Nuclear Power Plant Electronic System Reliability Study

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Abstract

Management of aging electronic systems is a problem faced by many industries. Management of these systems requires some understanding of their reliability performance. In the United States commercial nuclear industry several approaches are being taken in an attempt to understand the reliability performance of plant systems. This article describes one approach being used. The method is non- parametric and requires no specialized data analysis software.

I. Introduction

Although nuclear power in the United States is enjoying increased support in government as well as by the public, there is still a large financial risk involved with building new nuclear facilities in the United States. It is often much less risky to renew the license of existing facilities. However, this presents a different challenge, how to manage aging electronic systems beyond the original 40 year license period.

There are several options for managing these aging electronic systems; continue to maintain and monitor, technology refresh of individual modules or assemblies, or complete system replacement. Each of these options requires many inputs to consider. All require some knowledge of the reliability behavior of the system and its constituent components.

This paper presents one approach that is being used at a commercial United States nuclear power plant to help engineers understand the reliability behavior of electronic systems. This, in turn, helps engineers recommend not only which strategy is best for a given system, but also helps prioritize activities.

The remainder of this paper is organized as follows. Section II discusses the preparation of the maintenance data for analyses. Section III briefly describes the analytical methods used in the study while Section IV presents the result of the study. Some concluding remarks are found in Section V.

II. Data Preparation

Maintenance management systems (MMS) rarely provide data useful for reliability studies. Complicating this at the facility was the fact that the facility had used three MMS over the 32-year life of the plant. The first step in the study was to combine the relavent data in these three MMS databases into a single database.

Using Python and PyGTK, a database front end was designed that allowed analysts to create ”on the fly” queries without knowledge of SQL. This freed the study from another limitation of the plant's MMS of ”canned” queries. The most beneficial being the ability to keyword search the fields containing the problem description and the maintenance technician remarks.

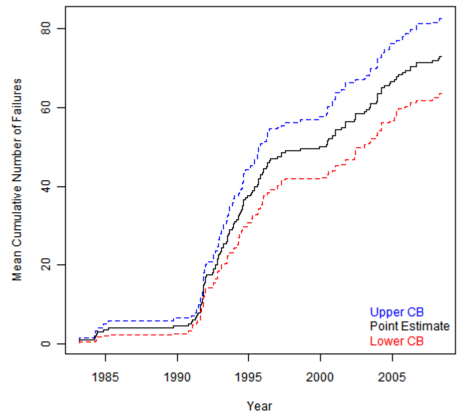

Fig. 1. System 1 Mean Cumulative Function (1977 - 2009)

Once the data was consolidated in a single database, there were over 425,000 maintenance records to review. The database was searched for records associated with the maintenance of the electronic systems at the plant. For each record, a list of assemblies repaired or replaced was added along with other information that didn't exist in the MMS (e.g., each assembly was denoted as a failure or suspension).

After spending several months sanitizing the database, reports were generated of failures/suspensions for each system. These reports were used as input files for the analyses.

III. Data Analyses

It was understood that the MMS data, even after review, would generally not be conducive to parametric analyses before beginning the study. Therefore, non-parametric methods were used to analyze the sanitized data. The two methods used were Kaplan-Meier (KM) and the Mean Cumulative Function (MCF) described in [2]. While [1] was used to analyze the data, both of these methods could be implemented using common business suite applications such as a spreadsheet application.

For each system studied, the plant was interested in understanding whether a trend exists in the system failure intensity. If a trend exists, is it degrading or improving. The MCF was useful in determing failure intensity trends. The MCF also lends itself to graphical display of failure intensity. These plots are beneficial to the decision makers in the organization as trends are easily discerned without relying on statistical tests.

Also of interest was whether the failure intensity for each system was *s*-different for the period prior to 1997 and the period from 2000 to date. Between 1997-2000, both units were shutdown and the plant was interested in the effect this long layup may have had on the systems. The KM was useful for comparing the failure intensity of these periods.

IV. Results

For each system, the first step was to find the MCF over the entire period for which records existed (1977-2008). Figure 1 is an example of one of the systems analyzed. In Figure 1, there is an abrupt change in the MCF beginning in 1992. This behavior was seen in the MCF for all systems analyzed.

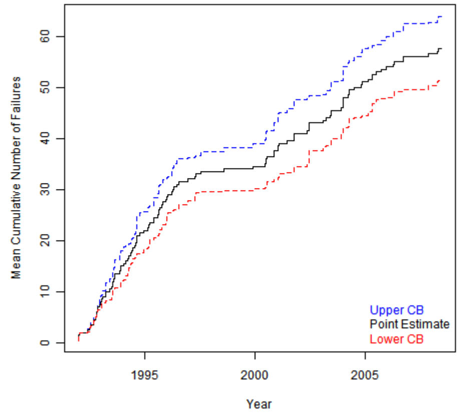

Fig. 2. System 1 Mean Cumulative Function (1992 - 2008)

These abrupt changes coincide with the implementation of the first computerized MMS. Since the change is seen in all systems and is coincident with implementation of a computerized MMS, it was concluded that the change was the result of a complete set of maintenance records rather than an actual change in the MCF. As a result the remainder of the analyses focused on the period after implementation of computerized MMS. Figure 2 is the MCF for the same system as Figure 1 excluding the period before computerized MMS.

Both Figure 1 and Figure 2 show a relatively flat region between 1997 and 2000. Similar to the change that corresponds with the implemenetation of a computerized MMS, this flat region was coincident with the three year outage. This was seen to differing degrees in all systems analyzed depending on how the system is operated during outage periods.

Finally, attention was turned to comparing the reliability of the system during the period preceding the three year outage and the period following the outage. Figure 3 is the Kaplan-Meier plot for the example system. From Figure 3, it appears there is a difference between the periods with the performance during the period after the outage being better. However, the logrank test described in [3] was used to formally test the hypothesis

$$H_0 : S_1 = S_2$$
$$H_1 : S_1 \neq S_2$$

For the system in this example, the p-value was ≈ 0 and it was concluded there is a s-significant difference. With the exception of one system studied, all systems either showed improvement or no change after the three year outage. For every system that showed improvement, the plant could identify in the maintenance history a recurring problem. The plant could also identify the corrective actions taken to address the recurring problem. Subsequently, the plant could identify in the MCF plot an apparent change in slope following the implementation of these corrective actions.

One of the systems studied showed a declining trend in the period following the three year outage. Ironically, this system underwent a major overhaul in 2006 resulting in an essentially new system. Figure 4 is the MCF plot of this system from 2006-2008. In this figure, the mean number of failures is seen to be increasing after 2007. From the vendor's root cause analysis, the plant knew that these failures were the result of a manufacturing defect. Thus, the analyses would be expected to

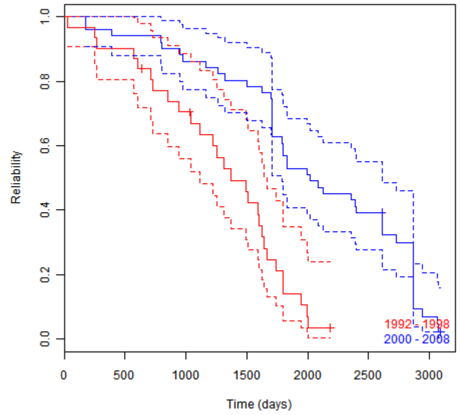

Fig. 3. System 1 Kaplan-Meier Plot (1992 - 2008)

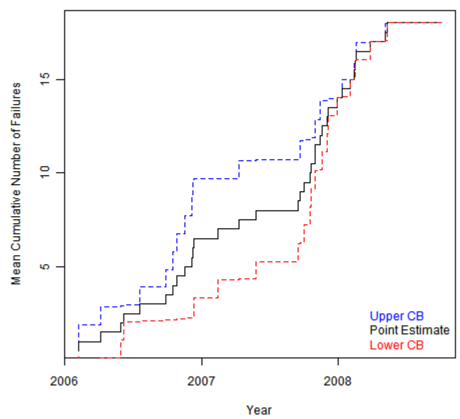

Fig. 4. System 2 Mean Cumulative Function (2006 - 2008)

show a declining trend.

In some instances, the system being studied had been replaced since implementing the computerized MMS. This allowed the plant to reconstruct the entire maintenance history since installation. When this condition existed, and there were a sufficient number of failures, the plant was able to perform parametric analysis of the data. The study tested for exponential, Weibull, and lognormal fits to the data, generally finding the Weibull to be the best fit.

Figure 5 is the Weibull plot of the problematic module from System 2. Estimates of the Weibull parameters were λ = (0.0004645654 , 9.736274e-05) and γ = (0.6317011 , 0.6546714) at 90% confidence. These results are consistent with a device dominated by quality defects.

Although not something the study was interested in when beginning the study, the study found that the false alarm rate of the systems was rather high. One system experiences a false alarm rate of 26%. Overall, the seven systems initially studied experience a false alarm rate of 15.5%. This insight was the result of spending the time to sanitize the data even though this was a manually intensive process.

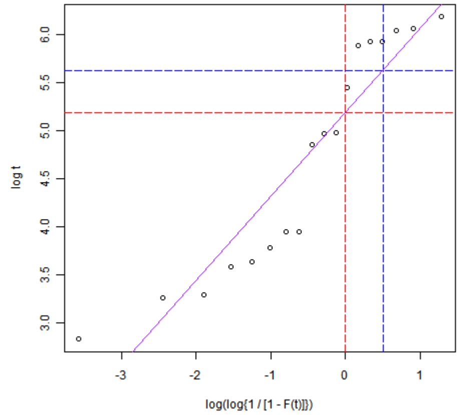

Fig. 5. System 2 Weibull Probability Plot of Problematic Module

V. Conclusion

Although the study did not identify any system with a declining trend in failure intensity, the plant was able to compare the systems non-parametrically. This comparison allows engineers to use fielded reliability as a input to the plant's long-range planning for electronic systems. In addition to using the results in long-range planning, the plant's approach allows engineering to statistically assess the impact of actions taken to improve system reliability. The approach used also does not require specialized data analysis software.

The study found that, contrary to a widely-held assumption at the facility, electronic systems are not ”wearing out.” In fact several systems are showing declining failure intensities over the past decade and many show no change over the past seventeen years. Reduced failure intensities can be shown to occur after actions have been implemented with the express purpose of improving system reliability. The results show that even 30-year old electronic systems can be managed through incremental improvements such as technology refresh of individual printed wiring assemblies or continuous optimization of the preventive maintenance policy. Complete system replacements may not be necessary as long as the existing hardware and software is supported by the vendor.

References

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[2] W. Meeker and L. Escobar, *Statistical Methods for Reliability Data*. New York, New York: John Wiley and Sons, 1998.

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