Basic factors to forecast maintenance cost and failure processes for nuclear power plants

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Abstract

Two types of maintenance interventions are usually administered at nuclear power plants: planned and corrective. The cost incurred includes the labor (manpower) cost, cost for new parts, or emergency order of expensive items. At the plant management level there is a budgeted amount of money to be spent every year for such operations. It is very important to have a good forecast for this cost since unexpected events can trigger it to a very high level. In this research we present a statistical factor model to forecast the maintenance cost for the incoming month. One of the factors is the expected number of unplanned (due to failure) maintenance interventions. We introduce a Bayesian model for the failure rate of the equipment, which is input to the cost forecasting model. The importance of equipment reliability and prediction in the commercial nuclear power plant is presented along with applicable governmental and industry organization requirements. A detailed statistical analysis is performed on a set of maintenance cost and failure data gathered at the South Texas Project Nuclear Operating Company (STPNOC) in Bay City, Texas, USA.

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1. Data description

There are several data sets relevant to this analysis that are populated and updated on a regular basis at South Texas Project Nuclear Operating Company (STPNOC): failure times, repair costs, equipment downtime, individual items' characteristics, total persons required for each repair, qualification of repair personnel. In addition, effects on the plant for each failure is maintained along with plant downtime power level required during repair, total production loss (in terms of megawatt-hours), and type of plant operation required in response to a failure (trip, power reduction, controlled shutdown).

Each individual piece of equipment can have several failure modes. The total number of the item-failure mode combinations is more than 46,000. As part of this study, a procedure that extracts the time of failure for each item-failure mode combination and computes the time between failures was constructed. The repair cost, including labor, is recorded for each item-failure mode combination. A detailed description of all the procedures necessary to construct these data sets can be found in Yu et al. (2004).

Any South Texas Project (STP) equipment events, including the corrective and preventive maintenance discussed above, that are of interest to the responsible engineer are kept in a database. The database is used for trending system and system component future events, future event intensity, and future downtime accumulation. The associated cumulative event downtime is also recorded for certain equipment and systems. Equipment-related events that would not necessarily be part of a classical failure trending database (for example those resulting from operator error or corrective action by the Regulator for added safety margin assurance) are also kept in a database of the cumulative number of events and the associated cumulative time to each occurrence.

2. Bayesian modeling of the failure times

The main difference between the parametrical classical statistics and Bayesian estimation is the assumption about the parameters of the proposed distribution. The classical approach assumes
The exponential assumption at a local level implies a constant failure rate for a given time interval. In this research we first tested the validity of this assumption by running a goodness-of-fit test on several groups of failure data. Using the first dataset we constructed 145 homogeneous groups. The results presented for most of the groups.

2.1. Goodness-of-fit test for Weibull lifetime distribution

The exponential assumption at a local level implies a constant failure rate for a given time interval. In this research we first tested the validity of this assumption by running a goodness-of-fit test on several groups of failure data. Using the first dataset we constructed 145 homogeneous groups. The results presented for most of the groups.

We analyze two cases:

Case 1. We fix $\beta$ at a sample point from the Uniform (0.2, 0.9) distribution based on empirical analysis. $\lambda$ has gamma prior distribution with hyper-parameters $a_0, b_0$ and density function

$$g(\lambda; a_0, b_0) = \left[ \Gamma(a_0) \right]^{-1} \lambda^{a_0-1} e^{-\lambda/b_0}. \quad (2)$$

We use the generic information (lognormal prior for $\lambda$) to assess the values of $a_0$ and $b_0$. First we calculate the mean and variance for the lognormal distribution with parameters:

$$M = \ln M_e - \frac{S^2}{2}, \quad (3)$$

$$S^2 = \left( \frac{\ln \text{EF}}{1.645} \right)^2 \quad (4)$$

where $M_e$ is the mean and $\text{EF}$ is the error factor as derived in Blanchard (1993). Then we compute the parameters of the

<table>
<thead>
<tr>
<th>Group</th>
<th>Mean</th>
<th>S.D.</th>
<th>Kurtosis</th>
</tr>
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<td>1</td>
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<td>17.31</td>
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<td>58.84</td>
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<tr>
<td>11</td>
<td>19.00</td>
<td>26.13</td>
<td>1.86</td>
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</table>

| Group Mean S.D. Skewness Kurtosis |
|----------------------------------|------------------|------------------|------------------|
| 1 | 19.67 | 32.71 | 2.75 | 8.40 |
| 2 | 17.31 | 17.41 | 2.77 | 9.28 |
| 3 | 41.25 | 55.82 | 2.20 | 5.29 |
| 4 | 150.38| 189.61| 1.51 | 1.28 |
| 5 | 117.65| 124.58| 2.76 | 9.91 |
| 6 | 49.86 | 22.58| 0.69 | 0.57 |
| 7 | 10.05 | 10.80| 2.84 | 10.46|
| 8 | 217.79| 603.46| 3.47 | 12.49|
| 9 | 18.28 | 17.36| 2.07 | 5.07 |
| 10| 58.84 | 61.68| 0.24 | 2.17 |
| 11| 19.00 | 26.13| 1.86 | 2.40 |

2.2. Bayesian model and computational algorithm

Here we present a Bayesian model for the failure times assuming that the lifetime distribution is Weibull with random parameters $\lambda$ and $\beta$ with two sets of prior distributions (defined below).

The sampling plan is as follows: if we have $n$ items under observation, $s$ of which have failed at ordered times $T_1, T_2, \ldots, T_s$, then $n-s$ have operated without failing. If there are no withdrawals then the total time on test is: $\sum = nT^\ast$, which is also the sufficient statistic for estimating $\lambda$ (also known as the rescaled total time on test).

We analyze two cases:

Table 2 shows the results (p-value) from the Kolmogorov-Smirnov goodness-of-fit test performed on the same set of data. To conclude that the Weibull distribution is a good fit, we need high p-value (usually more than 0.5). We see that this is the case for most of the groups.

<table>
<thead>
<tr>
<th>Group</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
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<td>p-value</td>
<td>0.69</td>
<td>0.51</td>
<td>0.99</td>
<td>0.15</td>
<td>0.39</td>
<td>0.82</td>
<td>0.59</td>
<td>0.34</td>
<td>0.54</td>
<td>0.06</td>
<td>0.45</td>
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</table>
The choice of the hyper-parameters values is not random. We used the values given in the DOE database (see Blanchard, 1993) for calculations. The corresponding results for this set of prior distribution parameters are shown in Table 3.

Table 3 Bayesian point estimates of the failure rates for Case 1

<table>
<thead>
<tr>
<th>Group code</th>
<th>$E[\lambda[z]]$</th>
<th>$E[\beta[z]]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>AON-LE-C</td>
<td>2.49E-05</td>
<td>1.13E-05</td>
</tr>
<tr>
<td>TKP-LE-C</td>
<td>3.71E-07</td>
<td>6.63E-07</td>
</tr>
<tr>
<td>XM-MLE-W</td>
<td>4.97E-06</td>
<td>5.58E-07</td>
</tr>
</tbody>
</table>

The posterior mean of $\lambda$ given the observed failure data $z$ is (see Martz and Waller, 1982):

$$E[\lambda|z, \alpha_0, \beta_0] = \frac{\alpha_0}{\alpha_0 + 1}.$$

We use this prior information and the current specific data to get the posterior distribution for $\lambda$. The posterior mean of $\lambda$ given the observed failure data $z$ is (see Martz and Waller, 1982):

$$E[\lambda|z, \alpha_0, \beta_0] = \frac{\alpha_0}{\alpha_0 + 1}.$$

Table 3 shows the Bayesian point estimates of the failure rates for selected six groups of data.

Case 2. Inverted gamma prior distribution on $\theta = 1/\lambda$, uniform prior distribution on $\beta$. Assume that $\theta$ has an inverted gamma prior distribution with hyper-parameters $\alpha_0, \beta_0$ and $\beta$ has a uniform prior distribution with hyper-parameters $\alpha_0, \beta_0$. We will follow the development from Martz and Waller (1982). The posterior expectations of $\lambda$ and $\beta$ are:

$$E[\theta|z] = \frac{J_2}{(s + 10)J_1}$$

$$E[\beta|z] = \frac{J_1}{J_1}$$

where $s$ is a summary of the sample evidence, $v = \sum_{i=1}^{n} T_i$, $\alpha_0 = nT_0 + \mu_0$, $\beta_0 = \frac{1}{2} \int_{\alpha_0}^{\infty} \frac{e^{-\alpha_0 t}}{t^{3/2}} dt$, $J_2 = \int_{\alpha_0}^{\infty} \frac{e^{-\alpha_0 t}}{t^{3/2}} dt$, and $J_1 = \int_{\alpha_0}^{\infty} \frac{e^{-\alpha_0 t}}{t^{3/2}} dt$.

The integrals do not have a closed form solution and thus the Bayesian estimates must be computed by numerical integration techniques. The corresponding results for this set of prior distributions are given in Table 4.

The choice of the hyper-parameters values is not random. We used the values given in the DOE database (see Blanchard, 1993) for the values of the inverted gamma parameters, and empirically assessed the parameters of the uniform prior distribution (see Yu et al., 2004).

3. Reliability growth modeling and analysis

Obtaining and processing data to calculate and trend the reliability of certain equipment is important at STP. Abernethy (2000) found that the Crow-AMSAA (CA) reliability growth model allows for "dirty" data since it models the process, not the system. He also found that CA allows for small data sets, missing data, and mixed failure modes. The Duane-AMSAA model was first developed by James T. Duane at General Electric (see Duane, 1964).

Larry Crow from the Army Material Systems Analysis 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; Brown et al., 2000). For that reason, CA is sometimes referred to as a "Weibull Power Process."

3.1. Crow-AMSAA calculation

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

For RGR, $\lambda$, the $\lambda$-intercept or scale parameter, and $\beta$, the slope parameter, are solved using the following equations:

$$\beta = \ln \left( \frac{n \sum_{i=1}^{n} t_i - \sum_{i=1}^{n} n(t) \sum_{i=1}^{n} t_i}{n \sum_{i=1}^{n} (t_i^2 - \sum_{i=1}^{n} t_i^2)} \right)$$

$$\lambda = \ln \left( \frac{\sum_{i=1}^{n} n(t) - n(t)}{n} \right).$$

where $n$ is the total number of events, $t$ the cumulative time, and $n(t)$ is the cumulative number of events at time $t$.

For MLE, the estimated values for $\lambda$ and $\beta$ are obtained by solving the system of equations:

- For failure terminated tests ($n$ is the total number of failures):

$$\lambda = \frac{n}{\ln \left( \frac{n}{\ln \left( \frac{\sum_{i=1}^{n} n(t) - n(t)}{n} \right)} \right)}$$

- For time ($T$) terminated tests:

$$\lambda = \frac{n}{\ln \left( \frac{\sum_{i=1}^{n} n(t) - n(t)}{n} \right)}$$

The equation of the line can be defined by:

$$n(t) = \ln \lambda + \beta \ln t.$$
Knowing the $\lambda$ and $\beta$ values, the instantaneous ($\rho(t)$) and cumulative ($C(t)$) failure rate can be obtained from:

$$\rho(t) = e^{-1}\beta \lambda$$  \hspace{1cm} (17) \\

$$C(t) = e^{-1}\beta \lambda t$$  \hspace{1cm} (18)

For the purpose of performance monitoring from the perspective of STP plant management, the NRC, and industry standards bodies (see NEL, 1996; Kee, 1996; INPO, 2005), the failure mechanism leading to equipment or system unreliability is not as important as the unreliability itself. For example, the Nuclear Regulatory Commission maintenance rule (see NRC, 2005) has a performance measure based on functional failure, a failure to support a process need (flow of fluid, start of a standby equipment, provide electrical power, and so forth), not a failure mechanism (fatigue failure, overload, stress corrosion cracking, and so forth). Additionally, identifying all failure mechanisms is not reasonable for a typical plant system that incorporates several different types of equipment even though performance indicators will many times be related to system performance.

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 this paper 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.

3.2. 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 forecast. Forecasting would be affected by calculating the expected number of future events, $n$, given the existing policy derived from Eq. (11):

$$n = \frac{t^{\beta}}{\lambda}$$  \hspace{1cm} (19)

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

$$\Delta N = n - \text{actual number of failures}$$  \hspace{1cm} (20)

Fig. 1 illustrates a phenomenon in the rod control system (RS) called incomplete rod insertion (IRI) which was experienced at STP. 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.

Knowing the net cash flow (CF) and discount rate (DR) associated with each event (in this case, primarily revenue loss) the net present value (NPV,) 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:

$$\text{NPV}_c = \lambda \text{CF} - \sum \left( \frac{(t_i - t_0)^{\beta}}{(1 + \text{DR})^{t_i}} - \frac{(t_{i+1} - t_0)^{\beta}}{(1 + \text{DR})^{t_{i+1}}} \right)$$  \hspace{1cm} (21)

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:

$$\text{NPV}_n = \lambda \text{CF} - \sum \left( \frac{(t_i - t_0)^{\beta}}{(1 + \text{DR})^{t_i}} - \frac{(t_{i+1} - t_0)^{\beta}}{(1 + \text{DR})^{t_{i+1}}} \right)$$  \hspace{1cm} (22)

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

In the IRI case, NPV, (in 1998 dollars) based on an average cost per event of $1,455,951 to year 2006 is estimated at roughly $30,000,000. On the other hand, NPV, to year 2006 is estimated at roughly $3,000,000. Therefore, introducing the new maintenance policy (new, robust fuel design) decreases expected maintenance cost for IRI by roughly $27,000,000.

3.3. 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 condenser air removal system (CARS) pumps as shown in Fig. 2.

Until September 2003, the six CARS pumps at STP had been failing with a failure rate decreasing with time. This is obvious because the $\beta$ value is less than one. After September 2003, the failure rate started increasing with time shown with a $\beta$ value greater than one. Around September 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 June 2004, and monthly overhauls were implemented until the modification for the drain installation was in place, resulting in failure rate decrease.

This information is also used to identify when a component’s failures are increasing with time. When the $\beta$ value is greater than one, it alerts the engineer to look through the failures to see if a particular failure mode or mechanism is causing the increase in failures. Increasing failure rate may be in...
dicative of infant mortality or end of life failures for life cycle management.

3.4. Maintenance unavailability

Maintenance unavailability for equipment important to production can be monitored using CA by looking at cumulative unavailability hours. Maintenance unavailability is especially 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 Fig. 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 ($\beta < 1$).

The new maintenance policy would produce improved hydraulic pump availability (depending on revisions, if applicable, to the preventive maintenance schedule). $A = \mu/(\mu + \lambda)$, 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 Fig. 4. As shown in the figure, a line of constant availability representing a desired availability limit can be drawn on a failure rate–repair rate phase plane. Plotting predictions of the rates (for example, over the next 4 years) helps show if the limit would be predicted to be violated (or met) thereby providing adequate warning if corrective action is required to maintain the system’s availability target.

4. Maintenance cost modeling, analysis, and forecasting

One of the tasks that a system’s engineer has to perform on a regular basis is to assess and, if necessary, recommend a better maintenance schedule for a given item or a system. An important part of this process is to include the proper cost for buying new parts, labor cost, etc. In what follows we present a new model to forecast the maintenance cost that involves several variables that account for frequency of failures, the item’s importance and risk characteristics, among others. In this analysis we include two additional databases, one contains the historical cost for maintenance, and the second one the specific (coded) characteristics of each item. The goal is to construct a model that explains the variability of the total repair cost (TRC) and use it to produce future forecasts.

Table 5 gives a detailed description of all the variables used in the subsequent models.

We have the historical records from 1987 to 2004 for the total cost of repair for each component. The first model (MODEL 1)}
The coefficient between TRC and RF is relatively high in Table 6. The correlation analysis shows that the correlation of TRC with RF is 0.72, indicating a strong positive relationship. Other factors that may affect the total cost include PGI, FRR, SC, ARF, and AVF. These factors are used as independent variables in the regression model.

The resulting model is:

\[ \text{TRC} = 5752.7 + 703.7RF + 4268 \text{PGI} - 549.3 \text{FRR} + 26495 \text{ERF} - 4268 \text{SC} \]

This model also shows high correlation among several of the explanatory variables. As a third model, we explore a step-wise regression between the TRC and the rest of the variables. The variables that get selected by the procedure are RF, PGI, FRR, ERF, and QR. The resulting model is:

\[ \text{TRC} = -1517.97 + 686.63RF + 11843 \text{PGI} + 5491.3 \text{FRR} + 26495 \text{ERF} - 4268 \text{SC} \]

This model also tests the linearity, independence, homoscedasticity, normality and collinearity assumptions. All of these assumptions are confirmed with one exception, the constant variance (homoscedasticity).

### Table 6

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRC</td>
<td>The sum of the maintenance labor and parts costs recorded with a work order</td>
</tr>
<tr>
<td>RF</td>
<td>The number of repairs that have been recorded for a particular piece of equipment</td>
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<tr>
<td>PGI</td>
<td>A code to indicate the equipment’s level of risk (due to failure) to core damage frequency</td>
</tr>
<tr>
<td>FRR</td>
<td>A code to indicate the equipment’s level of risk (due to failure) to loss of electrical generation</td>
</tr>
<tr>
<td>SC</td>
<td>A code to indicate if the equipment is used in fire protection required for safe shutdown of the plant</td>
</tr>
<tr>
<td>ARF</td>
<td>A code to indicate if the equipment is designed to withstand hypothesized earthquakes</td>
</tr>
<tr>
<td>AVF</td>
<td>A code that indicates the type of the American Society of Engineers code that applies to the equipment</td>
</tr>
</tbody>
</table>

### Table 7

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>QR</td>
<td>A code indicating the quality assurance/quality control code that applies to the equipment</td>
</tr>
<tr>
<td>EQ</td>
<td>A code to indicate if the equipment is designed to withstand hypothesized earthquakes</td>
</tr>
<tr>
<td>T</td>
<td>A code to indicate if the equipment is used in fire protection required for safe shutdown of the plant</td>
</tr>
<tr>
<td>PGI</td>
<td>A code to indicate the equipment’s level of risk (due to failure) to loss of electrical generation</td>
</tr>
<tr>
<td>FRR</td>
<td>A code to indicate the equipment’s level of risk (due to failure) to core damage frequency</td>
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</tr>
<tr>
<td>ARF</td>
<td>A code to indicate if the equipment is used in fire protection required for safe shutdown of the plant</td>
</tr>
<tr>
<td>AVF</td>
<td>A code that indicates the type (if any) of the American Society of Engineers code that applies to the equipment</td>
</tr>
</tbody>
</table>

### Table A.1

The resulting residual plot looks better than the first one but it is still not satisfactory. We could improve the fit by investigating other factors that may affect the total cost. First, we change some qualitative variables to nominal scaled variables and test the correlation among them. The multi-correlation matrix is given in Table 6. The correlation analysis shows that the correlation coefficient between TRC and RF is relatively high (0.72). It also shows high correlation among several of the explanatory variables.
The last model we explore is the one based on principle component analysis to reduce the number of variables, by including the most of the original variables. Another advantage is that after obtaining the principal components, all the principal components are uncorrelated. We select three principal components that explain 67.53% of the total variance. Table 7 shows the composition of each of the selected three principle components.

Next we perform factor analysis and use the factors defined in Table 7 as explanatory variables and TRC as dependent variable in a regression model. Table 8 shows the resulting model and the associated statistical characteristics.

## 5. Conclusion

The paper describes the development and implementation of a Bayesian Weibull lifetime distribution model. A sequence of statistical models are defined and tested to establish the best forecasting model for the cost for maintenance. The study shows that the combination of principle components analysis and factor regression gives the best model that explains most of the variability of the maintenance cost and has very satisfactory statistical characteristics.

The Crow-AMSAA method has been described along with its applications at STP. 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 are 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.

### Acknowledgments

This research has been partially supported by NSF grant #DMI-0457558 and STPNOC grant #B0285 \( ^{5} \).

### References


Savannah River Site, Aiken, South Carolina 29808.


### Table 8

Factor analysis estimates of the selected principle components

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>t-statistics</th>
<th>p-value</th>
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</thead>
<tbody>
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<td>Intercept</td>
<td>14471.00</td>
<td>16.84</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Factor1</td>
<td>4753.50</td>
<td>5.53</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Factor2</td>
<td>31930.50</td>
<td>37.15</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Factor3</td>
<td>21337.50</td>
<td>24.53</td>
<td>&lt; 0.0001</td>
</tr>
</tbody>
</table>

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