Atom Indonesia

Journal homepage: http://atomindonesia.brin.go.id

A Fault Tree Analysis and Importance Indexes Approach for Maintenance Optimization of the Chemical Volume Control System in Pressurized Water Reactors

I. W. Ngarayana[1*], A. C. Amelia[1], P. Widiastuti[2], M. Meireni[2], S. Djuliana[2], L. Masbait[2], N. A. Syabani[2]

[1]*Research Center for Nuclear Reactor Technology, Research Organization for Nuclear Energy, National Research and Innovation Agency, BJ Habibie Integrated Science Area Building No. 80, Serpong, Tangerang Selatan 15312, Indonesia*

[2]*Department of Physics, Faculty of Military Mathematics and Natural Sciences, The Republic of Indonesia Defense University, Sentul, Bogor 16810, Indonesia*

ARTICLE INFO

Article history:
Received 3 June 2025
Received in revised form 23 October 2025
Accepted 23 October 2025

Keywords:

Maintenance strategy
Complex systems
PWR
CVCS
FTA
Important indexes
Time mission
Failure probability data

ABSTRACT

Complex systems, such as Nuclear Power Plants (NPPs) require regular and effective maintenance to ensure their safety and reliability. Selecting an optimal maintenance strategy is challenging, because it must balance multiple, often conflicting criteria, including reliability, safety, and cost. This study proposes a maintenance optimization framework based on Fault Tree Analysis (FTA) and importance indexes, with a particular focus on sensitivity to mission time and failure probability distribution. The framework is demonstrated on the Chemical Volume Control System (CVCS), a vital subsystem of Pressurized Water Reactors (PWRs). Using FTA, 176 cut sets were identified, including 11 first-order cut sets where a single component failure (e.g., regenerative heat exchanger, motorized valve 4, check valve 1) could cause system failure. Quantitatively, for a 90-day mission time, 10 components exceeded ASME thresholds (FV > 0.005, RAW > 2), requiring prioritized inspection, whereas for a 30-day mission time, no components required immediate maintenance. These results demonstrate that maintenance recommendations are highly sensitive to both mission time and the assumed failure probability distribution. Unlike previous studies that applied FTA and importance indexes without systematically addressing this sensitivity, the present work explicitly quantifies these effects, thereby filling a critical research gap and providing an operationally realistic basis for maintenance optimization in PWR systems.

INTRODUCTION

Nuclear Power Plants (NPPs) are among the most complex engineered systems in the world, consisting of numerous interrelated Systems, Subsystems, and Components (SSCs) [1]. These SSCs perform essential functions that ensure the safe and reliable operation of the NPPs [2]. However, aging and degradation can cause SSCs to fail over time, potentially compromising plant performance and increasing the risk of accidents [3]. Therefore, regular and effective maintenance is crucial to mitigate failures and preserve their functionality [4].

Maintenance optimization refers to the process of selecting the most appropriate strategy for maintaining SSCs while balancing multiple, often conflicting criteria, such as reliability, safety, and cost [5]. Achieving this balance is challenging: increasing reliability may require more frequent maintenance, which raises costs, whereas reducing maintenance frequency may lower costs and improve availability, but at the expense of reliability

*Corresponding author.
E-mail address: iway018@brin.go.id
DOI: https://doi.org/10.55981/aij.2026.1718

and safety [6,7]. A systematic and rational approach is thus required.

Several methods have been proposed for maintenance optimization of complex systems [8,9]. Among them, Fault Tree Analysis (FTA) is one of the most widely applied techniques. FTA provides a graphical framework for modeling and analyzing the logical structure of system failures, enabling the identification of critical components and failure modes that contribute to a top event (i.e., the undesired system outcome) [10]. The results of FTA can be further quantified through importance indexes, such as Birnbaum, Fussell-Vesely (FV), Risk Achievement Worth (RAW), and Risk Reduction Worth (RRW), which measure the influence of individual components or failure modes on the probability of the top event [11-14]. These indexes are valuable for prioritizing and planning maintenance activities. However, most existing studies focus primarily on ranking components, without explicitly addressing how mission time and the choice of failure probability distribution affect the robustness of the results [14-17].

Because NPPs are not mass-produced systems, reliability data for SSCs are limited [18]. Even when historical failure data exist, they are often proprietary and not publicly available [19]. As a result, generic failure data for NPPs are frequently adapted from oil and gas installations or other thermal power plants, which may reduce their accuracy for nuclear applications [14,18-20].

The present study addresses this gap by investigating the sensitivity of importance indexes to variations in failure data, thereby providing a more operationally realistic basis for maintenance planning in Pressurized Water Reactor (PWR) systems. The proposed approach is applied to the Chemical Volume Control System (CVCS), which maintains coolant inventory and chemistry in the primary circuit of a PWR [21]. The CVCS comprises pumps, valves, heat exchangers, filters, and tanks, each subject to different failure modes [20]. FTA is employed to identify critical components and calculate their importance indexes, while explicitly considering variations in mission time and failure probability distributions. The results demonstrate how incorporating these factors can improve the robustness of maintenance optimization for complex systems. Without such considerations, maintenance recommendations may be misleading or invalid.

METHODS

This study employed a quantitative approach to model a maintenance optimization strategy based on Fault Tree Analysis (FTA) and importance indexes. The methodology consists of system selection, failure data modeling, fault tree construction, importance measure calculation, and sensitivity analysis.

The system selected for this study was the CVCS of a PWR. The CVCS is a vital system responsible for controlling coolant inventory, pressure, and chemistry in the reactor core [22]. Figure 1(a) presents a simplified schematic of the CVCS, while in fig. 1(b) provides a detailed diagram. Each of the 52 main components is labeled with a unique identifier corresponding to Table 1, enabling direct cross-reference between the schematic and the component list [20].

Two types of failure data were considered for each component: Exponential distribution (Table 2), with constant failure rates obtained from IAEA-TECDOC-478 [23,24]. This model assumes a time-independent hazard rate, commonly applied when data are limited or when components are expected to exhibit constant failure behavior. Weibull distribution (Table 3), parameterized by the characteristic life (η) and shape parameter (β), with the location parameter (γ) set to zero for simplification. These values were cited from Machinery Failure Analysis and Troubleshooting by Bloch and Geitner [25]. The Weibull probability density function is given as the function of time (t) in Eq. (1).

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \quad (1)$$

The Weibull model is more flexible than the exponential model, as it can represent different failure behaviors: β<1 (early-life /infant mortality failures); β = 1 (constant failure rate /reduces to exponential); β>1 (wear-out failures with increasing hazard rate). These parameters were used to capture time-dependent reliability characteristics and to assess how different assumptions about failure behavior influence importance indexes and maintenance recommendations.

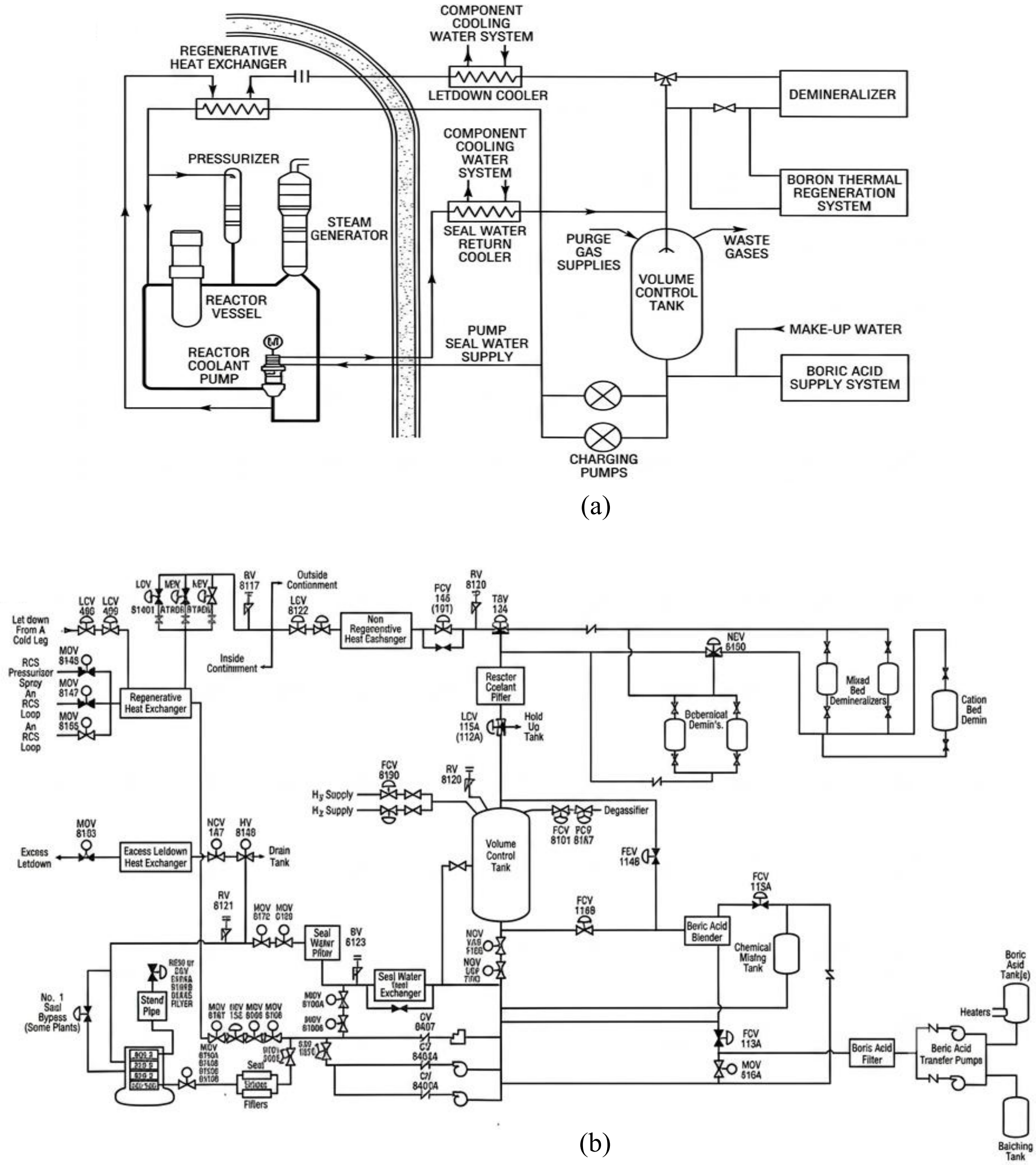

Fig 1. (a) Simplified schematic of the Chemical Volume Control System (CVCS) and (b) detailed schematic with several components which correspond to the component list in Table 1 [19].

FTA was applied to construct a fault tree for the CVCS, representing the logical relationships between system failure and component failures. The fault tree was analyzed using the Minimal Cut Sets (MCSs) method, which identifies combinations of component failures that can cause system failure. Calculations were supported by Arbre Analyst, a free FTA software developed based on Open-PSA and XFTA [26].

The importance indexes, such as Birnbaum, Fussell-Vesely (FV), Risk Achievement Worth (RAW), and Risk Reduction Worth (RRW), were calculated for each component based on the MCSs. The Birnbaum measure of the change in risk caused by a change in the state of a basic event [27]. The Birnbaum index is given by Eq. (2). FV given by Eq. (3), measures the fraction of the total risk that is contributed by a basic event [28]. RAW indicates the increase in risk caused by the unavailability of a basic event [29] and is given by Eq. (4). RRW given by Eq. (5) measures of the decrease in risk caused by the perfect availability of a basic event [30].

$$I_g = P(top|i=1) - P(top|i=0) \quad (2)$$

$$\mathrm{FV} = \frac{P\ cut\ set\ containing\ (i)}{P(top)} \quad (3)$$

$$\mathrm{RAW} = \frac{P(top|i=1)}{P(top)} \quad (4)$$

$$\mathrm{RRW} = \frac{P(top)}{P(top|i=0)} \quad (5)$$

A sensitivity analysis was performed to examine how variations in mission time and failure probability distribution (exponential vs. Weibull) affect the calculated importance indexes. This analysis provides insight into the robustness of maintenance prioritization under different reliability assumptions.

Table 1. Main component of typical CVCS (corresponding to the numbered labels in Fig. 1 (b)).

No	Components	No	Components
1	Regenerative heat exchanger	27	1 series extraction orifice
2	Filling line piping	28	2 series extraction orifice isolation valves
3	Air operated valve 8	29	2 series extraction orifices
4	Motorized valve 4	30	3 series extraction orifice isolation valves
5	Check valve 1	31	3 series extraction orifices
6	Manual valve 1	32	Air operated valve 5
7	Drain valve piping 1	33	Air operated valve 6
8	Air operated valve 1	34	Non regenerative cooling machine
9	Extra Extraction Cooling Machine	35	Air operated valve 7
10	Air operated valve 2	36	Filter 3
11	Air operated valve 3	37	1 series boric acid pump
12	Motorized valve 1	38	1 system check valve 1
13	Motorized valve 2	39	2 series boric acid pump
14	Filter 1	40	2 system check valve 1
15	Sealing water cooler	41	1 system filling pump
16	Source valve for extraction	42	1 system check valve 2
17	Air operated valve 4	43	2 system filling pumps
18	Extraction piping system	44	2 system check valve 2
19	Manual valve 2	45	3 system filling pumps
20	Drain valve piping 2	46	3 series check valve
21	Filter 2	47	1 system thermal sleep
22	Motorized valve 3	48	1 series air operated valve
23	Check valve 2	49	1 system check valve 3
24	Orifice	50	2 series thermal sleeve
25	Relief valve	51	2 series air operated valve
26	1 series extraction orifice isolation valve	52	2 series check valve 3

Table 2. Failure data sets for each CVCS component follow an exponential distribution [23].

No	Failure Probability	No	Failure Probability	No	Failure Probability
1	3.0E-6/h	19	4.7E-6/h	37	5.3E-4/d
2	3.0E-9/h	20	3.0E-8/h	38	3.9E-5/h
3	1.0E-5/h	21	2.7E-6/h	39	5.3E-4/d
4	3.7E-4/d	22	3.7E-4/d	40	3.9E-5/h
5	3.9E-5/h	23	3.9E-5/h	41	1.0E-5/h
6	4.7E-6/h	24	6.0E-7/h	42	3.9E-5/h
7	1.9E-6/h	25	3.0E-4/d	43	1.0E-5/h
8	1.0E-5/h	26	6.0E-7/h	44	3.9E-5/h
9	5.5E-5/h	27	4.7E-6/h	45	1.0E-5/h
10	1.0E-5/h	28	6.0E-7/h	46	3.9E-5/h
11	1.0E-5/h	29	6.0E-7/h	47	1.5E-6/h
12	3.7E-4/d	30	6.0E-7/h	48	1.0E-5/h
13	3.7E-4/d	31	6.0E-7/h	49	3.9E-5/h
14	2.7E-6/h	32	1.0E-5/h	50	1.5E-6/h
15	1.5E-6/h	33	1.0E-5/h	51	1.0E-5/h
16	3.9E-5/h	34	2.0E-5/h	52	3.9E-5/h
17	1.0E-5/h	35	1.0E-5/h		
18	9.4E-6/h	36	2.7E-6/h		

Table 3. Failure data sets with various life characteristics (η), and slope parameter (β) of each CVCS component modelled using a Weibull distribution[23].

No	Failure Probability		No	Failure Probability	
	β	η		β	η
1	1.1	50000	27	1.4	40000
2	1.8	50000	28	1.0	40000
3	1.4	50000	29	1.4	40000
4	1.1	50000	30	1.0	40000
5	1.0	40000	31	1.4	40000
6	1.0	40000	32	1.4	50000
7	1.0	50000	33	1.4	50000
8	1.4	40000	34	1.4	50000
9	1.4	50000	35	1.4	50000
10	1.4	40000	36	1.1	25000
11	1.4	40000	37	1.2	35000
12	1.1	50000	38	1.0	40000
13	1.1	50000	39	1.2	35000
14	1.1	25000	40	1.0	40000
15	1.4	50000	41	1.2	35000
16	1.4	40000	42	1.0	40000
17	1.4	50000	43	1.2	35000
18	1.8	50000	44	1.0	40000
19	1.0	40000	45	1.2	35000
20	1.0	40000	46	1.0	40000
21	1.1	25000	47	1.9	25000
22	1.1	50000	48	1.4	40000
23	1.4	40000	49	1.0	50000
24	1.4	40000	50	1.9	25000
25	1.0	40000	51	1.4	40000
26	1.0	40000	52	1.0	50000

RESULTS

Figure 2 presents the fault tree analysis of the CVCS, developed from the schematic in Fig. 1. The CVCS consists of two main sub-systems: the boric acid subsystem and the primary coolant extraction subsystem, connected by an OR gate. This configuration implies that the CVCS can operate if at least one of the subsystems functions.

The boric acid subsystem comprises several components, including the boric acid pump, filling pump, filling line, check valve 1, motorized valve 4, air-operated valve 8, drain valve piping 1, filling line piping, manual valve 1, and the regenerative heat exchanger, which are linked primarily by OR gates. The primary coolant extraction subsystem contains two parallel lines (extraction and extra-extraction), connected by an AND gate, indicating redundancy. Additional component-level dependencies, such as the boric acid pump's reliance on the orifice, check valve 2, motorized valve 3, and filter 2, were also modeled. Together, these relationships form the complete CVCS fault tree shown in Fig. 2.

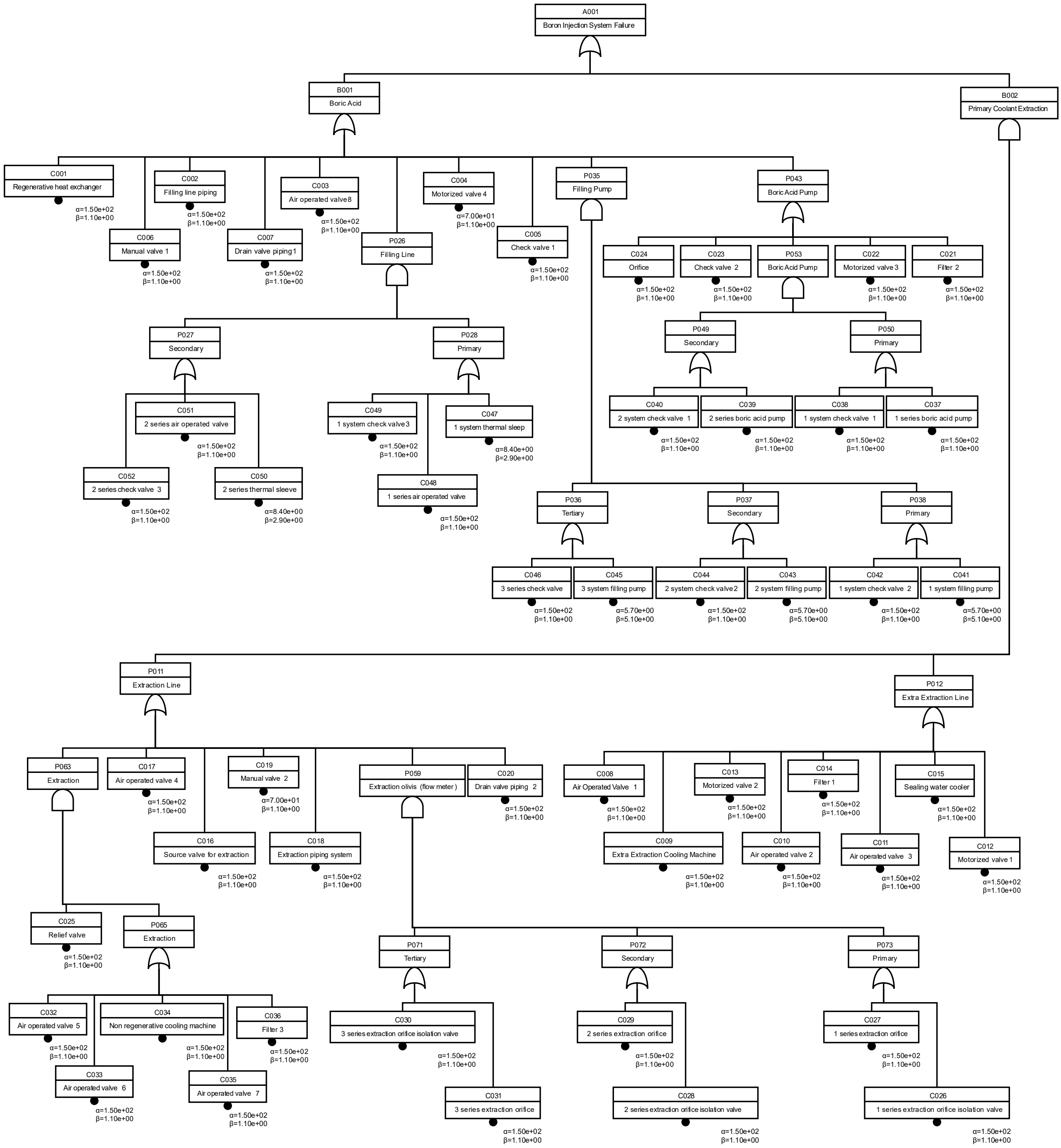

Fig 2. The FTA model of the studied CVCS consists of several components connected by Boolean algebra symbols to represent the relationship between the related components.

The fault tree analysis identified 176 minimal cut sets in total, consisting of 11 first-order, 53 second-order, 48 third-order, and 64 fourth-order cut sets.

First-order cut sets represent single-component failures that directly cause system failure. Eleven components were identified as first-order cut sets: the regenerative heat exchanger, filling line piping, air-operated valve 8, motorized valve 4, check valve 1, manual valve 1, drain valve piping 1, filter 2, motorized valve 3, check valve 2, and the orifice. Higher-order cut sets (second to fourth order) represent combinations of two or more failures. While these are less critical individually, they still contribute to overall system risk.

Using the failure data from Tables 2 and 3, the probability of each cut set was calculated. First-order cut sets exhibited the highest failure probabilities, ranging from 3.7×10^{-4}/d to 5.5×10^{-5}/h, which are one to two orders of magnitude greater than those of higher-order cut sets. This confirms that single-component failures dominate system risk.

The higher-order cut sets had significantly lower probabilities due to the multiplicative effect of combining multiple component failures. While this quantitative analysis complements the qualitative fault tree structure, it does not by itself provide sufficient insight for maintenance prioritization. For this purpose, importance indexes were evaluated.

The Birnbaum importance index quantifies the change in system risk when a component state changes. Results from both exponential and Weibull data sets (Tables 2 and 3) were consistent. Components associated with first-order cut sets, such as the source valve for extraction, air-operated valve 4, extraction piping system, manual valve 2, and drain valve piping 2, were identified as highly critical. These belong primarily to the extraction line of the primary coolant subsystem, where simultaneous operation is required. In contrast, components with redundancy, such as the extraction orifice and its isolation valves (series 1-3), showed low Birnbaum values, reflecting their limited contribution to overall system failure.

The Risk Reduction Worth (RRW) index, which measures the decrease in system risk if a component is assumed perfectly reliable, was also calculated. Following the criterion of RRW > 1.005 [31], the results again highlighted all first-order cut set components as critical, with additional contributions from selected second-order cut set components. This reinforces the conclusion that both single-point vulnerabilities and certain paired dependencies must be prioritized in maintenance planning.

The FV and RAW indexes reveal important results. According to NUMARC 93-01, components are considered significant if their FV and RAW values exceed 0.005 and 2, respectively [31]. Figures 3 (a), (b), and (c) present the FV and RAW values for different mission times (30 days, 90 days, and 1 year) based on exponential failure data.

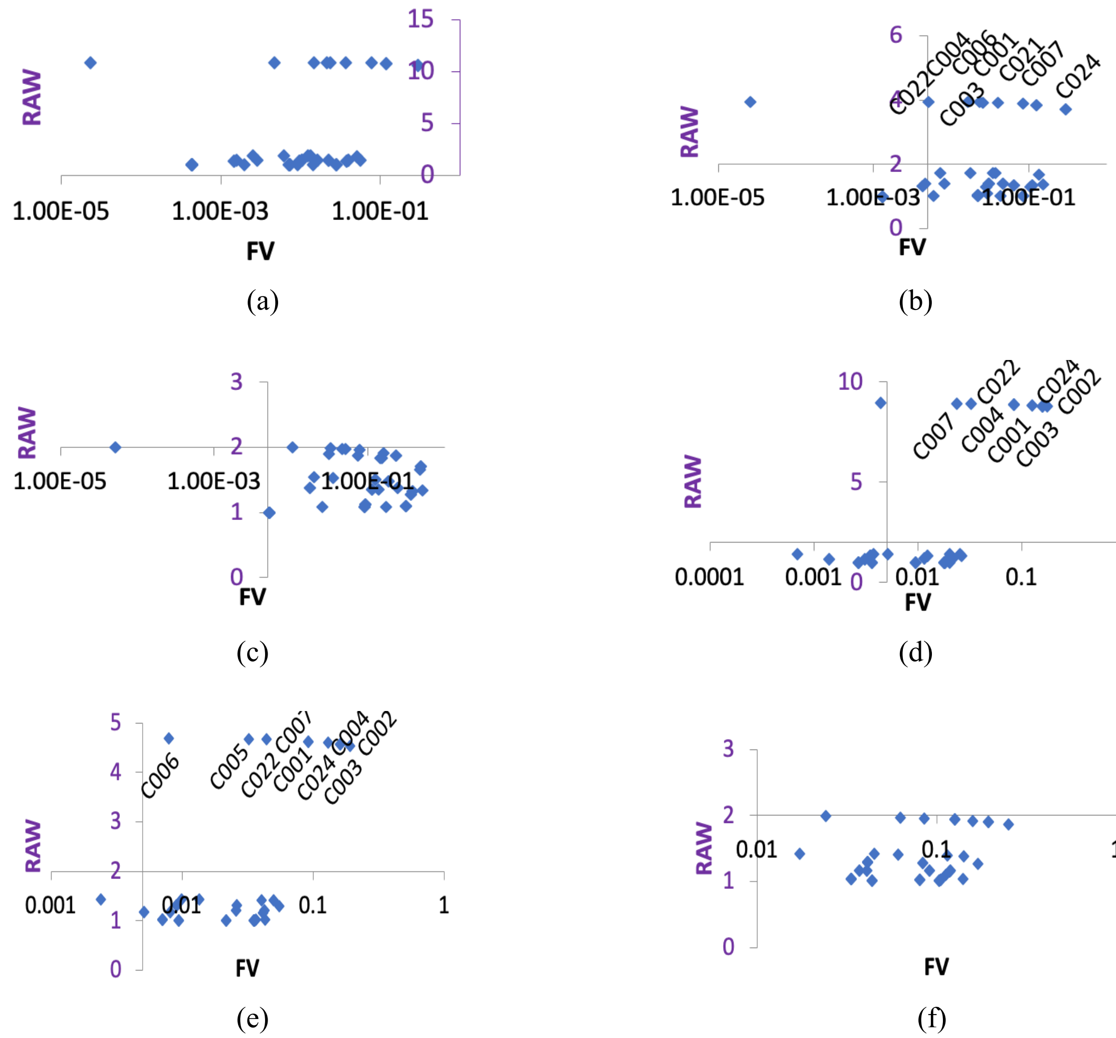

Fig. 3. Fussell-Vesely (FV) (X-axis) and Risk Achievement Worth (RAW) indexes (Y-axis) for CVCS components under different mission times and failure distributions: (a) 30 days, exponential data; (b) 90 days, exponential data; and (c) 1 year, exponential data; (d) 30 days, Weibull data; (e) 90 days, Weibull data; and (f) 1 year, Weibull data. Component numbers correspond to Table 1. Components exceeding ASME thresholds (FV = 0.005, RAW = 2) are considered critical for maintenance prioritization.

For 30-day mission times, the FV and RAW values are below the ASME thresholds (FV < 0.005 and RAW < 2), suggesting that the components have low failure probabilities and do not require maintenance. However, for 90-day mission times, 10 components exceed the ASME thresholds (FV > 0.005, RAW > 2) and therefore require inspection. These components are the orifice, drain valve piping 1, filter 2, regenerative heat exchanger, manual valve 1, air-operated valve 8, motorized valve 4, motorized valve 3, check valve 1, and check valve 2.

For 1-year mission times, most components have FV values above 0.005, but RAW values below 2. This indicates a higher total risk fraction and a greater probability of failure of overall system failure. However, the lower RAW values contradict the concept of RAW, which should reflect the increased risk due to the unavailability of a basic event. This may suggest that the system has a high probability of no longer functioning at 1-year mission times, rendering the RAW values invalid.

Figures 3 (d), (e), and (f) show a similar trend for failure data modeled with the Weibull distribution. For 30-day mission times, the same 10 components as in the exponential case may require inspection. For 90-day mission times, one additional component, the filling line piping, also exceeded the FV threshold, which was not observed under exponential assumptions. This highlights the importance of selecting appropriate failure probability distributions when applying importance indexes. For 1-year mission times, the RAW values again become invalid, as in the exponential case.

DISCUSSION

FTA and importance indexes are powerful tools for optimizing maintenance strategy. This study demonstrated their application by analyzing CVCS, a critical subsystem of a PWR consisting of 52 components. FTA enabled the identification of key components by classifying them into first-, second-, third-, and fourth-order cut sets. With appropriate failure data, the overall system failure probability was quantified, and further detailed insights were obtained through importance indexes.

Across different failure data sources and mission times, the Birnbaum and RRW indexes consistently identified the same critical components, those belonging to first-order cut sets. These indexes also ranked components by their contribution to system risk, from most to least significant. Importantly, Birnbaum and RRW were found to be relatively insensitive to variations in failure data and mission time, making them robust indicators of component criticality.

Table 4. CVCS component groups by cut set, Birnbaum, and RRW.

Critical component	Second priority	Last priority
1, 2, 3, 4, 5, 6, 7, 21, 22, 23, 24	19, 15, 10, 9, 20, 18, 17, 16, 14, 13, 12, 11, 8, 52, 51, 49, 40, 39, 38, 37, 50, 48	47, 25, 46, 36, 35, 34, 33, 32, 44, 42, 41, 30, 29, 28, 27, 26, 45, 43, 31

Note: The component numbers in this table match those in Table 1.

Table 4 groups CVCS components into three categories, critical, second priority, and last priority, based on cut set analysis, Birnbaum, and RRW results. Critical components, such as the regenerative heat exchanger, filling line piping, air-operated valve 8, motorized valve 4, check valve 1, manual valve 1, drain valve piping 1, motorized valve 3, check valve 2, and orifices, contribute most to system risk and therefore require preventive maintenance. Depending on the failure mode and sensor availability, this may be implemented as time-based or condition-based maintenance. Second-priority components contribute less to system risk and can be maintained with less frequent inspections. Last-priority components, often protected by redundancy, contribute negligibly to system risk and can be managed through corrective (run-to-failure) maintenance. This classification reduces unnecessary inspections and replacements, thereby optimizing maintenance resources. For deeper insight, additional indexes, such as FV and RAW, were also examined.

The FV index measures the fraction of system risk attributable to each component. As mission time increases, FV values rise, reflecting the higher probability of component failure and its effect on system reliability. However, FV is highly dependent on the assumed failure probability distribution. Different data sources or distributions can yield different FV values for the same mission time.

The FV and RAW indexes provided differentiated insights depending on mission time. For example, at 90 days, the RAW index identified 10 components as critical, whereas at 30 days, no components exceeded the thresholds. This demonstrates that maintenance recommendations are highly sensitive to mission time assumptions. When Weibull-distributed data were applied, the filling line piping also exceeded the FV threshold (FV = 0.006, RAW = 2.1), a result not observed under exponential assumptions. This highlights the importance of selecting appropriate failure probability distributions when applying importance indexes.

At longer mission times (e.g., one year), RAW values became invalid, likely because the system had a high probability of no longer functioning, making the concept of incremental risk meaningless. Moreover, Fig. 3 illustrates that even for the same mission time (30 days), different data sources led to different conclusions. Some components modeled with Weibull distributions required special attention, while others did not. These findings emphasize that FTA and importance indexes must be applied with careful consideration of both mission time and the reliability data used. To ensure accuracy, failure data should be validated and updated regularly, drawing on both plant-specific histories and data from similar systems.

To contextualize these findings, the proposed FTA-based approach was compared with conventional maintenance strategies. Traditional time-based preventive maintenance schedules inspections or replacements at fixed intervals for all components, regardless of criticality. For example, under a 90-day mission time, this would require inspection of all 52 CVCS components. In contrast, the proposed approach identified only 10 components exceeding ASME thresholds (FV > 0.005, RAW > 2), reducing the inspection workload by over 80% while maintaining system reliability. Corrective (run-to-failure) maintenance, while minimizing upfront inspection costs, risks unplanned downtime and safety concerns. By comparison, the FTA-based method provides a balanced, risk-informed framework that directs resources toward the most critical components, improving both safety and cost-effectiveness.

While these results are consistent with earlier studies that identified critical components using FTA and importance indexes, this study extends the literature by demonstrating that the validity of maintenance recommendations depends strongly on mission time and the assumed failure probability distribution. This sensitivity analysis highlights the need for careful parameter selection, an issue not explicitly addressed in previous research.

The observed sensitivity of the RAW index to mission time and failure distribution explains why this measure is emphasized as highly influential. Conversely, the relative stability of the Birnbaum and RRW indices across various assumptions supports their robustness in ranking critical components. The FV index, while useful, varies significantly over mission time, reinforcing the conclusion that maintenance recommendations must be carefully contextualized. Collectively, these findings suggest that meaningful results can only be obtained when accurate failure data is combined with appropriate mission time assumptions.

Future research could extend this framework in several directions. First, applying the methodology to other safety-critical systems in PWRs and different reactor types would help validate its generalizability. Second, incorporating more detailed, plant-specific reliability data, including condition-based monitoring information, would improve the accuracy of importance indexes and maintenance recommendations. Third, integrating economic and operational constraints into the optimization process could provide a more holistic decision-making tool that balances safety, reliability, and cost. Finally, exploring advanced probabilistic methods, such as dynamic fault tree analysis or Bayesian updating, may further enhance the adaptability of the framework to real-time plant conditions.

CONCLUSION

This study applied FTA and importance indexes to optimize maintenance strategies for the CVCS of a PWR. A total of 176 minimal cut sets were identified, including 11 first-order cut sets in which single-component failures could directly cause system failure. Quantitative analysis using both exponential and Weibull failure data demonstrated that maintenance recommendations are highly sensitive to mission time and the assumed probability distribution. For example, at a 90-day mission time, 10 components exceeded ASME thresholds (FV > 0.005, RAW > 2), whereas at 30 days, no components required immediate maintenance.

Among the indexes, Birnbaum and RRW provided consistent rankings across different assumptions, while RAW was highly sensitive to both mission time and data distribution. These findings highlight three essential requirements for effective maintenance planning: (1) prioritizing critical components identified by importance indexes, (2) tailoring inspection intervals to realistic mission times, and (3) ensuring accurate, continuously updated failure data.

By integrating these considerations, operators can reduce unnecessary inspections, focus resources on high-risk components, and enhance both the safety and cost-effectiveness of maintenance programs in PWR systems. Overall, the coherence between the sensitivity analysis and the behavior of different importance indexes underscores the central implication of this study: maintenance strategies derived from FTA are only reliable when grounded in realistic mission times and validated failure data.

Without this alignment, importance indexes may yield misleading conclusions, as demonstrated in the comparative results.

ACKNOWLEDGMENT

We would like to express our appreciation for the partial support received from the Research and Innovation Funding Program for Advanced Indonesia (RIIM) batch 3 Number B-848/II.7.5/FR.06/5/2023 and B-1031/III.2/ FR.06.00/5/2023 provided by LPDP (Indonesia Endowment Fund for Education Agency) and HITN (Hasil Inovasi Teknologi Nuklir) Project Number 4/III.2/HK/2025 provided by ORTN BRIN. We also acknowledge that the concept of this study originated from Kenta Murakami Sensei, who imparted knowledge on inspection and maintenance procedures in nuclear power plants to the authors.

AUTHOR CONTRIBUTIONS

Conceptualization and Methodology: I Wayan Ngarayana.; Resource and Visualization: Almira Citra Amelia. Software: Pertiwi Widiastuti; Validation: Mutia Meireni.; Formal Analysis: Safiya Djuliana; Investigation: Lorinri Masbait, Nabilah Annisa Syabani.

REFERENCES

1. I. W. Ngarayana, T. M. D. Do, K. Murakami *et al.*, J. Phys.: Conf. Ser. **1198** (2019) 022005.
2. K. Jamali, Reliab. Eng. Syst. Saf. **95** (2010) 935.
3. K. L. Murty, Materials Ageing and Degradation in Light Water Reactors: Mechanisms and Management, Woodhead Publishing (Elsevier). Cambridge (2013).
4. F. Schoeckle, H. Rothenhoefer, and G. Koenig, Nucl. Eng. Des. **269** (2014) 281.
5. International Atomic Energy Agency (IAEA) Maintenance Optimization Programme for Nuclear Power Plants, IAEA Nuclear Energy Series, No. NP-T-3.8, IAEA, Vienna (2018).
6. Y. Yuan, H. Xu, B. Wang, *et al.*, IEEE Trans. Evol. Comput. **20** (2016) 16.
7. A. V. Klimenko, Nucl. Energy. Technol. **2** (2016) 299.
8. P. Contri, I. Kuzmina, and B. Elsing, J. Pressure Vessel Technol. **134** (2012) 031602.
9. J. H. Purba, Atom Indones. **41** (2015) 113.
10. Z. Zhou, H. Nie Safety, C. Dong *et al.*, *Analysis Model of DUCG Based on FMEA/FTA,* in: Proceedings of the 26th International Conference on Nuclear Engineering (ICONE26), American Society of Mechanical Engineers (ASME), London (2018).
11. D. W. Jerng and M. C. Kim, J. Nucl. Sci. Technol. **52** (2015) 122.
12. D. D. S. Borges, D. D. Lava, A. C. F. Guimarães *et al.*, Ann. Nucl. Energy **81** (2015) 249.
13. K. A. Nguyen, P. Do, and A. Grall, Reliab. Eng. Syst. Saf. **168** (2017) 249.
14. F. K. Hwang, Oper. Res. Lett. **28** (2001) 75.
15. W. Wang, J. Loman and P. Vassiliou, *Reliability Importance of Components in a Complex System,* in: Proceedings of the Annual Reliability and Maintainability Symposium (RAMS 2004). Institute of Electrical and Electronics Engineers (IEEE), Piscataway, NJ (2004).
16. Y. H. Lin, Y. F. Li, and E. Zio, IEEE Trans. Reliab. **65** (2016) 547.
17. H. Dui, S. Si, and R. C. M. Yam, Reliab. Eng. Syst. Saf. **168** (2017) 98.
18. J. H. Purba, Prog. Nucl. Energy **76** (2014) 73.
19. T. B. Cochran, Bull. At. Sci. **37** (1981) 37.
20. A. C. F. Guimarães and C. M. F. Lapa, Prog. Nucl. Energy **44** (2004) 191.
21. K. Sun, and B. Ho, Nucl. Eng. Des. **193** (1999) 119.
22. H. Kawai, J. Nucl. Sci. Technol. **39** (2002) 1269.
23. International Atomic Energy Agency (IAEA), Component Reliability Data for Use in Probabilistic Safety Assessment (IAEA TECDOC 478), IAEA, Vienna (1988).
24. F. Ghaderinia, M. Rahgoshay, J. Jafari *et al.*, Atom Indones. **50** (2024) 249.
25. H. P. Bloch and F. K. Geitner, Machinery Failure Analysis and Troubleshooting, Gulf Publishing Company, Houston (1983).
26. E. Clément, A. Rauzy, F. Milcent *et al.*, *Arbre-Analyst – Présentation Des Évolutions Du Moteur De Calculs XFTA,* in: Proceedings of the Congrès Lambda Mu 23, Institut Pour La Maîtrise des Risques (IMdR) (2022).
27. P. Baraldi, M. Compare, and E. Zio, IEEE Trans. Reliab. **62** (2013) 37.
28. F. C. Meng, Reliab. Eng. Syst. Saf. **67** (2000) 55.

29. E. Borgonovo and C. L. Smith, Eur. J. Oper. Res. **222** (2012) 301.
30. D. Mandelli, Z. Ma, C. Parisi *et al*., Ann. Nucl. Energy **128** (2019) 160.
31. Nuclear Energy Institute (NEI), Industry Guideline for Monitoring the Effectiveness of Maintenance at Nuclear Power Plants, NUMARC 93-01 Revision 4A, NEI Washington, DC (2011).