A dynamic process for evaluating the reliability of fossil power plant assets

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Abstract
Budgets and maintenance programs in fossil power plants are frequently set based on engineering judgment rather than a Probabilistic Risk Assessment (PRA). Fossil power plants seldom use PRA due to a lack of practical processes, especially when field reliability data are not readily available. In the absence of field data, using general industry data may not be right for conducting PRA for a given organization as the operation and maintenance conditions significantly vary between organizations. To have a successful PRA, an organization needs to use its own field data, and have an efficient process for its organization. Studies have suggested using field data provides a robust model and accurate results. Use of Reliability Block Diagrams for Reliability, Availability, and Maintainability analysis is not new. However, applications of these techniques are new to fossil power plants. In this paper, we propose a practical process by integrating several existing reliability techniques for fossil plants to apply PRA. The process was tested at many power plants, and the results aligned well with the actual values. The methodology outlined in this paper is a forward-looking tool for managers to predict system reliability, and proactively develop maintenance plans and budgets.

Keywords
Monte Carlo simulation, power law, reliability, repairable systems, Weibull analysis

1 INTRODUCTION

The average age of a fossil power plant in the United States is approximately 43 years. As more and more renewables and gas plants are taking a significant share of the generation portfolio, the coal-fired plants are being subjected to increased cycling. Age, cycling, and competition are making the power plant operators find ways to evaluate the performance of their assets and improve their reliability.1-3 Understanding how the assets behave in the future helps the operators to develop a proactive maintenance regimen and make prudent run repair decisions. Hence, the main objective of this paper is to describe the application of the theory, process, and tools to help power plant engineers to develop Risk-Based Maintenance programs to improve the reliability of their plant systems.
Fossil Power plants are very complex entities with many systems and more than a hundred pieces of equipment per unit. These include pumps, heat exchangers, boilers, turbines, generators, and other equipment—some of which operate at high pressures, temperatures, and voltages. A typical arrangement of a fossil power plant is shown in Figure 1.

Reliability assessment of such complex systems with many pieces of equipment—redundant, repairable, and complex operation—is complicated and requires extensive knowledge, processes, and techniques. A reliability criteria must be set up to evaluate performance of such complex systems to develop and compare future requirements and develop plans for improving or sustaining the reliability. This requirement resulted in developing extensive methods, and modeling techniques as each industry or organization sets its own reliability standards and definitions. The goal of fossil plant engineers is to reduce the unplanned and unscheduled outages (forced outages) to a minimum. Hence the reliability in fossil plants is generally defined as one minus forced outage factor, and availability as one minus unit unavailability factor due to all causes such as planned, unplanned, scheduled, and forced outages. They are represented by the equations:

\[ R = \left(1 - \frac{t_f}{T}\right) \]  

where,
\( t_f \) = forced outage hours.
\( T \) = total period hours.

This definition of Reliability is used throughout this paper.

\[ A = \left[1 - \left(\frac{t_s + t_p + t_u}{T}\right)\right] \]  

where,
\( t_s \) = scheduled outage hours.
\( t_p \) = planned outage hours.
\( t_u \) = unplanned outage hours.

Even though generalized probabilistic analyses existed for quite some time, they may not work for these complex systems because failures on specific equipment in power generation are rare, and the repair cycles vary substantially. Traditionally, reliability analyses are based on deterministic methods such as Life Data Analysis (LDA). LDA methods are generally used for non-repairable equipment such as in the manufacturing and automobile industries. Since most of the equipment in power plants are repairable, they are seldom replaced until their end of life. Many reliability practitioners and academia caution against using LDA methodology, such as Weibull analysis, for analyzing repairable systems. Instead, they suggest the Non-Homogenous Poison Process (NHPP) models for repairable systems. Poisson distribution and exponential distribution models are appropriate when a system’s failure intensity is not affected by the system’s age.

Duane and Crow have developed methods for evaluating repairable equipment using NHPP models. NHPP methods predict the number of failure events, expected time to failure, and repair durations within given confidence bounds. This
information is the building block for the Probabilistic Risk Assessment (PRA)-based decision-making.\textsuperscript{8} NHPP models assume that the failures occur non-uniformly at random times. Also, it is assumed that the failure rate increases as the power of operating time “\textit{t}.” Duane initially developed the power-law model in 1964.\textsuperscript{9}

While the Duane mode assumes the cumulative Mean Time Between Failures (MTBF) is linear with respect to the cumulative time when plotted on a log-log scale,\textsuperscript{10} Crow—while working on Army Materiel Systems Analysis Activity (AMSAA)—developed a model\textsuperscript{11} which assumes the failure intensity of the underlying NHPP is linear when plotted on a log-log scale. This model is widely known as Crow AMSAA model. While the Duane model is empirically based, the Crow AMSAA model is statistically based.\textsuperscript{12}

Also, Crow noted that the Duane model could be stochastically evaluated using the Weibull process for complex repairable systems, and the time to the first failure follows a Weibull distribution.\textsuperscript{13} The Crow AMSAA model is also called a Power Law model and is extensively used for evaluating repairable systems.

In the Power Law model, the expected cumulative number of failures is given by the equation:

$$E[N(T)] = \int_0^T \rho(t)dt.$$  \hspace{1cm} (3)

where, $\rho(t)$ = Failure intensity at time “\textit{t}.”

$T$ = total time.

The Power Law failure intensity has the following form as per Crow,

$$\rho(T) = \frac{\beta}{\eta^\beta} T^{\beta-1}.$$ \hspace{1cm} (4)

where $\beta$ and $\eta$ are the location and scale parameters for the Weibull distribution for the first failure.

By introducing a new parameter

$$\lambda = \frac{1}{\eta^\beta},$$ \hspace{1cm} (5)

the cumulative failure rate for a repairable system can be derived as.

$$\lambda_c = \lambda T^{\beta-1}.\hspace{1cm} (6)$$

In Equation (6), $\lambda_c$ is the cumulative failure intensity. The above equations apply when the instantaneous failure intensity is a constant power law function as in Equation (4). However, the instantaneous failure intensity function can be different from repair to repair—due to imperfect repairs—and it significantly impacts the “virtual” age of the equipment.

As per Kijima, a repairable system after repairs can be restored to its original condition termed as “as-good-as-new” (Type I) or “same-as-before” (Type II). Kijima’s generalized model assumes extreme conditions—repairs are either as-good-as-new or same-as-before.\textsuperscript{14} However, in the real world, the repairs are not perfect and fall anywhere between the two extreme conditions. The term repair effectiveness ($q$) is introduced to quantify the effectiveness of the repairs. Hence the amount of life restored referred to as Restoration Factor (RF) is.

$$RF = (1 - q).$$ \hspace{1cm} (7)

The age of a component with an imperfect repair is governed not by the calendar age but by its virtual age.\textsuperscript{15} Virtual age for a component with imperfect repairs is given by.

$$v_i = q(v_{i-1} + x_i),$$ \hspace{1cm} (8)

where,

$v_i$ is the virtual age of the system after the $i$th repair.

$$q = (1 - RF).$$ \hspace{1cm} (9)
RF = restoration factor.

\[ x_i = \text{time between the repairs.} \]

\[ v_{i-1} = \text{virtual age at } (i-1) \text{ th repair.} \]

Nguyen et al developed an Arithmetic Reduction Age model for the baseline Weibull distribution.\(^{16}\) The three parameters \( \beta, \eta, \) and \( RF \) govern the virtual age with imperfect repairs.\(^{17}\)

The RF is critical in this process as it determines, from the data, how well the repairs have restored the equipment to its original condition. Most reliability professionals assume the repairs restore the equipment condition back to as good as new (\( RF = 1 \)) or leave it the same as before (\( RF = 0 \)). However, the restoration factor is \( 0 \leq RF \leq 1 \).

The uniqueness of the proposed Dynamic Reliability Assessment (DRA) process is that (a) it uses the field data (b) uses other methods such as Failure Mode Effect Analysis (FMEA) where data are not available or limited (FMEA is discussed in detail in Section 2.1) (c) calculates the repair success or RF, and uses it in the analysis rather than the extreme conditions “As-good-as-New” or “Same-as-Before.” Also, the DRA provides an expected number of failures and predicts future performance at equipment, system, and unit level. It is a dynamic process, as what-if scenarios can easily be performed to evaluate various alternative decisions.

The process outlined produces a multitude of results that are extremely useful to the engineer in decision making. The output includes:

- Reliability (Equipment, System, Unit).
- Probability of Failure, Reliability, Failure Criticality Indices/Risk Ranking, MTBF, Mean Time To Repairs, Number of Failure Events and Durations, Number of Derate Events and Durations.
- Maintainability.
- Inspection, Preventive Maintenance, Corrective Maintenance Policies.
- Projected Maintenance Activity, Resource Requirements, and Durations.
- Critical Spares List, Optimal Replacement Timing, Direct & Indirect Costs. Annual & Life Cycle Costs.

The process was successfully tried at many plants with excellent results.

2 | METHODOLOGY

DRA is a systematic process to evaluate the reliability of equipment, systems, and units based on historical data, use of statistical analysis, and Monte Carlo simulation to predict their future behavior. It is Dynamic with capabilities to perform several What-if scenarios simultaneously.

The primary objective of System Reliability Analysis is to obtain a failure distribution of the entire system based on the failure distributions of its components, as shown in Figure 2 (also see Appendix).

In the DRA process, a Reliability Block Diagram (RBD) is created for a system arranging the equipment reliabilitywise. Shutdown event data for each piece of equipment—usually for the past 5 years—is collected, and failure distribution

\[ \text{FIGURE 2 System modeling concept} \]
parameters are developed using Weibull distribution. Equipment characteristics, along with the cost and repair times, are entered into each block in the RBD.

A Monte Carlo simulation is performed for a given number of years in the future to predict Failures, Shutdown Days, and Costs.

The DRA process consists of
1. Data collection
2. Data cleaning
3. Developing statistical failure models
4. Creating RBDs
5. Model simulation
6. Sensitivity analysis
7. Evaluation of results

The DRA Process is shown graphically in Figure 3.

2.1 Data collection

A significant amount of data on Reliability, Availability, and Maintainability (RAM) analyses is available in the industry. Many individuals or organizations have performed RAM analyses, and listed various sources available to perform statistical analysis, or collected statistical parameters from benchmarking or from equipment manufacturers. Many professional organizations also have published failure rates and repair duration data for various standard equipment. For example, the Electric Power Research Institute (EPRI) published failure rates and repair times for many common types of equipment in the power industry through their benchmarking effort. Similarly, the American Petroleum Institute (API) produced methods and tables for heat exchanger tube design and failures. Also, the American Institute of Chemical Engineers compiled data for various equipment used in the chemical industry. However, this data are more generalized for the equipment or the industry. It is useful for developing a RAM model during a design phase or evaluating a new plant. Each piece of equipment is unique, and the operation and the operating environment vary considerably between the equipment and the units. Also, the age of the equipment plays a significant role in the reliability of individual equipment. Hence, generalized data from these sources cannot be used for a specific piece of equipment or unit to project the performance of an operating unit. Wendai Wang et al, in a paper discussing the application of RBDs for power systems...
applied to IEEE Std. 493, noted that “If actual data recorded from the facility or vendor are available, it is better to proceed with analysis using these data”. In addition, Gilar-Doni et al suggested that when failure history is available, the analysis will provide more accurate results leading to a cost-effective maintenance regimen.23

In the DRA process, two pieces of data are required (1) the time to a failure event from a chosen starting point, and (2) the duration of each failure event. The data collection is limited to the past 5 to 7 years since the plants are very dynamic, and maintenance and replacements are performed continually. The units in power plants typically have a major outage every 3 to 5 years, during which major repair and replacement of the equipment are performed. For this reason, quite often, the reference date is selected after a major outage. Similarly, the reliability projections are made for 5 to 7 years. The uniqueness of this conceptual model is that future behavior can be accurately predicted with just the last 5-7 years’ data.

Usually, this data come from the Computerized Maintenance Management System (CMMS) or the Generating Availability Data System (GADS). In some cases, the data are either limited or not available. Particularly, in the case of low probability high consequence equipment, it is vital to develop methods and processes to improve the accuracy of the analyses 24 where data are limited. Where quantitative information is not available or limited, tools such as FMEA and interviews with subject matter experts (SMEs) are used to collect the qualitative data and converted to statistical parameters using various methods.25

FMEA is a systematic approach in evaluating the failures of equipment to determine how, when, and what causes a failure, and the effect of those failures on the system reliability.26 In an FMEA process, a group of SMEs reviews each piece of equipment and identifies the possible failure modes. Also, the group determines the impact of each failure on the system and the cause of the failure. During this process, the SMEs collectively determine the severity of each failure, occurrence of the event in a given period, and whether a failure mode can be detected before the actual failure occurs. Since the failure rate of equipment depends on the age, environment, and how it is operated, performing FMEA on specific equipment that did not have data is more accurate than using generalized failure rates from the industry.

A mixed analysis also is performed where the generalized failure data from the industry are discussed with the SMEs, and the data are adjusted to match the current equipment scenario based on the experts’ experience in operating and maintaining that equipment.

An example of the data collection template is shown in Table 1.

### Table 1: Typical data collection template

| Unit | Start date and time | Finish date and time | Event duration (h) | Description               |
|------|---------------------|----------------------|--------------------|---------------------------|
| 1    | 11/15/11 00:34     | 11/19/11 04:18       | 92                 | Superheater leaks         |
| 1    | 5/10/09 14:01      | 5/11/09 17:28        | 26                 | Turbine oil leak          |
| 1    | 1/7/13 18:07       | 1/12/13 9:06         | 120                | Steam—load mismatch       |
| 1    | 5/28/10 07:53      | 5/30/10 19:45        | 58                 | Generator bearing oil leak|
| 2    | 11/27/11 00:01     | 11/27/11 7:00        | 6                  | FD fan damper is broken    |
| 2    | 9/5/13 15:27       | 9/21/3 13:44         | 91                 | IP BFP motor failure      |
| 3    | 4/10/12 15:26      | 6/13/12 14:33        | 528                | A hot well pump failure   |

2.2 Data cleaning

Failure and operational data are generally used for system performance monitoring and reliability predictions. However, due to errors in collecting the data, raw field data cannot be used for reliability modeling unless it is cleaned and sorted. Also, certain appropriate assumptions have to be made to use this data with the existing statistical modeling tools.27

Much of the CMMS data in the power industry is either wrong, spurious, or outliers. Since it is a true statement that “garbage in garbage out,” it is essential to clean and validate the data. According to Dr. Ballinger, “Collecting and using data from CMMS must be carefully considered and preplanned by thoughtful analysis to prevent accumulating non-useable garbage data. Lack of accuracy in age to failure is a common deficiency”.28 The important thing is to extract
the correct and relevant failure event data for the right equipment. The data for each piece of equipment in a system are listed in chronological order from the data reference date. At least three data points are needed to develop a meaningful equipment failure distribution. The data starting point is the same for all equipment in the analysis. An example of cleaned data for a superheater is shown in Table 2.

### 2.3 Developing statistical failure models

Once the equipment data are cleaned and sorted, the data are exported to statistical software to generate the failure distribution for each piece of equipment. The authors have selected ReliaSoft's software Weibull++ and BlockSim to create the statistical models and the RBDs. Since most of the equipment in power plants is repairable, the time to failure data is uploaded into the “Recurring Data Analysis” module of the Weibull++. The output of the Weibull analysis provides the Shape Parameter $\beta$, the scale parameter $\eta$, and the restoration factor RF. Typical Weibull input and results are shown in Figure 4.

Since repair durations are independent and unique, LDA is used to obtain repair duration distributions.

### 2.4 Reliability block diagram

In a dynamic process, the behavior of each piece of equipment is evaluated statistically, and the equipment is connected reliabilitywise into a system and further into a unit. This is accomplished by using RBDs. Each block in the RBD represents a piece of equipment in the system. Figure 5 is an example of an RBD for a typical power plant shown in Figure 1.
The equipment in an RBD may be connected in series, parallel, or a combination of the two depending on the plant configuration and redundancy. Unlike a flow diagram, RBD shows how each component affects the overall reliability of a complete system. Any failure of a piece of equipment in an RBD could affect the availability, reliability, and output of the whole system.

The statistical models created for each piece of equipment in step 2 are entered into the blocks. Also, preventative maintenance data, event costs, crews, the capacity of each piece of equipment, and lost opportunity costs are entered into the model.
2.5 | Model simulation

After all the data are entered into the RBD, a Monte Carlo simulation is performed (see Appendix). Usually, the simulation is performed for 1000 to 2000 times, and the results are projected for 5 to 7 years in the future. As mentioned earlier, most of the units undergo major outages every 2-4 years, so 5-7-year projections are enough to develop outage plans.

2.6 | Sensitivity analysis

Sensitivity analysis aims to identify the impact of each input variable on the output in a model. Also, the objective is to determine which variable has the most significant impact on the output and which input(s) can be neglected or insignificant.29

One-at-a-time (OAT) is a type of sensitivity analysis where each input is independently tested to see its impact on the output. It is a simple and easy technique. However, when there are multiple inputs, OAT will not be able to determine the impact of a combination of input variables that would govern the output. Many methods, such as regression analysis (linear and rank regression), the Morris method, and Sabol indices, are available to perform sensitivity analysis with multiple inputs. The Morris method is a specialized randomized OAT that is a global sensitivity analysis method. In the Morris method, each input variable is changed by the same relative amount.30 On the other hand, Sabol indices method factor the variance of the output of the system into fractions, which can be assigned to inputs. The primary use of Sabol indices is quantifying the importance of variables.30

Sabol indices are used to evaluate either a single variable or a set of variables. Sabol indices are estimated by calculating the output uncertainties by sampling from the distributions of the input variables through a function. The Sabol indices range from 0 to 1, and the closer the index to 1, the better the corresponding input variable rationalizing the output.

In the reliability analysis proposed by the authors, the first failure is determined by Weibull Analysis.31 In the power law, each failure is treated as a single point, and the duration is insignificant. The successive failures are governed by the RF \((1 - q)\) as per Equation (7). The RF is the only variable that governs the number of subsequent failures in the power law and hence the reliability. This is illustrated in Figure 6.

Figure 6 shows the impact of RF on the reliability of a subsystem for the same Weibull Parameters. Since there is only one input variable, a simple OAT sensitivity analysis is performed on each of the subsystems, and the resulting reliability is compared with the actual failure history to select the optimum RF.

Also, the model is simulated for the years for which the data were collected. The resulting output is compared to actual reliability, failures, and other measures. If there is a significant deviation between the simulation results and actual values, the input data are rechecked, assumptions or input data are corrected, and the models are rerun.

3 | CASE STUDY

The process was beta tested at a plant with four identical units in 2010. The objectives identified were (1) predict the reliability of each unit for the next 5 years, (2) identify the systems and equipment contributing to the loss of reliability, (3) identify where and when failures do occur, and (4) the total cost of maintenance and revenue loss.
Data were collected from the plant’s CMMS system. Where data were not available, data from published industry data were used with modification after consulting with the SMEs. Also, a high-level FMEA were conducted, and the SMEs’ input was obtained to develop the failure probabilities. Since we were interested in the probability of failure, only the Occurrence projection by the SMEs was used in the model. A Monte Carlo simulation of the unit RBD was performed for the years 2010 to 2015.

Reliability projections from the simulation are shown in Table 3.

The model was validated by comparing the actual reliability values with the predicted values. Figure 7 shows the comparison of actual reliability to the predicted values for Unit 2.

The results showed that Unit 2 would have the lowest reliability of the four units, and the reliability would drop by 14% between 2010 and 2015. Criticality analysis performed on Unit 2 (Table 4) showed that Water Walls would contribute to 30.3% of the total shut down events on the unit, followed by the superheater.

| Year | Unit 1 | Unit 2 | Unit 3 | Unit 4 |
|------|--------|--------|--------|--------|
| 2010 | 93.5%  | 87.7%  | 90.1%  | 91.1%  |
| 2011 | 92.5%  | 85.6%  | 89.7%  | 90.1%  |
| 2012 | 92.5%  | 82.3%  | 88.4%  | 89.0%  |
| 2013 | 91.6%  | 79.9%  | 86.9%  | 88.2%  |
| 2014 | 90.8%  | 76.8%  | 86.1%  | 87.5%  |
| 2015 | 90.4%  | 73.5%  | 85.1%  | 85.8%  |

**Table 3** Unit reliability projections

| Year | Unit 2 Reliability Vs Year |
|------|---------------------------|
| 2005 | 100 | 100 | 100 | 100 | 100 |
| 2006 | 95 | 95 | 95 | 95 | 95 |
| 2007 | 90 | 90 | 90 | 90 | 90 |
| 2008 | 85 | 85 | 85 | 85 | 85 |
| 2009 | 80 | 80 | 80 | 80 | 80 |
| 2010 | 75 | 75 | 75 | 75 | 75 |

**Figure 7** Comparison of actual to predicted reliability

**Table 4** System failure criticality 2010-2015

| System failure criticality 2010 | System failure criticality 2015 |
|--------------------------------|--------------------------------|
| System                         | Criticality                    | System                         | Criticality |
| Water walls                    | 31.0%                          | Superheater                    | 44.5%       |
| Superheater                    | 22.3%                          | Water walls                    | 29.0%       |
| Boiler other                   | 9.8%                           | Boiler other                   | 5.4%        |
| Generator                      | 6.3%                           | Boiler circ pumps              | 3.2%        |
| Boiler circ pumps              | 5.6%                           | Generator                      | 2.4%        |
| Turbine—HP/IP                  | 4.6%                           | Turbine RHT stop valves        | 2.3%        |
| Economizer                     | 4.2%                           | Economizer                     | 2.3%        |
| Reheat stop valves             | 3.9%                           | Turbine—HP/IP                  | 2.2%        |
| Turbine—LP 1                   | 1.8%                           | Air heater A                   | 1.8%        |
| Transformer                    | 1.34%                          | Air heater B                   | 1.4%        |
| Balance of plant               | 9.2%                           | Balance of plant               | 5.5%        |
The 2010 results agreed with what the utility knew, and the utility was already planning to replace the problematic Water Walls in their 2015 outage. However, the simulation results for 2015 showed that the criticality of the superheater would change with time. In 2015 Superheater would contribute to 43.5% of the total shutdown events compared to 22.3% in 2010, surpassing the Water Wall failure, as shown in Table 4. Besides, the RF of 0.37 suggested that the repairs are only 37% successful in restoring the superheater to the as-good-as-new condition. The analysis also showed that the number of events and the duration of each event would increase over time, indicating a possible creep problem. Further metallurgical evaluations by the plant confirmed this finding.

An economic analysis conducted, using the results, showed that the revenue loss would be $22M due to superheater related shutdowns alone between 2010 and 2015. Based on these results, the utility decided to move the outage from 2015 to 2012 and replace the Superheater tubes.

Now equipped with the models, the utility performed a what-if analysis to determine what actions had to be taken during a major outage to restore the unit reliability to 95%. The what-if analysis showed that replacing the superheater would improve the unit reliability from 73.5% to 86% but would not meet the utility's corporate reliability objective of 95%. In addition to replacing the Superheater tubes, the Water Wall problem must be corrected to achieve the organizational goals.

Further analysis performed on the Water Walls showed that most of the Water Wall failures were localized only in the 10 tubes at the four corners of the boiler. The utility determined these tubes could be replaced during a short outage. With both conditions corrected, the what-if analysis predicted the unit reliability would improve to 96%.

3.1 | Lessons learned

Lessons learned from the beta test are:

- The model predictions matched the actual values very closely.
- A unit performance can be accurately predicted by careful selection of data, modeling and analyzing the output.
- Risk ranking allows for identifying the equipment or system that is affecting the overall performance.
- Identifying the changes in risk ranking allows for making informed decisions for repair or replacements in the future.
- What if scenarios provide the impact of decisions on the overall performance so engineers can select a prudent decision to achieve the corporate objectives.
- The RF provides the effectiveness of the repairs and identification of possible failure modes.

4 | SUMMARY

PRA-based maintenance planning and budgeting are not usually practiced in Fossil Power plants. The engineers frequently depend on their engineering judgment for developing maintenance and repair plans, and budgets. Fossil plants consist of many equipment and complex systems. Generalized reliability models may not adequately and accurately predict the reliability and availability. Specialized statistical methods are required to evaluate these complex systems. Deterministic methods and models use general industry data, but they do not allow for performing maintainability analysis and cost analysis. Studies have shown that using field data provides a robust model with results for a specific system or unit. A process was developed using the NHPP model to evaluate the reliability of fossil power plants. The proposed process uses limited field data and Monte Carlo simulations for projecting equipment reliability, the number of failures, shutdown time, and cost of repairs. This process is tried at several power plants, and the results validated with the actual values. The power plant engineers can use the process and procedure to develop fact-based budgets proactively and in making equipment replacement or repair decisions.

PEER REVIEW INFORMATION

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CONFLICT OF INTEREST

The authors declare no potential conflict of interest.
AUTHOR CONTRIBUTIONS

Satyanarayana Palakodeti: Data curation; formal analysis; methodology; validation; visualization; writing-original draft; writing-review and editing. P.K. Raju: Formal analysis; methodology; supervision; validation; writing-review and editing. Huairui Guo: Data curation; formal analysis; validation; visualization; writing-review and editing.

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REFERENCES

1. Wang W, Loman JM, Arno RG, Vassiliou P, Furlong ER, Ogden D. Reliability block diagram simulation techniques applied to IEEE Std. 493. IEEE Indus Appl. 2004;40:887-895.
2. El-Metwally M, et al. Reliability assessment of wind turbine operating concepts using reliability block diagrams (RBDs). Paper presented at: Nineteenth International Middle East Power Systems Conference (MEPCON); 19–21 December 2017; Cairo, Egypt.
3. Duquian A. Average age of US power plant fleet flat for 4th-straight year in 2018. Stand Poor Market Intell. & P market research report. New York, NY: Standard & Poor; 2019. https://www.spglobal.com/marketintelligence/en/news-insights/trending/gfjeFt8GTPYNK4WX57z9g2.
4. A-Shaalan AM. Reliability evaluation of power systems. In: Kounis DLD, ed. Reliability and Maintenance—An Overview of Cases. London, UK: Intechopen Ltd.; 2019:1-25.
5. Valdma M, KEEL M, TAMMOJA H, KILK K. Reliability of electric power generation in power systems with thermal and wind power plants. Oil Shale. 2007;24(2):197.
6. Palakodeti SR, Goebel DJ. Research on reliability assessment of mechanical equipment based on the performance–feature model. Appl Sci MDPI. 2018;8(9):1619.
7. Singh V, Rakesh K, Israr M. Comparison of Duane Growth Model & Crow Amsaa Model. Int J Adv Res Innov Ideas Educ. 2016;2(1):535–551.
8. Palakodeti SR. Reliability assessment in asset management—an utility perspective. Paper presented at: Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015); 2016.
9. Kaminskiy MP, et al. G1-Renewal_Process_as_Repairable_System_Model. [Online]. https://www.researchgate.net//publication/45924573. Accessed November 2019.
10. Wels HC. Data collection and reliability analysis of power plants in The Netherlands. Nuclear Research Consult Group NRG Report. Petten, Netherlands: Nuclear Research & Consultancy Group NRG; 2003. ftp://ftp.nrg.eu/pub/www/nrg/riskman/faildatacollection.pdf.
11. American Petroleum Institute, (API). Calculation of Heater Tube Thickness in Petroleum Refineries. Washington DC: American Petroleum Institute (API); 2003.
12. Zio E, Patelli E. A power-flow emulator approach for resilience assessment of repairable power grids subject to weather-induced failures and data deficiency. Appl Energy. 2018;210:339-350.
13. Calixto E. Gas and Oil Reliability Engineering, Modeling and Analysis. Oxford, UK: Gulf Professional Publishing; 2016 pp. 7, 8, 473.
14. Institute for Healthcare Improvement, Failure Modes and Effects Analysis (FMEA) Tool. Boston, MA: Institute for Health Care Improvement (IHI); 2017. http://www.ihi.org/resources/Pages/Tools/FailureModesandEffectsAnalysisTool.aspx.
APPENDIX A

Calculation of system reliability from component and subsystem reliability.

A system reliability can be calculated from the component reliabilities using RBDs.32 The key for developing the system reliability is first developing a mathematical description for the entire system. The reliability function of the system is basically that probabilistic mathematical description and describes the system reliability in terms of component reliabilities. The resulting reliability of the system is a function of time based on individual components reliability functions.

The failure probability distribution of each component in the system is developed from the failure data. These components are then arranged in an RBD reliabilitywise in series and parallel configurations. The system RBD can be reduced to a simple system and analyzed using formulae for series and parallel configurations. An example of a simple system is illustrated below.

In Figure A1, a simple system is shown with equipment connected in parallel and series configuration with two subsystems.

\[
R_S = R_1 \times R_A \times R_B \times R_7. \\
R_A = [1 - (1 - R_2) (1 - R_3) (1 - R_4)]. \\
R_B = [1 - (1 - R_5) (1 - R_6)].
\]

where,

\( R_S \) = Reliability of the system.
\( R_A, R_B \) = Reliability of subsystems A and B respectively.
\( R_{1,2,3,...} \) = Reliability of components.

**Figure A1** RBD of a simple system
It is easy to calculate the system reliability for simple systems and where the uncertainty in the input data is nonexistent or for deterministic models. When the system becomes complicated with many components and where uncertainty exists, Monte Carlo simulation is employed.\textsuperscript{33} Many computer software packages, such as BlockSim, GoldSim, Crystal Ball, MatLab, TRYDYN, and so on, are available to perform sophisticated Monte Carlo simulations.

As mentioned earlier, power plants are very complex systems, and there is much uncertainty in the failure data. The failure interval is not constant as the age of the components is different, and each component is subjected to different stress levels due to varying power demand, cycling, and redundancy of the equipment. Hence a failure distribution is developed for each component, and the final system reliability is calculated using Monte Carlo simulation.

Monte Carlo simulation is a method to evaluate deterministic models, iteratively, using random numbers as inputs. To perform a Monte Carlo simulation, random inputs, in this case, Reliability, for each component is developed based on the individual failure distributions, and an algorithm is developed for the system reliability, as shown in the example above. The deterministic model is then run multiple times to generate the output, which can be a distribution, histogram, or any other specified by the user.