A Hybrid Method for Reliability Modeling of Reactor Protection Systems

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Abstract: This work presents a two-step hybrid method based on Markov theory to assess the reliability of the reactor protection systems (RPSs) in nuclear power plants (NPPs). In the initial step, a module-level Markov model was developed to estimate the failure probability of main functional modules throughout a typical refueling cycle. The model was subsequently solved using Monte Carlo simulation (MCS) techniques. In the second step, the integration of event sequence analysis facilitated the determination of time-dependent failure probability for RPS to generate the actuation signal for a reactor trip. The computed results revealed that the probability of the system failing to generate a trip signal upon demand was around 1E-6 within a cycle, and a structural vulnerability was identified in the signal preprocessing system module (PIPS), with its undetected common cause failures (CCFs) dominating the overall system reliability. Finally, the results of the proposed hybrid method were benchmarked against those from the fault tree analysis (FTA) conducted using the Risk-Spectrum (RS) probabilistic safety assessment (PSA) software to validate its effectiveness.

Keywords: PSA, Module-level Markov model, MCS, Event sequence analysis.

1. INTRODUCTION

Reactor protection system (RPS) is one of the most important safety-related systems in nuclear power plants (NPPs). When the operating parameters of the reactor (e.g., neutron flux, pressure and temperature) exceed the threshold, the protection system will send the drive signal to the reactor shutdown circuit breaker and engineered safety features to control the remaining reactivity of the reactor in time. With the advancement of computer technology, many NPPs worldwide have achieved the digitalization of the RPS (e.g., FirmSys in China). In digital RPS, online self-diagnostic tools are used to enhance the system reliability, but this also increases the system's complexity. Therefore, it is necessary to study reliability modeling methods that apply to digital RPS.

In recent years, several advanced approaches have been proposed to model the dynamic behavior of systems with high reliability, including Markov models [1,2], dynamic Bayesian networks [3], Petri Nets [4] and so on. Among them, Markov modeling is a potent and established technique that can account for various factors, such as repair, periodic testing, and common cause failures (CCFs) [5]. The method has been widely used for system reliability assessment in many fields [6,7].

The reminder of this paper is organized as follows. Section 2 introduces the RPS's structure and the main modules' functions. Section 3 gives a detailed description of the module-level Markov model and the corresponding Monte Carlo simulation (MCS) solution. Section 4 provides a case study for calculating the failure probability of RPS's reactor trip function during a refueling cycle. As an important application of the proposed method, vulnerabilities in the system's design structure have been identified. Section 5 discusses the validation of the hybrid method. And Section 6 draws some conclusions.

2. DESCRIPTION OF TARGET SYSTEM

The schematic diagram of the four-channel RPS is provided in Figure 1. The system includes four channels. (i.e., IP, IIP, IIIP, and IVP). Each channel comprises two subchannels with functional diversity. These subchannels share the sensor module (SENSORS) and the instrument signal pre-processing system module (PIPS), and each contains a reactor protection cabinet (RPC). Based on the connection relationships of the communication network, eight RPCs are divided into two subsystems (i.e., subsystem-1 and subsystem-2). To distinguish them, the number behind it marks each RPC; the first number represents the channel, while the second represents the subsystem (e.g., RPC-11 is in IP, belongs to subsystem-1).

The detailed architecture of a channel is shown in Figure 2. When accidents occur, there are multiple signals (e.g., temperature, pressure and flux) that may trigger the reactor trip. To capture them, a SENSORS including four sensors is equipped. The PIPS then isolates and assigns the field sensor signals to the two RPCs in the programmable logic controller (PLC). Each RPC includes an analogy signal input module (AI), two communication modules (COMs), two microprocessor modules (MPUs) and a digital signal output module (DO). Among them, COMs and MPUs are redundant with main and standby components (i.e., COM-1 means the main communication card while COM-2 means the standby one). When the failure of the main component is detected, the standby one will automatically replace it to perform the necessary function. The AI transmits signals from PIPS to COMs. The MPU receives the signal from the COM and compares it to a predetermined protection set point. Once the threshold is reached, a local coincidence signal (LCS) is generated. The LCS will be sent to three other COMs within the same subsystem. Then, the MPU performs a two-out-of-four (2oo4) voting logic using signals from four subchannels and generates a channel-level reactor trip signal (RTS) when there are two or more LCSs. Finally, DO transmits the RTS to the reactor trip breakers.

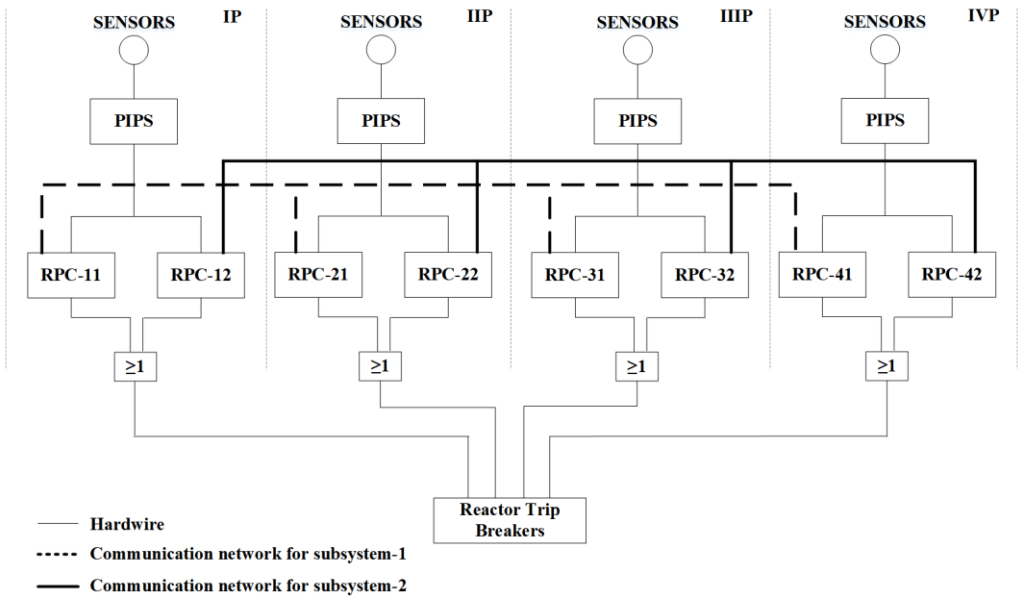

Figure 1. The schematic diagram of the four-channel RPS

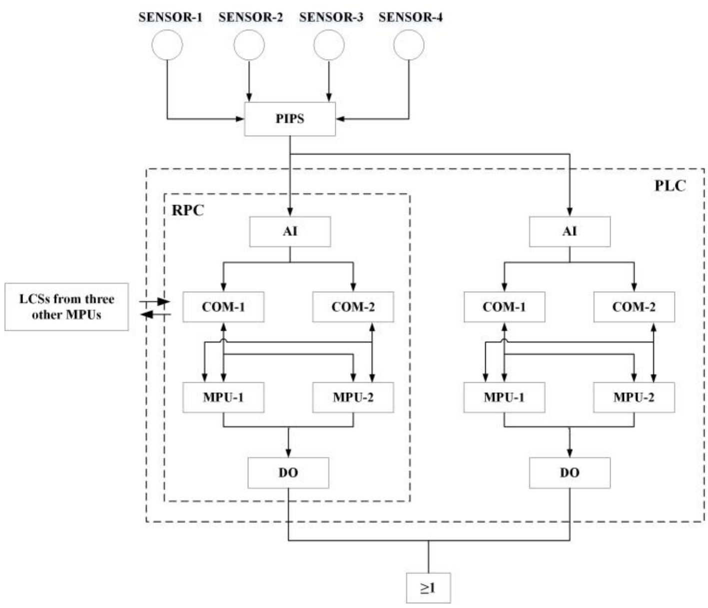

Figure 2. The layout and signal flow of a channel (the arrows indicate the direction of signal transfer)

3. MODULE-LEVEL MARKOV MODEL

To quantify the reliability of RPS, we propose a two-stage hybrid method based on Markov theory. This method ingeniously integrates the Markovian framework, which characterizes the evolution of system states, with the event sequence analysis technique. We first establish a module-level Markov model that provides the probability of basic events for the calculation of the system's failure probability. Then, through event sequence analysis, we obtain the cutset information for the top event. Finally, the cutset information is used to derive the formula for calculating the system's failure probability.

3.1. Assumptions

To describe the state transition of modules in RPS, we consider the transition process as a homogeneous Markov process. And the following assumptions are satisfied.

A1. Time interval between two failures of a single component follows an exponential distribution of constant parameter λ;

A2. Once the failure of a component is detected, the repair operation will be performed immediately. Moreover, the repair time follows an exponential distribution of constant parameter μ;

A3. Redundant modules will occur CCFs, which means that the main and standby components may fail simultaneously due to the same reasons;

A4. A module can only experience one type of failure at a time (i.e., detected or undetected, CCF or not). Failures between different modules are independent.

3.2. Definition of transfer between states

For a single component, the normal state indicates that it has no failure. This state is defined as “0”. When the online self-diagnostic tools can detect the failure of a component, the component is considered in a detected failure state. Otherwise, it is in an undetected failure state, defined as “1” and “2” respectively. For redundant modules, further analysis should be done on the relationship between the main and standby components. When an undetected failure occurs in the main component, the module cannot switch to the standby component. These module failures are regarded as undetected. When a detected failure occurs in the main component and switches to the standby component, such failure is also undetected if a further undetected failure occurs in the standby one. Meanwhile, the undetected CCFs of the redundant module also need to be considered (**see Assumption A3**). Therefore, the “2” state of the redundant module includes the above three cases. As for the “1” state, detected failure occurs if and only if failures of both components are detected. The remaining cases are defined as the “0” state of the module.

After defining the states of the module, the transfer between states satisfies the well-known Chapman-Kolmogorov equation according to the Markov theory (see Eq. (1)), where $p_{ij}^{(k)}$ represents *k*-step transfer probability between state *i* and *j*. As mentioned before, states “0”, “1”, and “2” denote normal, detected failure and undetected failure, respectively.

$$p_{ij}^{(n+m)} = \sum_{k=0}^{2} p_{ik}^{(n)} p_{kj}^{(m)} \quad \left(i, j \in \{0,1,2\}\right) \tag{1}$$

Furthermore, we can describe the transfer between module states by drawing a Markov chain [8], using circles to indicate the different states of the module, directed arcs to indicate the transfer between different states, and letters on the transfer arcs to indicate the state transfer rate. Figure 3 shows the Markov chain structures of a single component and redundant modules, where λ_D, λ_U, λ_{CD}, λ_{CU}, μ are detected failure rate, undetected failure rate, detected CCF rate, undetected CCF rate and repair rate, respectively. The number “0” indicates a normal state, the number “1” indicates a detected failure state, and the number “2” indicates an undetected failure state. State “2” is also known as an absorbing state because no more state transfers occur after the module enters an undetected failure state. Since the redundant system contains two components that can fail independently, the transition rate from state "1" to state "2" in Figure 3(b) for redundant modules is twice the undetected failure rate of a single component.

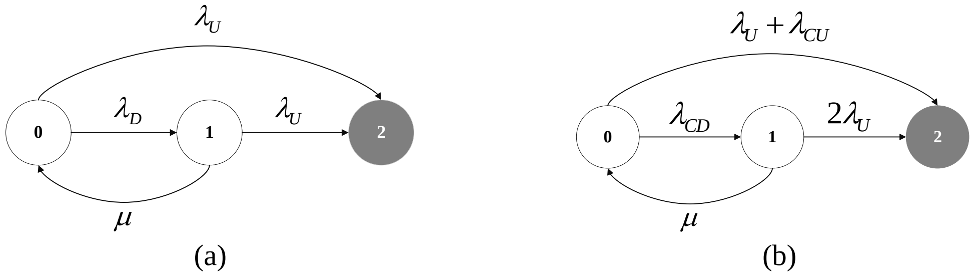

Figure 3. (a) Markov chain of a single component; (b) Markov chain of redundant modules

3.3. Monte Carlo simulations

Since the time for a module to stay in a specific state follows an exponential distribution (**see Assumption A1**), the real change of the state can be simulated by sampling different sojourn times. Therefore, the Monte Carlo simulation (MCS) method is used to solve the module-level Markov model. Specific steps are as follows.

Step 1: Confirmation of sojourn times: according to **Assumption A4**, we first sample the sojourn time of different failure types. They are $\tau_D \sim \exp(-\lambda_D t)$, $\tau_U \sim \exp(-\lambda_U t)$, $\tau_{CD} \sim \exp(-\lambda_{CD} t)$, $\tau_{CU} \sim \exp(-\lambda_{CU} t)$, respectively. Then select the minimum as the sojourn time $\tau_{min}^{(1)} = \min(\tau_D, \tau_U, \tau_{CD}, \tau_{CU})$. The module state transfer to the state corresponding to the failure type (e.g., if $\tau_{min}^{(1)} = \tau_D$, the next state is "1").

Step 2: Judgment of failure state: it can be seen from the Markov chain that the transfer rate is related to the current state. Therefore, judging the module's state after each state transfer is essential. For state "0", MCS can be performed as in Step 1. For state "1", considering the repair mechanism, we sample the repair time according to **Assumption A2**, and then restore the component's state to "0". Repeat the above steps to obtain a series of sojourn time $\tau_{min}^{(i)}$, where the superscript indicates the *i*-th state transfer. Once the module enters the absorbing state or the sum of sojourn times exceeds the mission time $T_{mission}$, the sampling is terminated, as shown in Figure 4.

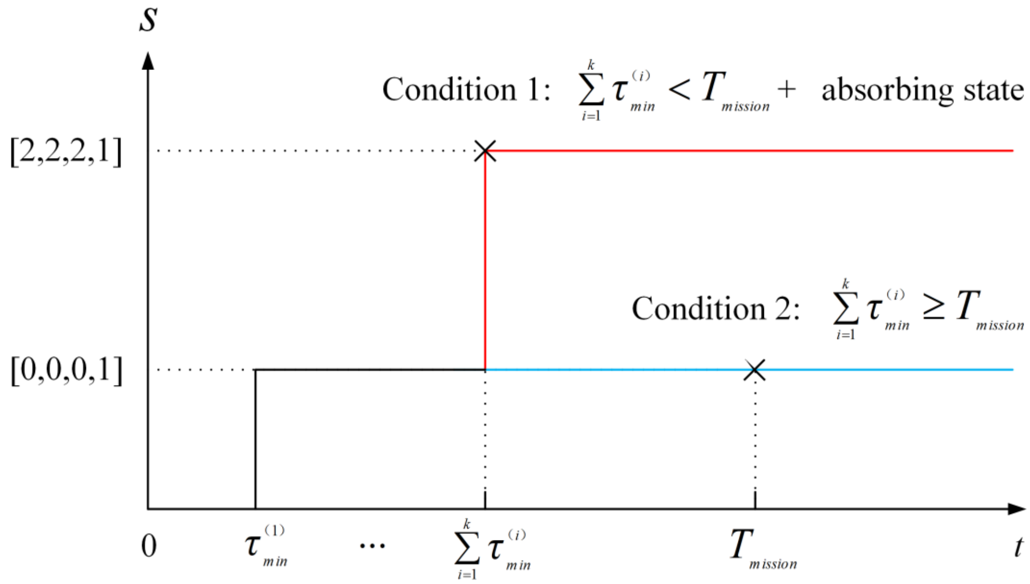

Figure 4. The diagram of the simulation process

Step 3: Consideration of periodic testing: in engineering situations, periodic testing is often used to find and fix undetected failures that occur in modules, so we include the consideration of periodic tests in our model. Once the periodic test interval is reached, components that occurs undetected failures will be repaired to normal. It means that if the module is not in the absorbing state when the periodic test is reached, the state of the component in which the undetected failure occurred is modified to "0". At this point, the mission time can be divided into equal intervals according to the periodic test interval (i.e., $[0,T_I],\ldots,[nT_I,T_{mission}]$), and the sampling steps can be repeated at each interval.

Step 4: Estimation of time-dependent failure probability: the sampling results can be divided into two categories according to whether the final state of the module is an absorbing state or not. If MCS is conducted for N times, the number of times the module ends up in the absorbing state is n. Then, the failure probability of the module time converges to the frequency (i.e., n/N) when the simulation number is large enough. Similarly, the number of times the module ends up in any non-absorbing state at the end of mission time can likewise be counted. Therefore, the above MCS algorithm can theoretically give the probability of the module being in any state at any moment.

4. CASE STUDY

4.1. Input data

Table 1 lists basic parameters needed for the calculation, including detected failure rate λ_D, undetected failure rate λ_U, mean time to repair (MTTR), and mean time to test (MTTT) (i.e., the periodic test interval) for all modules [9-12]. The beta and alpha CCF models [10,12] are used to quantify the failure probability of modules within a common cause group (CCG). All parameters of CCF models are given in Table 2. Given that the COM and MPU are redundant modules, we use a two-order beta model to quantify the CCF between main and standby components. Since the spatial separation of sensors between different channels, only the CCFs within the four sensors in SENSORS are considered, and these sensors form a CCG. As the PIPS is shared among subchannels, we group four channels' PIPS into a CCG, and a fourth-order alpha model is used to calculate the CCFs between them. Similarly, four PLCs are also grouped into a CCG.

Table 1. Basic parameters of modules

Modules \ **Parameters**	λ_D (1/h)	λ_U (1/h)	MTTR (h)	MTTT (month)
SENSORS	1.8×10^{-6}	1.0×10^{-7}	6	18
PIPS	6.3×10^{-8}	3.5×10^{-9}	6	18
AI	3.0×10^{-6}	1.7×10^{-7}	6	18
COM	1.5×10^{-6}	8.4×10^{-8}	6	18
MPU	5.9×10^{-7}	3.3×10^{-8}	6	72
DO	3.5×10^{-6}	2.0×10^{-7}	6	2

Table 2. Parameters of different CCGs

Modules	**CCF model**	**Parameters**	**Values**
COM	Beta	β	5.0×10^{-2}
MPU	Beta	β	5.0×10^{-2}
SNESORS	Alpha	$[\alpha_1,\alpha_2,\alpha_3,\alpha_4]$	$[9.0\times10^{-1},6.0\times10^{-2},3.0\times10^{-2},5.0\times10^{-3}]$
PIPS	Alpha	$[\alpha_1,\alpha_2,\alpha_3,\alpha_4]$	$[9.0\times10^{-1},6.0\times10^{-2},3.0\times10^{-2},5.0\times10^{-3}]$
PLC	Alpha	$[\alpha_1,\alpha_2,\alpha_3,\alpha_4]$	$[9.9\times10^{-1},1.9\times10^{-3},1.2\times10^{-4},1.1\times10^{-5}]$

4.2. Event sequence analysis

An event sequence analysis is required to obtain the relationship between the time-dependent failure probability of RPS and the time-dependent failure probability of different modules. The analysis is done by listing the sequence of events that led to the failure of RPS. Each event sequence is represented as a combination of functional module failures. Table 3 gives the main results of event sequence analysis.

The reliability block diagram of the RPS is shown in the Figure 5. The reactor trip breakers adopt a 2oo4 logic and cannot perform their trip function when more than three channels fail, so the failure situations can be classified as failures of three channels and failures of four channels. Since a single channel consists of a SENSORS, a PIPS, and a PLC in series, any failure in them will lead the channel to fail to generate the RTS. Eventually, the probability of each event sequence in Table 3 is summed to calculate the probability of the demand trip failure (see Eq. (2)). The probability of CCFs in the alpha model [12] is given by Eq. (3).

$$\begin{aligned} P_{RT} = {} & P_{PIPS}^{(\alpha_3)} + P_{PIPS}^{(\alpha_4)} + C_2^1 \times P_{PIPS}^{(\alpha_2)} \times P_{SENSORS} + C_2^1 \times P_{PIPS}^{(\alpha_2)} \times P_{PLC} + \left(C_4^2 - 1\right) \times P_{PIPS}^{(\alpha_2)} \times P_{PLC}^{(\alpha_2)} \\ & + C_3^2 \times P_{PIPS}^{(\alpha_1)} \times P_{PLC}^{(\alpha_2)} + C_2^1 \times P_{PLC}^{(\alpha_2)} \times P_{SENSORS} + P_{PLC}^{(\alpha_3)} + P_{PLC}^{(\alpha_4)} \end{aligned} \tag{2}$$

$$\begin{cases} P_{specific\ module}^{(\alpha_1)} \approx P_{specific\ module} \\ P_{specific\ module}^{(\alpha_2)} = \dfrac{\alpha_2}{3\alpha_1} \times P_{specific\ module} \\ P_{specific\ module}^{(\alpha_3)} = \dfrac{\alpha_3}{3\alpha_1} \times P_{specific\ module} \\ P_{specific\ module}^{(\alpha_4)} = \dfrac{\alpha_4}{\alpha_1} \times P_{specific\ module} \end{cases} \tag{3}$$

Table 3. Event sequence analysis for the RPS

Failure cases for 2oo4 system		**Sequence of events leading to the failure of system**	
	No.	**Event 1**	**Event 2**
Failure of three channels of RPS	1	Failure of PIPS in three channels	
	2	CCF of PLC in three channels	
	3	Failure of PIPS in two channels	Failure of PLC in another channel
	4	Failure of PIPS in two channels	Failure of SNESORS in another channel
	5	Failure of PIPS in one channel	CCF of PLC in other two channels
	6	CCF of PLC in two channels	Failure of SNESORS in another channel
Failure of four channels of RPS	7	Failure of PIPS in four channels	
	8	CCF of PLC in four channels	
	9	Failure of PIPS in two channels	CCF of PLC in other two channels

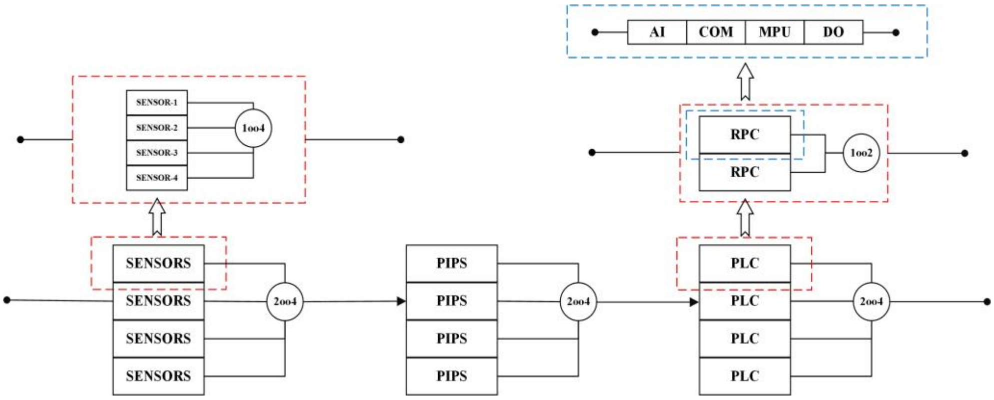

Figure 5. The reliability block diagram of the RPS

4.3. Results and Discussion

Table 4 gives the failure probability of all modules within a refueling cycle (i.e., 18 months), where SENSORS represents a CCG of four sensors with a 1oo4 logic, PIPS represents a CCG of four modules with a 2oo4 logic, COM and MPU represents a CCG with main and standby components, AI and DO represents a single component. The results indicate that the independent failure probability of the SENSORS in a channel is 6.57E-6, while the independent failure probability for the CCG of PIPS is 7.02E-7. Since the four modules within an RPC are connected in series and two RPCs are connected in parallel, we can use Eq. (4) - Eq. (6) to calculate the failure probability of the PLC in a channel. The calculation gives a result of 4.41E-5. These results show that the event sequence only needs to be analyzed to the second order, as shown in Table 3. Since the third-order event sequence is equivalent to splitting CCFs in the second-order sequence into two independent failure events, the contribution of the event sequence above the third order is a small amount and negligible compared to the second-order event sequence.

$$R_{RPC}^{subchannel} = R_{AI} \times R_{COM} \times R_{MPU} \times R_{DO} \tag{4}$$

$$P_{RPC}^{subchannel} = 1 - R_{RPC}^{subchannel} \tag{5}$$

$$P_{PLC} = P_{RPC}^{subchannel} \times P_{RPC}^{subchannel} \tag{6}$$

By substituting the results into Eq. (2), the final failure probability of the demand trip function of RPS within a refueling cycle is 7.04E-7. It is found that the failure probability of the PIPS accounts for 99.7 percent of the whole probability. We further calculate the probability of the third-order and the fourth-order CCFs of the PIPS by Eq. (6). The results are 4.54E-7 and 2.27E-7, respectively. Their sum accounts for 97.0 percent of the failure probability of the PIPS.

Since two subchannels share a PIPS, once a CCF of more than three orders occurs in the PIPS, RPS cannot perform its trip function. Therefore, for the assumed RPS structure, the PIPS is a weak link in the overall system design. Moreover, it is necessary to perform a sensitivity analysis for the CCF parameters of the PIPS. The CCF parameters are influenced by a variety of factors, which may originate from hardware (e.g., material and design), environmental conditions (e.g., temperature and humidity), and operational conditions (e.g., vibration or shock), thus exhibiting significant uncertainty. Statistical data also indicate that the reliability of PIPS has a high degree of uncertainty [11], with an error factor of 16 for the failure rate distribution (where the error factor is defined as the square root of the ratio of the 95th percentile to the 5th percentile). Therefore, we study the following three cases:

- Case 1: the CCF probability of PIPS module increases by 100%
- Case 2: the CCF probability of PIPS module increases by 400%
- Case 3: the CCF probability of PIPS module increases by 900%

The calculation results are shown in Table 5. It shows that the system failure probability increases approximately linearly with the increase of the CCF parameters. The reliability of the RPS is highly sensitive to changes in CCF parameters. Such insight suggests that if some engineering measures can reduce the values of α_i in the alpha CCF model, the reliability of RPS can be significantly improved.

Table 4. Modules' failure probability within a refueling cycle

Modules	SENSORS	PIPS	AI	COM	MPU	DO
Failure probability	6.57×10^{-6}	7.02×10^{-7}	2.19×10^{-3}	1.19×10^{-3}	5.46×10^{-4}	2.73×10^{-3}

Table 5. Sensitivity analysis for CCF parameters of PIPS

Case	Base case	1	2	3
CCF probability increase	0%	100%	400%	900%
Failure probability of RPS	7.04×10^{-7}	1.36×10^{-6}	3.39×10^{-6}	6.81×10^{-6}

5. VALIDATION

To verify the results of the proposed hybrid method, the software Risk-Spectrum (RS), which is widely used in PSA analysis of nuclear power plants, is selected to model the fault tree (FT) for reactor trip function. Figure 6 shows the top logic of the FT modelled in RS. The mission time of 18 months is selected, and the calculation results of RS give the point estimation of the average probability of the top event within the mission time, which can be used as the verification index.

The failure probability $p_i\left(i=1,...,540\right)$ is calculated for each day during the refueling cycle using the proposed hybrid method. And the verification index q_t' is estimated by Eq. (7). The hybrid method gives the result of 3.53E-7, while RS gives the result of 3.36E-7. Table 6 provides the top ten minimal cut sets of the FT model. The results indicate that the proposed hybrid method can provide a reasonable estimation of the average failure probability for trip demand, while also delivering a time-varying failure probability of the RPS.

$$q_t' = \frac{1}{540\times\Delta t}\sum_{i=1}^{540} p_i \times \Delta t \tag{7}$$

Table 6. The top ten minimal cut sets of the fault tree

No.	**Probability**	**Ratio**	**ID**	**Description**	**ID**	**Description**
1	1.12×10^{-7}	33.32%	CCF PIPS UU-ALL	Undetected CCF of PIPS in IP\IIP\IIIP\IVP	-	-
2	5.59×10^{-8}	16.66%	CCF PIPS UU-134	Undetected CCF of PIPS in IP\IIIP\IVP	-	-
3	5.59×10^{-8}	16.66%	CCF PIPS UU-123	Undetected CCF of PIPS in IP\IIP\IIIP	-	-
4	5.59×10^{-8}	16.66%	CCF PIPS UU-234	Undetected CCF of PIPS in IIP\IIIP\IVP	-	-
5	5.59×10^{-8}	16.66%	CCF PIPS UU-124	Undetected CCF of PIPS in IP\IIP\IVP	-	-
6	1.65×10^{-12}	0.00%	1 PIPS UU	Undetected failure of PIPS in IP	CCF PIPS UU-23	Undetected CCF of PIPS in IIP\IIIP
7	1.65×10^{-12}	0.00%	1 PIPS UU	Undetected failure of PIPS in IP	CCF PIPS UU-24	Undetected CCF of PIPS in IIP\IVP
8	1.65×10^{-12}	0.00%	1 PIPS UU	Undetected failure of PIPS in IP	CCF PIPS UU-34	Undetected CCF of PIPS in IIIP\IVP
9	1.65×10^{-12}	0.00%	2 PIPS UU	Undetected failure of PIPS in IIP	CCF PIPS UU-13	Undetected CCF of PIPS in IP\IIIP
10	1.65×10^{-12}	0.00%	2 PIPS UU	Undetected failure of PIPS in IIP	CCF PIPS UU-14	Undetected CCF of PIPS in IP\IVP

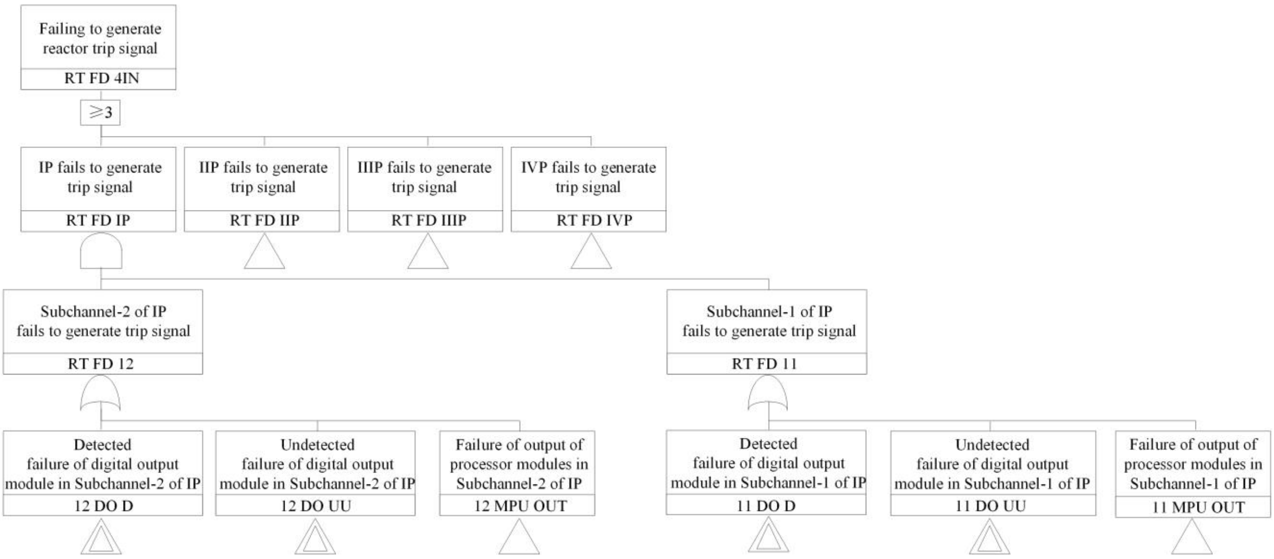

Figure 6. Top logic of FT model in RS

6. CONCLUSION

In this paper, we propose a hybrid method to assess the reliability of a safety-related digital four-channel RPS. The hybrid method includes MCS algorithms for solving the module-level Markov models and event sequence analysis for determining the relationship between system failure and module failure. The results indicate that the failure probability for the RPS to perform its trip function is 7.04E-7 per demand during a refueling cycle. It is also found that undetected CCFs of the PIPS module contributes the most of the RPS's failure. The sensitivity analysis indicates that the failure probability of the RPS increases almost linearly with increasing CCF parameters over an 18-month refueling cycle.

In the future, optimization analysis will be performed to determine feasible system design optimization options, such as changing the periodic test interval or adjusting the system's logic architecture.

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