A METHOD TO QUANTIFY PLANT AVAILABILITY AND INITIATING EVENT FREQUENCY USING A LARGE EVENT TREE, SMALL FAULT TREE MODEL

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ABSTRACT
South Texas Project uses a large fault tree to produce scenarios (minimal cut sets) used in quantification of plant availability and event frequency predictions. On the other hand, the South Texas Project probabilistic risk assessment model uses a large event tree, small fault tree for quantifying core damage and radioactive release frequency predictions. The South Texas Project is converting its availability and event frequency model to use a large event tree, small fault tree in an effort to streamline application support and to provide additional detail in results. The availability and event frequency model as well as the applications it supports (maintenance and operational risk management, system engineering health assessment, preventive maintenance optimization, and RIAM) are briefly described. A methodology to perform availability modeling in a large event tree, small fault tree framework is described in detail. How the methodology can be used to support the South Texas Project maintenance and operations risk management is described in detail. Differences with other fault tree methods and other recently proposed methods are discussed in detail. While the methods described are novel to the South Texas Project Risk Management program and to large event tree, small fault tree models, concepts in the area of application support and availability modeling have wider applicability to the industry.

NOMENCLATURE
A  Availability (-).
BOP  Balance of plant.
CDF  Core damage frequency.
D  Scenario total average duration per calendar year (hr).
E  Exposure to failure over a calendar year (hr).
EXMFW  Excessive Main Feed Water initiating event.
F  Frequency (hr⁻¹).
GRA  Generation Risk Assessment.
I  Scenario impact (-).
LCV  Loss of Condenser Vacuum initiating event.
LERF  Large early release frequency.
LOIA  Loss of Instrument Air initiating event.
LOMT  Loss of Main Transformer initiating event.
LOPF  Partial Loss of Flow initiating event.
PLMFW  Partial Loss of Main Feed Water initiating event.
PRA  Probabilistic Risk Assessment.
PWR  Pressurized Water Reactor.

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STP  South Texas Project.
T  Repair time or repair duration (hr).
TLFW  Total Loss of Feed Water initiating event.
TTRIP  Turbine Trip initiating event.
U  Unavailability (-).
X,Y  Event, equipment failure mode.
λ  Failure rate over demand \( (\text{demand}^{-1}) \).
\( \lambda_d \)  Failure rate over time \( (\text{hr}^{-1}) \).

INTRODUCTION AND BACKGROUND

The South Texas Project (STP) plant site in Bay City, Texas, operated by the South Texas Project Nuclear Operating Company (STPNOC), generates about 2500 MW of commercial electrical power sold on the Texas power grid, ERCOT. Two identical, Westinghouse-designed, pressurized water reactor (PWR) nuclear power plants at the STP plant site went on line for commercial operation in 1988 (Unit 1) and 1989 (Unit 2). Since shortly after startup of the two plants, we have been working to improve the quality, accuracy, usefulness, and scope of plant risk models as well as their applications to various aspects of STP risk estimation.

Although we have continually reduced resources and staff, we have successfully increased risk modeling scope and quality using modeling technology to simplify and streamline our methods and model maintenance. In the following, we discuss such a recent streamlining effort. We are merging the models for core damage risk (expressed as core damage frequency, “CDF” and large early release frequency, “LERF”), electrical production risk, and initiating event (IE) frequency onto a single application platform which uses large event tree, small fault tree logic to develop scenarios of STP production loss events.

The electrical production risk, and initiating event (IE) frequency part of the model is currently being converted to the RiskMan software. RiskMan has the capability to convert system cutsets (probabilities) into scenarios (frequencies). An enhancement to the RiskMan software is planned for next year which will allow component-specific repair times. Also, RiskMan has the capability of solving fault trees using Binary Decision Diagrams, which enables the electrical production risk, and initiating event (IE) frequency model to be solved as a large event tree or large fault tree when it is incorporated into the CDF and LERF model (a large event tree, small fault tree model).

Risk Models

Since very early in the initial operation of Units 1 and 2, we have been developing and applying the STP Probabilistic Risk Assessment (PRA) Model in the STP Comprehensive Risk Management Program [1] and the STP Maintenance Management Program [2]. The basic model framework of the STP PRA is a large event tree, small fault tree logic model [3] of equipment important to preventing and mitigating core damage. Consistent with the modeling framework initially used in the US Nuclear Regulatory Commission landmark study, WASH-1400 [4], the STP PRA excludes implicit calculation of availability. Instead, the PRA models the frequency of the rare events, CDF and LERF.

Beyond “PRA”

Using the PRA, we initially evaluated the effect of (primarily) engineered safety features (ESF) standby equipment unavailability on CDF. However, by the late 1990’s we began to study the effect of on-line maintenance on the frequencies of IEs originating in the secondary plant. Our models showed that secondary plant maintenance policy (equipment unavailability and maintenance strategy) does have a strong effect on secondary plant IE frequencies. On the other hand, industry practice used average IE frequency values (that is, ignoring the effect of on-line maintenance). We then sought to do better in this area.

We developed a new model [5] of the balance of plant (BOP) capable of estimating the effect of BOP maintenance configuration on IE frequency. The model assumes that scenarios start when the plant is at 100% power. The model can be used to quantify the effect of BOP online maintenance policy on CDF from 100% power by estimating IE frequencies contributing to CDF given different maintenance configurations.

Event Frequency and Availability Model Overview

Our BOP Model satisfies two primary objectives: more detailed models of the contribution that BOP systems make to the initiation of accident sequences at STP; and inclusion of production issues in the risk management program scope. Using standard fault tree modeling techniques, we constructed a
logic model of scenarios based on a large fault tree in the SAPHIRE [10] software application. The fault tree was organized around BOP systems analyzed to have a significant impact on production [5].

Accurate estimates of the parameters of interest in the current scope of our BOP Model require analysis of three types of production loss scenarios; plant trips, manual plant shutdowns, and reduced power operations from the plant systems: Main Feed water; Condensate; Circulating Water; Open Loop Auxiliary Cooling; Main Steam; Main Turbine; Main Generator; Closed Loop Cooling Water; Instrument Air; Electro-Hydraulic Control; Iso-Phase Bus Duct Cooling; and Electric Power. The plant trips in the model are also IEs in the PRA.

Eight IE frequencies (plant trips) important to CDF in the STP PRA are estimated: Total Loss of Main Feedwater (TLMFW); Partial Loss of Main Feedwater (PLMFW); Excessive Main Feedwater (EXMFW); Loss of Main Transformer (LOMT); Loss of Condenser Vacuum (LCV); Partial Loss of Flow (LOPF); Loss of Instrument Air (LOIA); and Turbine Trip (TTRIP). In addition to the eight IEs important to CDF, the BOP model estimates frequencies of several power derate scenarios.

The STP BOP Model fault tree is developed and solved in the software application, SAPHIRE. The individual system fault trees are approximations to Markov models as described in Reference [11]. Figure 1 is a reliability block diagram of a two component system in which both components are normally running. Figure 2 shows a fault tree (sans common cause considerations) for determining an initiating event frequency for the system. The notion is extended for systems with more than two operating components required to fail the system. In such cases it is assumed that the component with the quickest repair time is used. The cut sets of the fault tree solution are expanded into scenarios, the scenario frequencies are quantified, and the plant performance parameters are calculated. Quantification of the baseline reliability model produces the average frequencies for the modeled IEs and the total average trip frequency. Minimal cut sets from the SAPHIRE solution are quantified initially in the software application, PlantForma [12] and later in the BOPPP software application [13].

Fault tree construction.

The plant systems we included in the model are combined into a large “OR” gate conceptually illustrated in Figure 4 to obtain all scenarios that result in a loss of production. Specific scenarios included are those that lead to a plant trip, a manual plant shutdown, or a reduced power operation state. For each plant system modeled, the associated scenarios are kept in the system fault trees. To identify the impact of the scenario, each of them is “flagged” with a house event (for example, \( C_b \) and \( R_b \)) as shown in Figure 3 so that the scenario impact (plant trip, manual plant shutdown, etc.) is kept with the fault tree solution (minimal cut sets). Beyond identifying the scenario impact, the flags also serve to preserve all scenarios within a system. The solution to the system fault tree shown in Figure 3 is summarized in Table 1. In the example, the flag, \( R_b \), might represent a 50% power scenario and the flag \( C_b \) might represent a plant trip. Note that under the scheme we are using, the flags result in the retention of cut set number 3 because without them it would not be part of the (minimal) solution.

<table>
<thead>
<tr>
<th>Cut Set Number</th>
<th>Cut set</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>( R_b, U_l )</td>
</tr>
<tr>
<td>2</td>
<td>( R_b, A_m )</td>
</tr>
<tr>
<td>3</td>
<td>( C_b, U_l, A_m )</td>
</tr>
</tbody>
</table>
Basic events

The basic events (in the example, $A_m$ and $U_t$, the leaves of the fault trees) actually represent frequency of a particular equipment failure mode and repair time for the failure mode. We create the fault tree in a fault tree solver with the only purpose to obtain minimal cutsets. We get all the minimal cutsets by setting the failure probability to 1.0 for all basic events and house events in the fault tree solver (and retain all the minimal cutsets regardless of the order). When the fault trees are solved for the cutsets, the basic events (as well as the house events) are recast into equations which can produce the impact and duration of an event.

Cutset Expansion

The cutsets from the fault tree solution contain the event impact in the house event “flags” as described above as well as the basic events representing equipment failure modes. Flag categories are the eight IEs already mentioned plus non-trip categories, manual shut down (MSD) and reduced power operation (RPO). In the RPO category, several levels of reduced power are included up to 50% power reduction. The frequencies and repair times for the various impacts modeled are gotten from solving the cutsets based on the failure experienced for the particular scenario represented by the cutset.

However, the cutsets can not be solved directly to obtain all the necessary information required for availability and frequency simulation. Instead, we use the information contained in the flags (representing categories of plant level effects resulting from the cutset in which they appear) in combination with the basic events in the cutset to solve for availability and frequency.

Planned outages

Because STP operates as a base load plant, the time spent in planned outages is relatively straightforward. The long term refueling schedule is set by the plant owners at generally the maximum allowed by the current agreement with the NRC. We know of planned plant level outage schedule and duration (generally the refueling schedule) to set the maximum possible plant availability. That is, if the time between, $T_O$, and duration of, $T_D$, planned outages is known, then it is relatively simple to get the fraction, $\phi$, of time spent in the outages:

$$\phi = \frac{T_O}{T_O + T_D}$$

Scenarios

The fraction of time that remains between planned outages is divided into the time the plant is on-line (available) and the time otherwise operating at less than full capacity. Availability is defined as the time the plant is connected to the electrical grid and producing net power. The capacity factor is defined as the fraction of power produced compared to the nameplate power.

The cutsets in the cutset expansion are enumerated with an identifier, $i$. For the IE and MSD impacts, the plant is unavailable (off the electrical grid). For the other impacts, the plant is available (on the grid) but not operating at full rated capacity but instead at a power level, $P$. To calculate plant availability, $A$, we are using the time between failures, $T_i$, and repair time, $M_i$, for the $i^{th}$ scenario as follows:

$$A = \phi \prod_i \frac{M_i}{T_i + M_i}.$$
The reduced impact to capacity factor in the reduced power scenarios (that is, scenarios for when the plant remains on-line), we included the power level impact, of the scenario (with the impact for the IE and MSD scenarios taken to be 0.0% power) to get the plant capacity factor, $CF$:

$$CF = \phi \prod_i \left(1.0 - P_i\right) \cdot M_i \left(\frac{T_i}{T_i + \left(1.0 - P_i\right) \cdot M_i}\right),$$

Data and data maintenance

Because we support performance monitoring, we keep the basic event failure rate and repair rate data up to date each month. We found that the best way to keep data up to date is by maintaining a default exposure database for all the basic events in the model. In this way, we only need to enter new failures every month (which are few) and then update the entire database using the default exposure time assigned to the applicable basic event.

STP plant-specific distributions were created using DOE distributions as priors then updating them with plant-specific failure histories and repair times. In general, we used two types of reliability data, (power) curtailing events and (power) non-curtailing events. Non-curtailing event data come primarily from the computerized work management system (CWMS). Curtailing event data primarily come from the plant process computer and the failure is assigned to the appropriate basic event. Historical non-curtailing reliability data for each basic event is obtained by querying the CWMS database (by equipment identification number, TPNS) and assigning the failure to the proper basic event. The equipment clearance order (ECO) duration is used for the equipment downtime. The source and data kept for each failure are summarized in Table 2.

The data are reviewed by hand to assign the failure mode and other data related to the maintenance activity. The types of data retrieved from the query are summarized in Table 1 separate worksheet and the total production loss is found by integrating the power history over the time of the event. A typical event worksheet is shown in Figure 10. Data assignment by the analyst is the most time-consuming part of the data analysis and is a hole in the STPNOC CWMS record-keeping. Although it would be much more efficient to store the failure mode data with work histories in the CWMS database, comprehensive FMEA (as is being done in the work described in here) has not been accomplished for all STPNOC systems (including FW) at STPNOC. As a consequence, the CWMS was not set up to collect these data. Instead, the description of work must be read by the analyst for each work activity. The repair time for each activity is set based on the tag-out time (ECO time) for the activity. The ECO time is not the most accurate estimate for equipment repair time, but it is a reasonable approximation. It is used in our work primarily because the time can be obtained directly from a CWMS query.

<table>
<thead>
<tr>
<th>Source</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>CWMS Query</td>
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</tr>
<tr>
<td>CWMS Query</td>
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<td>System</td>
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<tr>
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<td>Start date/time</td>
</tr>
<tr>
<td>CWMS Query</td>
<td>Finish date/time</td>
</tr>
<tr>
<td>CWMS Query</td>
<td>Activity description</td>
</tr>
<tr>
<td>CWMS Query</td>
<td>Downtime</td>
</tr>
<tr>
<td>Plant process computer</td>
<td>Megawatt hour loss</td>
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<tr>
<td>Analyst</td>
<td>Failure mode code</td>
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<tr>
<td>Analyst</td>
<td>NERC-GADS code</td>
</tr>
<tr>
<td>Analyst</td>
<td>EPIX code</td>
</tr>
</tbody>
</table>

Figure 5. CONSTRUCTION OF A SYSTEM ALIGNMENT FOR A SYSTEM WITH TWO ALIGNMENTS (EA1 and EA2) AND ONE IMPACT.

Alignments

In some cases, we have systems with redundancy in the BOP. In those systems, we have modeled possible alignments which represent which (if any) of the components is set to be operating and the fraction of time in that state. For example, a system with two components, only one of which is required to operate at full power, could be aligned with only one of the components in operation or with both of them in operation. Referring to Figure 5,
the fraction of time spent in each of the alignments is represented by EA1 and EA2. In this case, EA1 might represent the time the spent with both $U_i$ and $A_m$ in operate, say 5% of total time and EA2 would represent the remaining 95% of time (because we remove the scheduled plant down time explicitly, the alignment fractions sum to 1.0). When the cutsets are expanded, the alignments have to be treated differently than the other basic events to account for the fact that they aren't random events and also, they have no associated repair time.

While alignments complicate the fault model and the cutset expansion process, they also provide the opportunity to capture the demand failure frequency associated with other components required to support the device in standby. For example, active valves, support equipment (lube oil, cooling water, etc.) along with "passive" devices like check valves are required to operate when large pumps start. The demand failure of these components can be explicitly modeled using alignments. The alignment capability allows for more accurate representation of on-line maintenance states.

APPLICATIONS

We have traditionally supported three primary risk-based applications with the BOP model, the online maintenance program, system health, and risk-informed asset management (RIAM). Each of these applications is described briefly in the following sections.

Online Maintenance

Because we construct the plant systems’ fault trees to represent possible equipment alignments, we can use the model to quantify contributions to the IE frequencies (TLMFW, PLMFW, EXMFW, LOMT, LCV, LOPF, LOIA, and TTRIP) as applicable to each system, for all possible alignments. This process includes generating the reliability model minimal cutsets for a selected configuration, and processing the cutsets to calculate the IE frequency contributions. The result of this process is a database of IE frequencies for each system, for all possible system configurations which we use in RAsCal [14, 15] to incorporate the impact of BOP equipment configuration changes on CDF (through IE frequency change) and reactor trip for online risk calculations. Decision-making is based on core damage probability for the duration of maintenance activities. Because maintenance is conducted on a rolling weekly schedule (based on pre-defined compatible equipment groupings) the week normally will start with no equipment out of service.

In the RAsCal application, each possible BOP equipment configuration is assigned a unique Maintenance State. Each unique maintenance state identification is the combination of a BOP maintenance state and a PRA maintenance state. RAsCal is fundamentally a database application that uses a graphical user interface to retrieve a stored CDF and plant trip frequency value associated with a unique Maintenance State. RAsCal builds unique Maintenance States for a given work week based on user schedule inputs. The user enters information (equipment designators, equipment states, and lengths of time out of service) that allows RAsCal to determine the duration of a Maintenance State occurring during the maintenance week. The equipment designator is referred to as either a PRA RAsCal designator or a BOP RAsCal designator. In general, the PRA RAsCal designators take on functional or non-functional states while the BOP RAsCal designators take on the states of RUN, STDBY, and MAINT. Besides being unavailable due to maintenance (MAINT) some BOP equipment, if not in standby (STDBY) can cause a reactor trip if required to operate due to the failure of redundant equipment in run.

Besides the calculation of CDF based on the weekly schedule, RAsCal generates useful maintenance week reports and return to service priority information to help the operator make informed decisions on returning equipment to service in a way that minimizes CDF. A CDF calculator module allows the operator to know in advance the impact of taking equipment out of service. With the BOP equipment included in version 4.0, RAsCal looks up IE frequencies associated with BOP model configurations and further modifies the PRA-calculated CDF (also a look up value in the RAsCal database) by the ratio of the IE value assumed in the PRA with the corresponding IE value calculated by the BOP model. The ratio is further modified by the IE contribution to CDF as calculated by the PRA. The modifications described are done as post processing in RAsCal.

System Health

We are using the BOP Model to help the system engineers track changes in system-level performance due to maintenance policy decisions (maintenance duration, equipment design, reliability modifications, and so forth). The system health application is a natural extension to the online maintenance program application whereby the predicted performance of each of the systems in the BOP model is estimated anew each month following update of the failure and repair rates of the equipment in the model. The actual rates apply to failure modes (and their repair times) which appear as basic events in the fault tree model. The new estimates are based on actual equipment performance. Because there are several hundred basic events to update, a method referred to as “update by exception” is used each month to maintain the basic event data in the BOP Model. Because most of the equipment operates without failure (censored data) it is convenient to maintain a database of default exposures for each of the failure modes in the model. By default a failure mode is updated with no failures unless a failure has been entered in the event database for that failure mode. This is why we call it "update by exception" because we only need to keep track of the
Risk-Informed Asset Management (RIAM)

We have been working on getting better predictions of future plant performance for use in maintenance policy decision-making. The BOP Model plays an important role in this effort because it can be used to accurately estimate the effect of changes to equipment maintenance policy on production, but we can additionally estimate the effect of the changes on CDF. These two inputs are primarily drivers for management decision-making and with the BOP Model, their distributions for any set of change options can be accurately estimated.

After we had the BOP Model constructed, the next step was the integration of nuclear safety, plant generation, and plant cost models to determine economic risk impact of plant performance both nuclear safety and plant generation performance [16]. The integration was the key element of the so-called RIAM approach. The concept of the approach is described in [17]. We have used RIAM in modeling and probabilistic quantification of decision support performance indicators. It helped our plant management to determine not only which plant improvement investment options should be implemented, but also how to prioritize resources for their implementation based on predicted levels of profitability. Profitability calculations rely on the BOP Model for accurate plant performance predictions.

Some of the key results we have been able to provide using the RIAM process are: Net Present Value Projected Earnings (sometimes referred to as profitability in RIAM), Projected Costs, Nuclear Safety (core damage frequency, etc.), Power Production (availability, capacity factor, etc.), Efficiency (heat rate), Regulatory Compliance. The examples of using RIAM at STP could be found in references [7], [18].

The benefits of the RIAM approach have been realized by the entire nuclear industry. On a wave of the growing interest to possible applications, Texas A & M University has developed the Safety Assured Financial Evaluation of Maintenance (SAFE-M) model. The model can assist in evaluating strategic management decisions regarding allocation of funds for nuclear power plant maintenance [19]. The model can be used as a simulation tool; various scenarios can be studied to answer what if questions, allowing a better understanding of the relationship between maintenance, economic performance, and safety, and consequently leading to better decision-making.

BOP MODEL METHODOLOGY

Recent Methods

Several commercial nuclear plant investigators have been looking into models of availability and event frequencies originating in the BOP. Recently a significant effort was completed by EPRI [20]. However, with the possible exception of the Iberdrola model GERDIS [21], all current approaches in commercial nuclear power plant applications (including the STP BOP Model) lack the ability to estimate lifetime performance. Also, none of the IE frequency and availability estimation methods in use in commercial nuclear power applications are capable of estimating generalized state transitions. Instead, they rely on a “two state equivalent mapping” that, in concept, is either full power or zero power.

We think the importance of models capable of dealing with generalized state transitions is that online maintenance applications require risk estimates from operational states other than full power. For example, if sufficient equipment is in maintenance that a reduced power state is required, the two state model may give a plant shut down result when, in fact the plant is simply operating at reduced power and transition probabilities to either a higher or lower power state can not be estimated. In the opinion of the authors it may be possible to relax some of these restrictions by using different methods. Finally, for asset management applications, total time to make an estimate is a significant consideration, especially for portfolio management.

Entry time models

While fault trees are the easiest and most widely used technique in probabilistic risk assessment, traditional fault trees are not at all suited to modeling systems in which there are strong dependencies between systems or components. In order to be able to model component dependencies, one must resort to dynamic models [22]. The most popular dynamic models are Markov processes which has been demonstrated to comprise a viable tool for analysis of risk-informed asset management (RIAM) activities in nuclear power plants [23].

For traditional finite-state Markov processes, the transition rates do not depend on the most recent arrival time; hence it is difficult for the models in risk assessment to include aging effects. Motivated by the potential application to optimization of preventive maintenance activities within RIAM in nuclear power plants, entry-time models are a natural extension, to permit inclusion of aging wearout and wearin effects that are central to modern study of reliability issues [24] and that appear likely to become increasingly important within the nuclear energy industry. Entry-time processes are finite-state continuous-time processes with transition rates depending on the two states involved, the calendar time, and the most recent arrival time (entry-time). The generalized state-transition (Chapman-Kolmogorov) equations are expressed as a coupled set of integro/partial-differential equations.
Decision-Dependent Uncertainty

The fault/event tree model creates a static view of the system and the resulting estimates correspond to the specific state of the system when that snapshot was taken. Ideally one would like to be able to incorporate the time-dynamics into the model. The Markovian models ignore the history - only the current state of the system is important to predict the future behavior of the system. In addition, none of the two methodologies allow a change in the future failure behavior of the system due to maintenance interventions done in the past. Galenko and Popova [25] present a model for a system with general dependency structure and find the optimal preventive maintenance schedule when each maintenance intervention changes the future age of each of the system’s components.

CONCLUSIONS

A method has been described in detail to develop an event frequency and availability estimation model for a nuclear power station that could be incorporated into a large event tree, small fault tree model. Differences with other fault tree methods and recently proposed methods have been described. While the methods described are novel to the South Texas Project Risk Management program and to large event tree, small fault tree models, the concepts in the area of application support and availability modeling have wider applicability to the nuclear industry.

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