Effect of Including Motor-Driven Auxiliary Feed Water Pump and Operators' Load-Shedding Action Time in SBO's CCDP Calculation

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ABSTRACT

Station blackout (SBO) is one of the most significant initiating events that can lead to core damage in a nuclear power plant. Therefore, accurately assessing the risk of SBO is a critical task. Since the outcome of an SBO scenario is highly affected by the time required for the recovery of off-site power, it is essential to precisely evaluate the available time margin for power recovery. In previous studies, the convolution approach was introduced to improve the accuracy of conditional core damage probability (CCDP) by addressing the excessive conservatism inherent in the conventional event tree/fault tree (ET/FT) approach. This paper enhances the consistency of the computational methodology used in prior convolution-based analyses and further improves accuracy by incorporating a motor-driven auxiliary feedwater pump (MDAFWP) that is powered by the Alternative AC diesel generator (AAC DG). In addition, the battery depletion time, previously assumed to be constant without considering operator action, is modeled as a function of the operators' load-shedding action time. The revised convolution model is validated through Monte Carlo simulations. Furthermore, the results obtained from the revised convolution model are compared with those from the previous convolution model, and key differences are discussed.

Keywords: Station Black Out, Convolution, Load-Shedding, Motor Driven Auxiliary Feed Water Pump

I. INTRODUCTION

Station blackout (SBO), a representative initiating event in nuclear power plants, refers to the loss of all alternating current (AC) power following a loss of offsite power (LOOP) and the subsequent failure of emergency diesel generators (EDGs). In such scenarios, critical safety systems responsible for decay heat removal lose their AC power supply, making the availability of the auxiliary feedwater pumps (AFWPs) a crucial safety issue. Under SBO conditions, an alternative AC diesel generator (AAC DG) is expected to power the motor-driven auxiliary feed water pump (MDAFWP) to maintain core cooling. If the AAC DG fails, a turbine-driven auxiliary feed water pump (TDAFWP), temporarily operable via Class-1E DC batteries, can be still used. Thus, both MDAFWP and TDAFWP perform secondary-side cooling roles, and the operable time of TDAFWP is determined by the depletion time of the DC battery in the absence of AC power. SBO has been recognized as one of the most significant contributors to core damage in many probabilistic safety assessment (PSA) reports.

Conventionally, event tree/fault tree (ET/FT)-based analysis methods have been widely used for assessing SBO risk. Convolution-based methods have been proposed to overcome the limitations of these approaches in addressing time-dependent phenomena. In the previous study [1], the convolution approach integrates the non-recovery probability of AC power with the failure timing distributions of AAC DG and TDAFWP to calculate the conditional core damage probability (CCDP) of each accident sequence. However, previous convolution models did not explicitly consider the contribution of the MDAFWP powered by the AAC DG, nor did they incorporate the dependency of battery depletion time on operators' load-shedding action time.

To reflect the time-dependent characteristics, this study proposes an extended convolution-based CCDP evaluation model that includes two key improvements. First, the model explicitly incorporates the MDAFWP powered by the AAC DG. Second, the TDAFWP's battery depletion time is modeled as a function of operators' load-shedding action time rather than being treated as a fixed parameter, allowing for a more realistic representation of time-dependent behavior. The updated convolution formulation integrates the failure probability density functions of AAC DG, MDAFWP, and TDAFWP, along with the non-recovery probability of AC power, and introduces a logical condition that activates MDAFWP operation only when the AAC DG has successfully started.

The validity of the proposed model is verified through the Monte-Carlo simulation, and the results are quantitatively compared with those from a previous convolution model.

This study enables a more realistic assessment of SBO risk by incorporating operator actions and system configurations, potentially reducing the conservatism inherent in traditional PSA models. The results can serve as a basis for improving plant design and developing more effective accident management strategies.

II. COMPARISON OF SBO SEQUENCES IN THE PREVIOUS AND UPDATED CONVOLUTION APPROACH

In the previous convolution model, the failure modes of the AAC DG and the TDAFWP were divided into fail-to-start (FTS) and fail-to-run (FTR), allowing for more detailed modeling than the conventional ET/FT approach, where these modes were combined into a single branch.

In this study, the convolution model is updated by incorporating the MDAFWP, adding new sequences. The modification of battery depletion time from a constant to a variable did not require the introduction of new sequences. Figure 1 presents the updated convolution approach.

In the updated model, the FTS and FTR of the MDAFWP are considered under the following conditions: "When the AAC DG experiences an FTS, the MDAFWP cannot receive power, and therefore, its failure modes (FTS and FTR) are not modeled. Similarly, if the AAC DG fails to run after being successfully started, the MDAFWP also loses power, and its FTR is not modeled." As such, no branch is created for the MDAFWP failure in sequences where the AAC DG fails to start.

III. MATHEMATICAL FORMULA FOR SEQUENCE PROBABILITY

In this study, we consider SBO scenarios in which EDGs fail to start following a loss of offsite power (LOOP). Before presenting the mathematical formulas, we define the parameters and subscripts used throughout the equations. Sequence probabilities are denoted by P, component failure probabilities by p, and failure rates by λ. The probability density function and cumulative distribution function are represented as $f(t)$ and $F(t)$ respectively, while the reliability function is represented as $R(t)$. The subscripts $A, O,$ and T refer to the AAC DG, MDAFWP, and TDAFWP, respectively. The subscripts S and R indicate FTS and FTR. Additionally, the subscripts op and bd denote the operators' load-shedding action time and battery depletion time.

For example, the subscript AS refers to the FTS of the AAC DG and the probability $P_{AS,BD}$ denotes the sequence probability in which the FTS of AAC DG and the TDAFWP operates successfully until the battery depletion time, at which point it fails. p_{OS} and $f_{TR}(t)$ denote the FTS probability of the MDAFWP and the FTR probability density function of the TDAFWP. $T_{bd}(t_{op})$ represents the battery depletion time as a function of the operators' load-shedding action time, and $f_{op}(t_{op})$ is the probability distribution of the operators' load-shedding action time.

The operators' load-shedding action time is assumed to follow a lognormal distribution, based on empirical evaluations in human reliability analysis (HRA). The non-recovery time of offsite power is also assumed to follow a lognormal distribution, based on NUREG/CR-6890 and its update report[2,3].

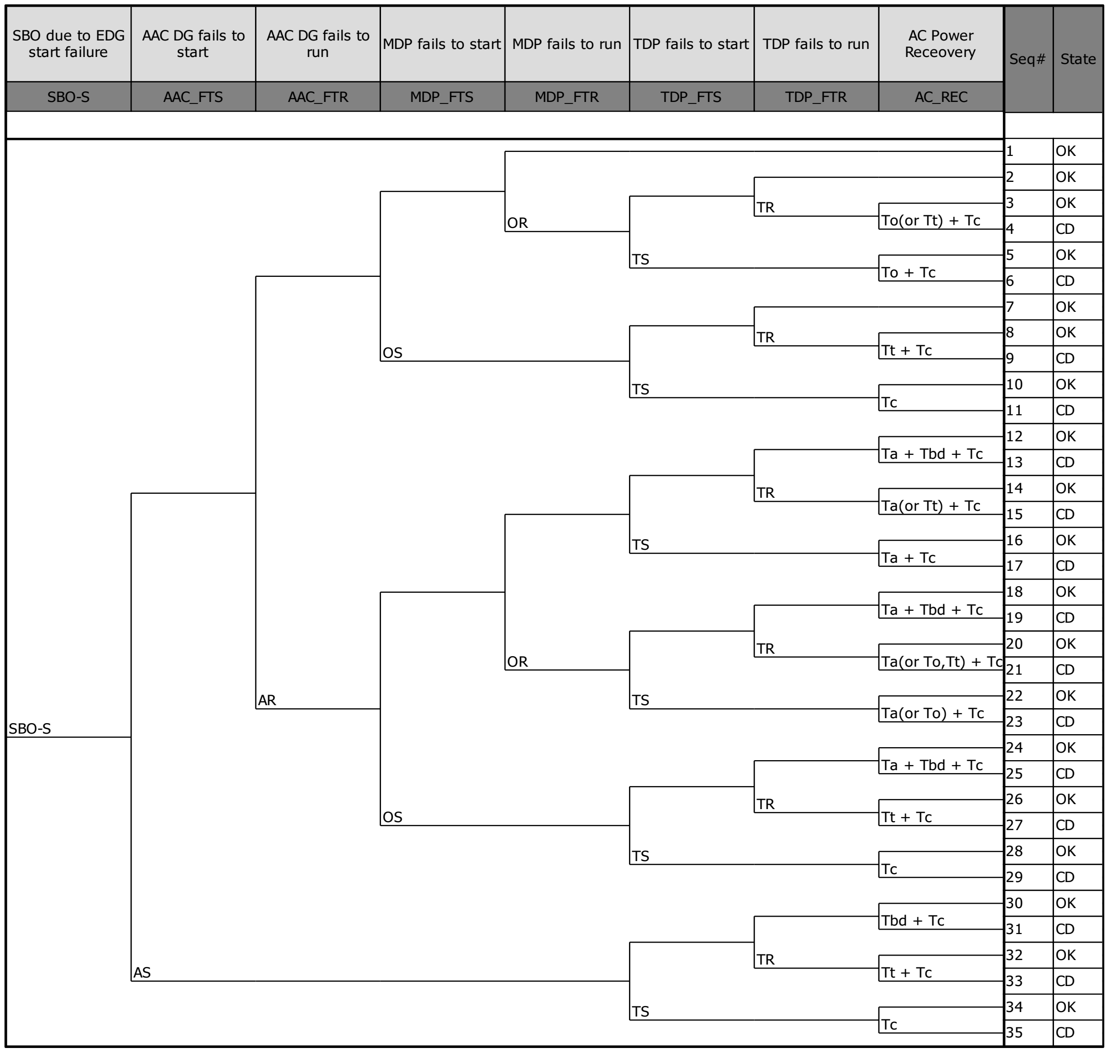

FIGURE 1. Updated Convolution Approach

Using interpolation, the battery depletion time, expressed as a function of the operators' load-shedding action time, is assumed by the following equation:

$$T_{bd}(t_{op}) = \begin{cases} 12 - 8t_{op} & (t_{op} \leq 1)\ [\mathrm{h}] \\ 4 & (t_{op} > 1)\ [\mathrm{h}] \end{cases} \tag{6}$$

For comparing with previous convolution model, minimum of $T_{bd}(t_{op})$ was set to 4 hours, since the previous model assumed a fixed battery depletion time of 4 hours without considering the operators' load-shedding action time.

III.A. Updated Convolution Approach

In this section, mathematical formulas are presented for calculating the sequence probabilities based on the updated convolution approach, which incorporates the MDAFWP and the variable battery depletion time. As shown in Figure 3, a total of 16 equations are developed. One representative equation, corresponding to sequence 4, is presented as an example. This formula corresponds to a sequence in which the AAC DG successfully operates and the TDAFWP fails to run, but core damage occurs due to the failure of the MDAFWP. This sequence had not been considered as leading to core damage in the previous convolution model but is newly identified as a core damage sequence in the updated model by incorporating MDAFWP failure. The example illustrates how previously non-consequential sequences can newly contribute to the core damage probability when additional failure modes and system dependencies are considered. The example formula is given as:

$$P_{OR,TR} = (1 - p_{AS})R_{AR}(T_m)(1 - p_{OS})(1 - p_{TS})$$
$$[\int_0^{T_m}\int_{t_O}^{T_m} f_{TR}(t_T)f(t_O)p_{NRAC}(t_T + T_c)dt_T dt_O + \int_0^{T_m}\int_{t_T}^{T_m} f_{OR}(t_O)\, f_{TR}(t_T)\, p_{NRAC}(t_O + T_c)dt_O dt_T] \quad (7)$$

IV. VALIDATION AND RESULTS

In this section, the formulas for sequence probabilities are validated through Monte Carlo simulation, and the results are compared with those from a previous study. Monte Carlo simulations were performed with 10^9 trials for each sequence. This trial count ensures each dominant sequence ($P \geq 10^{-6}$) is sampled thousands of times, yielding ≤1 % uncertainty per sequence. The numerical data used for the calculations and the simulations are presented in Table I. Failure probability, failure rate, and μ_2, σ_2 are taken from NUREG/CR-6928, NUREG/CR-6890, and their updated reports[4,5].

Lognormal distribution parameters, μ_1 and σ_1, for the operators' load-shedding action time are assumed values. The time to core damage T_c-when the failure of secondary side heat removal using the AAC DG, MDAFWP and TDAFWP- and the mission time T_m are assumed to be typical values. The calculation results and Monte Carlo simulation results can be found in Table II. In Table III, the CCDP values obtained from the previous convolution model, the updated convolution model, and the Monte Carlo simulation are presented.

Table I. Numerical data for calculation

Symbol	Description	Numerical data
p_{AS}	The probability of the AAC DG fail-to-start	2.94E-2
p_{OS}	The probability of the MDAFWP fail-to-start	5.88E-4
p_{TS}	The probability of the TDAFWP fail-to-start	5.32E-3
λ_{AR}	The failure rate of the AAC DG	1.13E-3 [h^{-1}]
λ_{OR}	The failure rate of the MDAFWP	8.12E-6 [h^{-1}]
λ_{TR}	The failure rate of the TDAFWP	6.35E-3 [h^{-1}]
μ_1	Mean of the natural logarithm of the operators' load-shedding action time	-0.77
μ_2	Mean of the natural logarithm of the AC power recovery time distribution	0.44
σ_1	Standard deviation of the natural logarithm of the operators' load-shedding action time	0.37
σ_2	Standard deviation of the natural logarithm of the AC power recovery time distribution	1.66
T_c	The time to core damage after the failure of secondary-side heat removal using the AAC DG, MDAFWP, and TDAFWP	1 [h]
T_m	The mission time	24 [h]

Table II. Sequence probability of calculations and Monte Carlo simulation

Sequence number	Sequence probability	Updated convolution	Monte Carlo simulation	Relative error (%)
4	$P_{OR,TR}$	2.34E-06	2.37E-06	1.27
6	$P_{OR,TS}$	1.43E-07	1.57E-07	8.92
9	$P_{OS,TR}$	1.18E-05	1.19E-05	0.84
11	$P_{OS,TS}$	1.79E-06	1.75E-06	2.29
13	$P_{AR,BD}$	1.29E-03	1.29E-03	0.00
15	$P_{AR,TR}$	2.79E-04	2.79E-04	0.00
17	$P_{AR,TS}$	2.03E-05	2.04E-05	0.49
19	$P_{AR,OR,BD}$	6.71E-08	7.00E-08	4.14
21	$P_{AR,OR,TR}$	3.56E-08	3.00E-08	18.67
23	$P_{AR,OR,TS}$	2.74E-09	3.00E-09	8.67
25	$P_{AR,OS,BD}$	7.61E-07	7.05E-07	7.94

27	$P_{AR,OS,TR}$	1.61E-07	3.07E-07	47.56
29	$P_{AR,OS,TS}$	4.91E-08	4.00E-08	22.75
31	$P_{AS,BD}$	4.10E-03	4.10E-03	0.00
33	$P_{AS,TR}$	4.02E-04	4.02E-04	0.00
35	$P_{AS,TS}$	9.46E-05	9.42E-05	0.42
	CCDP	6.21E-03	6.20E-03	0.16

Table III. CCDP of previous convolution, updated convolution

	Previous convolution	Updated convolution	$\Delta CCDP$ (%)
CCDP	9.54E-03	6.21E-03	34.9

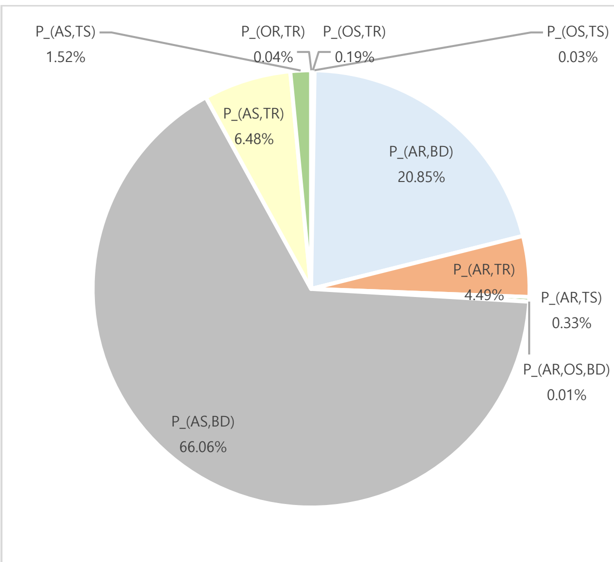

Figure 2. Contribution of top 10 sequences to CCDP (updated convolution model)

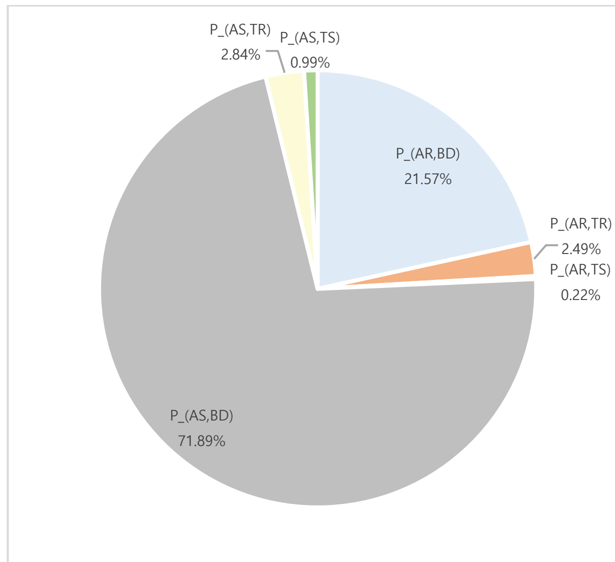

Figure 3. Contribution of each sequence to CCDP (previous convolution model)

To assess the validity of the proposed convolution formula, the results were compared with those obtained from Monte Carlo simulation. The calculated results (6.21E-03) and the simulation results (6.20E-03) show a relative difference of approximately 0.16%. Based on this comparison, the proposed formulas can be considered valid for evaluating CCDP under the given modeling conditions.

As shown in Table 3, the updated convolution model resulted in a 34.9% reduction in CCDP compared to the previous convolution model. Figure 4 illustrates the p_{NRAC}. When the battery depletion time is modeled as a function of operator action time, the updated model incorporates lower values of p_{NRAC}, up to approximately 66% smaller than those in the previous model. The sequences that contributed most significantly to the reduction in CCDP were $P_{AS,BD}$ and $P_{AR,BD}$, which decreased by 2.76E-03 and 7.7E-04, respectively. In relative terms, these correspond to reductions of 40.2% and 37.4%.

Incorporating the failure of the MDAFWP makes the evaluation more conservative, whereas reflecting battery depletion time as a function of operators' load-shedding action time reduces the conservatism of the previous model. The significant decrease in CCDP suggests that the impact of modeling battery depletion time based on the operators' load-shedding action time is greater than the impact of considering MDAFWP failure. As shown in Table 1, the failure probabilities of the MDAFWP are approximately 2% and 11% of those of the AAC DG and TDAFWP, respectively, and the failure rates are approximately 0.7% and 0.1%, respectively. This supports the conclusion that the inclusion of MDAFWP failure (FTS & FTR) has a limited impact on the overall CCDP.

A closer examination reveals two contributing factors. First, in the updated model, sequences that include the failure of all components, including TDAFWP battery depletion, have extremely low probabilities and therefore negligible contributions to the CCDP. This is evident in sequences 13, 15, and 17 compared to sequences 19 through 29, as shown in Table II. Second, sequences such as 4, 6, 9, and 11 reflect scenarios where core damage occurs despite AAC DG success, due to subsequent MDAFWP failure. However, the combined contribution of these additional sequences to the CCDP is only about 0.26%.

By incorporating the variable battery depletion time, the probability contribution profile of the CCDP across sequences was slightly altered. In sequences involving TDAFWP BD, T_{bd} used in $p_{NRAC}(t)$ in the previous model was replaced by $T_{bd}(t_{op})$, which has a minimum value equal to $T_{bd} = 4$ hours. As a result, the sequence probabilities decreased. Conversely, in sequences involving TDAFWP FTR, the extended battery depletion time allows the TDAFWP to operate for a longer time, thereby increasing the chance of failure within that extended period, leading to higher probabilities for those sequences.

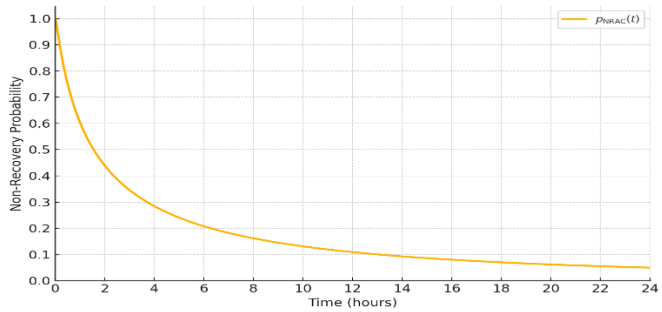

Figure 4. Probability of non-recovery of AC power (p_{NRAC})

V. CONCLUSION

This study proposes an updated convolution model for evaluating the CCDP under SBO by incorporating two key elements that were not explicitly considered in previous models: the MDAFWP and the operators' load-shedding action time. The updated model logically enables MDAFWP operation only when the AAC DG successfully starts and models the battery depletion time as a function of the operators' load-shedding action time rather than assuming a constant value.

The updated convolution formulas were validated through Monte Carlo simulations and the results showed good agreement, with a relative error of 0.16%. The CCDP calculated by the updated model was 6.21E-03, representing a 34.9% reduction compared to the previous model. In addition to the CCDP reduction, the sequence probability profile was also affected. $P_{AS,BD}$, $P_{AR,BD}$ which had been dominant in the previous model became less significant due to changes in the battery depletion time modeling, while $P_{AS,TR}$, $P_{AR,TR}$ which previously constituted the second most contributing group, gained more importance. This is because of the longer availability of the TDAFWP, resulting from time-dependent battery modeling, and thus becoming more dominant in the updated profile. Despite this change, the overall ranking of dominant sequences concerning contribution remained consistent.

This study showed that while the modeling of MDAFWP failure had a limited effect on CCDP, the introduction of a variable battery depletion time significantly reduced conservatism in the previous model. The proposed approach enables a more realistic and less conservative evaluation of SBO risk. Therefore, it may contribute to better-informed decisions in plant design and accident management planning.

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