum_i \left[\frac{(t_i - t_0)^{\beta_n}}{(1+DR)^i} - \frac{(t_{i-1} - t_0)^{\beta_n}}{(1+DR)^i} \right], \qquad \text{Eq. 13}$$

where the subscript *n* refers to the new maintenance policy.

In IRI case, *NPVc* (in 1998 dollars) based on an average cost per event of $1,455,931 for the existing maintenance policy to year 2006 for IRI is estimated at roughly $30,000,000. The *NPVn* to year 2006 is estimated at roughly $3,000,000. Therefore, introducing the new maintenance policy (new, robust fuel design) decreases maintenance cost for IRI by roughly $27,000,000.

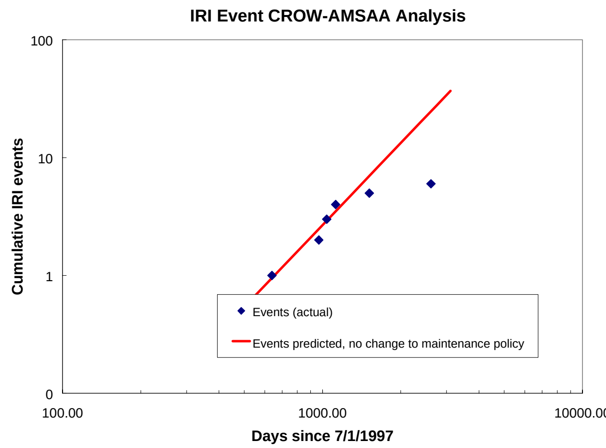

Figure 1. Crow-AMSAA graph of past IRI event trend and actual events.

4.2 COMPONENT HEALTH TREND

The CA method is also being used by system engineering in the system health reports. Graphs are used to illustrate the trend of a component or system. Each system engineer defines the failure for their component or system. An example is the

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condensate air removal system (CARS) pumps as shown in Table 2 and Figure 2.

Until 9/2003, the eight CARS pumps at STPNOC had been failing with a failure rate decreasing with time. This is obvious because the β value is less than one. After 9/2003, the failure rate started increasing with time shown with a β value greater than one. Around 9/2003, the CARS pumps started trapping moisture in the second stage bearing which caused the failure of the pump blades. The problem was identified in 6/2004, and monthly overhauls have been implemented until the modification for the drain installation is in place.

This information is also used to identify when a component's failures are increasing with time. When the β value is greater than one, it alarms the engineer to look through the failures to see if a particular failure mode or mechanism is causing the increase in failures. It may be indicative of infant mortality or end of life failures for life cycle management.

Table 2. CARS pumps data.

Date	Cumulative days	Type	Cumulative failures
10/1/98		Start date	
6/15/99	14	Failure	1
6/21/99	21	Failure	2
7/9/99	38	Failure	3
8/31/99	92	Failure	4
2/20/00	265	Failure	5
4/22/00	326	Failure	6
6/5/00	370	Failure	7
7/30/00	426	Failure	8
9/15/00	472	Failure	9
12/5/00	554	Failure	10
2/9/01	619	Failure	11
4/27/01	696	Failure	12
12/10/01	923	Failure	13
1/4/02	949	Failure	14
1/5/02	949	Failure	15
3/14/02	1018	Failure	16
6/9/02	1105	Failure	17
6/10/02	1105	Failure	18
6/11/02	1106	Failure	19
3/17/03	1385	Failure	20
5/12/03	1442	Failure	21
8/19/03	1541	Failure	22
8/22/03	1544	Failure	23
9/22/03	1574	Failure	24
10/28/03	1610	Failure	25
1/5/04	1679	Failure	26
1/26/04	1700	Failure	27
2/24/04	1729	Failure	28
3/1/04	1735	Failure	29
5/13/04	1808	Failure	30
10/1/04	1949	Suspension	30

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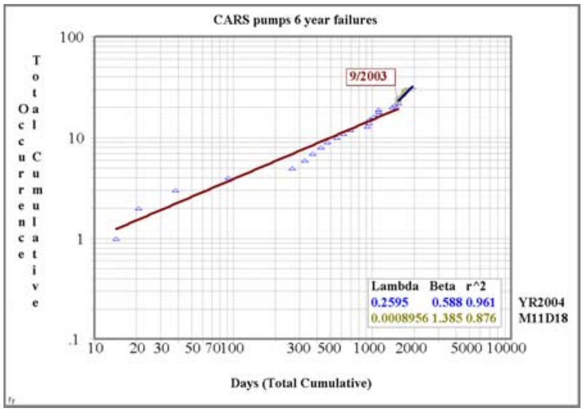

Figure 2. Crow-AMSAA plot of CARS pump failures.

4.3 MAINTENANCE UNAVAILABILITY

Maintenance unavailability for equipment important to production can be monitored using CA by looking at cumulative unavailability hours. Maintenance unavailability is important to standby equipment availability. Results of CA analysis of maintenance unavailability can be used to estimate future production performance. The performance of maintenance policy changes with an objective to reduce maintenance unavailability, can also be estimated (when the maintenance schedule is given or estimated).

STP uses two pumps (EHC pumps) in a hydraulic power plant that supplies high pressure hydraulic oil to operate steam supply valves on the electrical production generator. Only one pump is required to maintain full electrical production but if both pumps fail during plant operation, the plant will trip (lose all electrical production).

A CA plot of maintenance unavailability for these two pumps is shown in Figure 3. The trend shows two distinct behaviors, one rapidly increasing and another less rapid. In fact, the early trend could not be sustained because the unavailability would be theoretically (and practically) impossible. The change in maintenance policy that resulted in the second trend is one that continually reduces maintenance unavailability of the EHC pumps ($\beta < 1$).

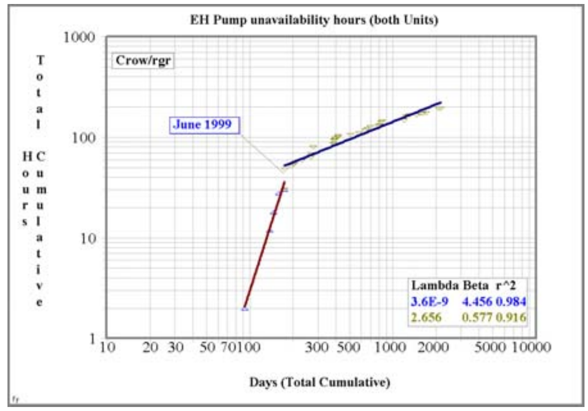

Figure 3. CA plot of EHC pump unavailability.

The new maintenance policy would produce improved hydraulic pump availability (depending on revisions, if applicable, to the preventive maintenance schedule), $A = \frac{\mu}{\mu + \lambda}$, if the EHC pump failure rate decreases, remains constant, or grows at a sufficiently low rate. Using CA prediction, evolution of the failure rate over time (t_0, t_1, t_2, t_3) and maintenance unavailability (repair rate) can be observed for approach to an equipment availability limit (set by other criteria) as illustrated in Figure 4.

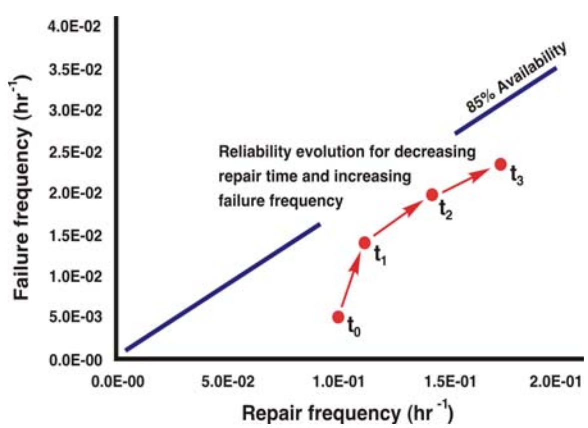

Figure 4. Relationship between failure and repair frequency and effect on availability.

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5. CONCLUSION

The Crow-AMSAA method has been described along with its applications at South Texas Project. Because of difficulties in obtaining failure data, CA has been a preferred method in calculating a time dependent failure rate and projecting the number of events (failure or unavailability) in the future. It is useful for evaluating the economic benefit of a change in maintenance strategy. CA can also identify when failures in a component or system has changed trends for general tracking or for life cycle management studies. Using CA to trend unavailability can identify when a component will exceed certain thresholds for maintenance rule.

Crow-AMSAA is a useful alternative to Weibull distributions when little data is available. When able, STP will apply a classic failure distribution when fit. In a study done at STP with over 40,000 component/failure mode, only six sets of component/failure mode combinations had enough data to fulfill the criteria of a classic distribution. For that reason, CA has been used to evaluate failure trends (Yu, 2004).

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