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Bayesian belief-based model for reliability improvement of the digital reactor protection system

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Abstract The digital reactor protection system (RPS) is one of the most important digital instrumentation and control (I&C) systems utilized in nuclear power plants (NPPs). It ensures a safe reactor trip when the safety-related parameters violate the operational limits and conditions of the reactor. Achieving high reliability and availability of digital RPS is essential to maintaining a high degree of reactor safety and cost savings. The main objective of this study is to develop a general methodology for improving the reliability of the RPS in NPP, based on a Bayesian Belief Network (BBN) model. The structure of BBN models is based on the incorporation of failure probability and downtime of the RPS I&C components. Various architectures with dual-state nodes for the I&C components were developed for reliability-sensitive analysis and availability optimization of the RPS and to demonstrate the effect of I&C components on the failure of the entire system. A reliability framework clarified as a reliability block diagram transformed into a BBN representation was constructed for each architecture to identify which one will fit the required reliability. The results showed that the highest availability obtained using the proposed method was 0.9999998. There are 120 experiments using two common component importance measures that are applied to define the impact of I&C modules, which revealed that some modules are more risky than others and have a larger effect on the failure of the digital RPS.

Keywords Nuclear power plants · Reactor protection system · Bayesian belief network

1 Introduction

Nuclear engineering has implemented computer software into all facets of this field. There are a wide variety of fields associated with nuclear engineering with computers, and associated software is used in design and analysis [1–5]. NPPs are the world's energy resources, with nuclear energy now providing about 10% of the world's electricity from about 440 power reactors. The most critical issues in the design and operation of NPPs are safety systems. NPP safety systems are employed for safe operation and shutdown of the reactor in emergency cases to mitigate the consequences of events or accidents [6]. The digital RPS is a complicated NPP control system that comprises a collection of nuclear safety components designed to initiate a reactor trip if safe operating limits are exceeded, initiate the actuation of engineered safety features, and stop the emission of radioactive materials. The trip action of the digital RPS results in the full insertion of all control rods, safely shutting down the reactor and returning the NPP to a stable controlled state [7]. Automatic shutdown signals include source range high neutron flux, ionization channels, overtemperature, overpower, pressurizer low pressure, pressurizer high water level, reactor coolant pump undervoltage, turbine trip, low reactor coolant flow, etc [8].

To assure safe reactor operations, the RPS is designed according to redundancy criteria such as a "1-out-of-2,"

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"2-out-of-3," or "2-out-of-4" (2oo4) configuration, including sensors, reactor trip logic circuits, actuators, and complex connections between these devices [9]. Figure 1 shows a generic block diagram of the digital 2oo4 RPS architecture. The 2oo4 RPS system consists of four channels, each with the same architecture. All channels are electrically and physically separated from the other channels, so the failure of each channel is independent. The output trip signal generated by RPS follows the following voting logic rules. The 2oo4 architecture provides reliable operation in the case of a single-channel failure. If two or more channels fail and failures are detected, the reactor is tripped by the digital RPS. The single channel of the RPS consists of the following components and modules, sensors and transmitters (TR), pressure/level transmitter (PT), analog input (AI), digital input (DI), bistable processor (BP), coincidence processor (CP), digital output (DO), shunt circuit (ST), undervoltage circuit (UV), and circuit breaker (CB). Reliability analysis of safety systems in the NPP is one of the most important requirements to ensure that safety systems will be in a state to perform the required functions under given conditions over a time interval. Many techniques have been utilized to analyze the reliability of a system such as Monte Carlo simulation [10], fault tree analysis [11], Markov chain model [12], dynamic flow graph [13], reliability block diagram [14], and Bayesian belief networks (BBNs) [15]. BBNs have several different names, such as Bayesian networks (BNs), belief networks, and causal probabilistic networks. BNs are utilized to predict software faults through software reliability analysis at the RPS of RSG-GAS based on the software development life cycle (SDLC). The model structure consists of eight nodes. The results show that a software defect follows a statistical binomial distribution. The progression of a software defect concentration range of the posterior distribution compared with the prior distribution is also specified [16].

The software failure probabilities in NPP digital I&C systems were quantified using BBN to model the causal

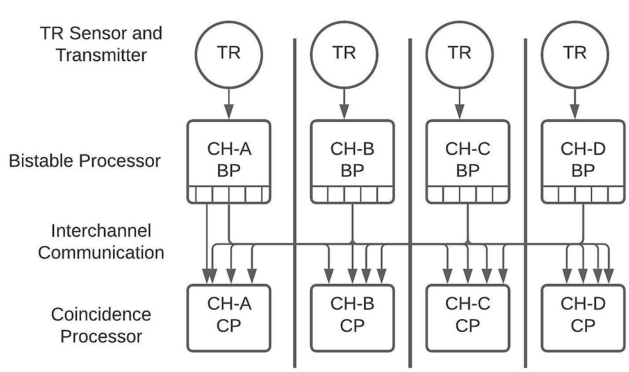


Fig. 1 Digital RPS generic block diagram

relationships among the SDLC, the number of residual defects within the software, and the software failure probability. The SDLCs were categorized into five phases: requirements, design, implementation, testing, and installation/checkout. A BBN sub-model was then developed for each phase to estimate the number of remaining software defects [17]. A model using BBN with a distribution-based node probability table (D-NPT) was developed to assess the number of software faults within the I&C system in the NPP considering the SDLC. A pilot study of software reliability statistical analysis was performed by collecting several experts' opinions. Sensitivity studies were performed by removing the considerably different NPT appreciations to examine the impact of different specialist views on BBN parameter uncertainties [18].

The BBN model was applied to evaluate the software reliability of the digital protection software by estimating the number of faults in a software program, considering its SDLC. The proposed model can estimate the failure probability for both developing and deploying safety-related NPP software. The BBN model structure and parameters are specified based on the information introduced to NPP safety systems, and evidence was gathered from three stages of expert elicitation [19]. A BN model was developed to diagnose waste-water treatment systems based on modified sequencing batch reactors (MSBRs). The knowledge deduced from the literature and obtained from experts was used to establish the network and then parameterized using independent data from a pilot test. A 1-year pilot study was performed to verify the diagnostic analysis. The suggested model is reasonable, and the diagnosis results are accurate [20]. The present study aims to improve the reliability of RPS in NPP using the BBN tool to model the digital RPS hardware architecture. BBN can be an added value compared to other methods because of its popularity as a tool for reliability analysis and modeling of many problems and complex systems. Using BBNs provides more capability and flexibility, with minimum effort and perfect results. BBNs are a marriage between probability theory and graph theory, so they are more appropriate techniques for handling dependencies between components, complexity, causality, and uncertainties in failure data and modeling [21]. They yield exact results because their analysis is based on conditional probabilities. BBNs are also closely related to influence diagrams, which can be used to make optimal decisions. The construction of the BBN model is easier than the development of a fault tree. Although the development of a fault tree requires effort, it provides good insight into failure details, especially in a complex system in terms of cut sets. However, with BBN, we are more interested in the reliability features of the system and the importance of components in terms of risk contribution, not in the details of the failure mechanisms of the system. Therefore, in this study, BNN is used instead of the fault tree to model the system architecture because BBN yields results without truncation and less effort is required for sensitivity analysis.

The biggest arguments against a Monte Carlo simulation are probably the computational requirements involved. Calculations can take longer than analytical models, and solutions are not exact but depend on the number of repeated runs used to produce the output statistics. Thus, all outputs are estimated. Despite the extensive use of Markov models, they cannot be derived rigorously from deterministic, dynamical models. Studies based on Markov models rarely provide the range of time for which the Markov model is suitable for modeling dynamical systems. Markov models are generally inappropriate over sufficiently short time intervals. Dynamic programming for finding the best path through a model with different states and edges is high in terms of both memory and computational time. Various arrangements of the digital RPS I&C components and modules were constructed in this study. The reliability block diagrams (RBDs) and BBN models were developed for each architecture to show the effect of the I&C components on the entire RPS failure.

In this article, a parameter called a failure probability increasing factor is proposed for the creation of the conditional probability table (CPT). This factor increases due to failures. It may be described as the ratio of the availability of a specified node affected by its parent node failure and not by its own failure. In addition, a combination of failure rate and downtime of the I&C components was suggested to be included in the reliability analysis and development of the RPS. All the different permutations in a fault tree can be simplified using the proposed method, as will be shown later in the CPT, which allows iterative methods to be applied to analyze highly complicated architectures. The calculated unavailability using the proposed method is compared to the other five methods and gives a minimum value equal to 1.43E−07. The significance of the I&C components was determined using BBN, which confirms its impact on the risk of the entire system. In Sect. 2, the BBN model is described, Bayes' theorem is explained, and the conditional probability distribution (CPD) is explored. In Sect. 3, a detailed description of the main steps for the calculation of the availability in the RPS I&C is detailed; a brief summary of the software tool used in this study is described; various architectures of the I&C components for digital RPS, its related RBDs, and BNN structures are presented; and the BBN probabilities assessment analysis of the RPS I&C modules is illustrated. In Sect. 4, experimental results on different architectures are presented and discussed. In the last section, concluding remarks and recommendations are presented.

2 Bayesian belief network model

BBN techniques have been used to predict failures in fields such as artificial intelligence, medical diagnosis, information technology, and machine failure since the 1990s. BBN model is shown in Fig. 2 as a probabilistic graphical structure that uses Bayesian probability, which allows a tractable graph-based representation for inference, under uncertainty, about a given problem. The BN depicts the dependency relationships (represented by arcs) between a group of nodes (random variables) and their CPD, through a directed acyclic graph (DAG). The initial step in solving the problem is defining the topology of a Bayesian network DAG and providing the dependency relationship among the nodes [22–24]. The next step is defining the CPD for each node, and finally, the joint probability must be considered to model the posterior probability distribution after observing new evidence. Bayes' theory is the main component of BNs and Bayesian inference and is utilized to infer the probabilities of unknown events. It updates probabilities according to recent information. Bayes' formula was developed as a formal statistical inference and decision-making method. Thomas Bayes was an eighteenth-century British mathematician who developed a mathematical formula for calculating conditional probability, which is the likelihood of an outcome occurring based on a previous outcome. Bayes' theorem provides a method to revise existing predictions or theories (update probabilities) given new or additional evidence. This mathematical formula is well known as either the Bayes' theorem, Bayes' rule, or Bayes' law. It relies on incorporating prior probability distributions to generate posterior probabilities. Prior probability, in Bayesian statistical inference, is the probability of an event before new data are collected. The posterior probability is the revised probability of an event occurring after considering new information. The posterior probability is calculateby updating the prior probability using Bayes' theorem. The formula for Bayes' theorem is given by Eq. (1):

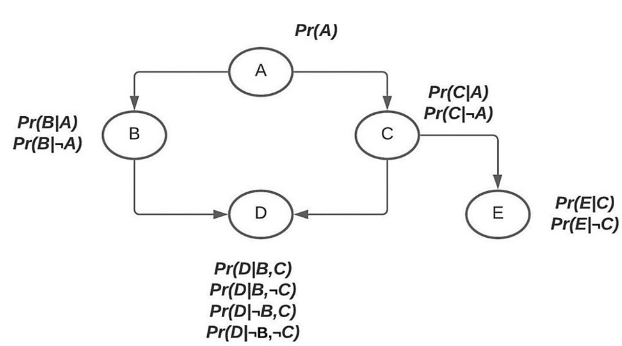


Fig. 2 Bayesian belief network model

$$P(A|B) = P(B|A) \cdot P(A)/P(B). \quad (1)$$

$P(A|B)$ is a posterior probability, the probability of event A occurring given that B is true. $P(B|A)$ is the likelihood, the probability of event B occurring given that A is true. $P(A)$ and $P(B)$ are known as prior probability and the marginal likelihood, respectively [25–27]. The relationship between the marginal probability and posterior probability is described by Bayesian analysis using Bayes' theorem. If an edge is from node A to node B, then A is B's parent variable. CPD can be defined as CPT when all the nodes are discrete-valued. For each combination of parent's values, the probability that the child has one each of its different values is listed in the CPT. Bayesian networks can be constructed either manually with knowledge of the entire problem or automatically using software given a large dataset.

3 Model development of I&C for the RPS as a Bayesian belief network

Figure 3 shows the main steps of the proposed methodology for evaluating the availability of the entire RPS. First, the main I&C modules are identified in the digital RPS channels. Second, we construct the RBD and BBN graph based on the I&C modules' architecture information data. Each module in the I&C system is represented by a basic node of the BN graph. Then, the different nodes are connected by arcs to identify the dependencies and independencies between the nodes. Next, a prior probability table for root nodes and CPD for other nodes were set up to establish the relationship between the child and parent nodes of the BBN model. Finally, we estimate the availability of the digital RPS based on prior given inputs and evidence.

3.1 Microsoft Bayesian network (MSBNx)

Microsoft Bayesian network (MSBNx) is a Microsoft component-based windows software application for modeling and obtaining inference with Bayesian networks. It creates, manipulates, evaluates, and infers BN. It can perform multistate failure and time-dependent analysis with continuous, integer, or discrete intervals. Once a model has been created, it can be used to diagnose and troubleshoot. AMSBNx appreciates the causes-to-effects model by implementing it inversely from effects to causes. Each model is represented as a graphical structure diagram. The random variables are represented by ellipses, called nodes, and the conditional dependencies are represented by directed arcs between nodes. The basic functions within aMSBNx are constructing and modifying model diagrams, working with model diagrams, evaluating models by updating probabilities based on the relationships and the evidence, and assessing probability by maintaining prior probabilities. In this study, BN models were implemented and evaluated using the MSBNx tool [28].

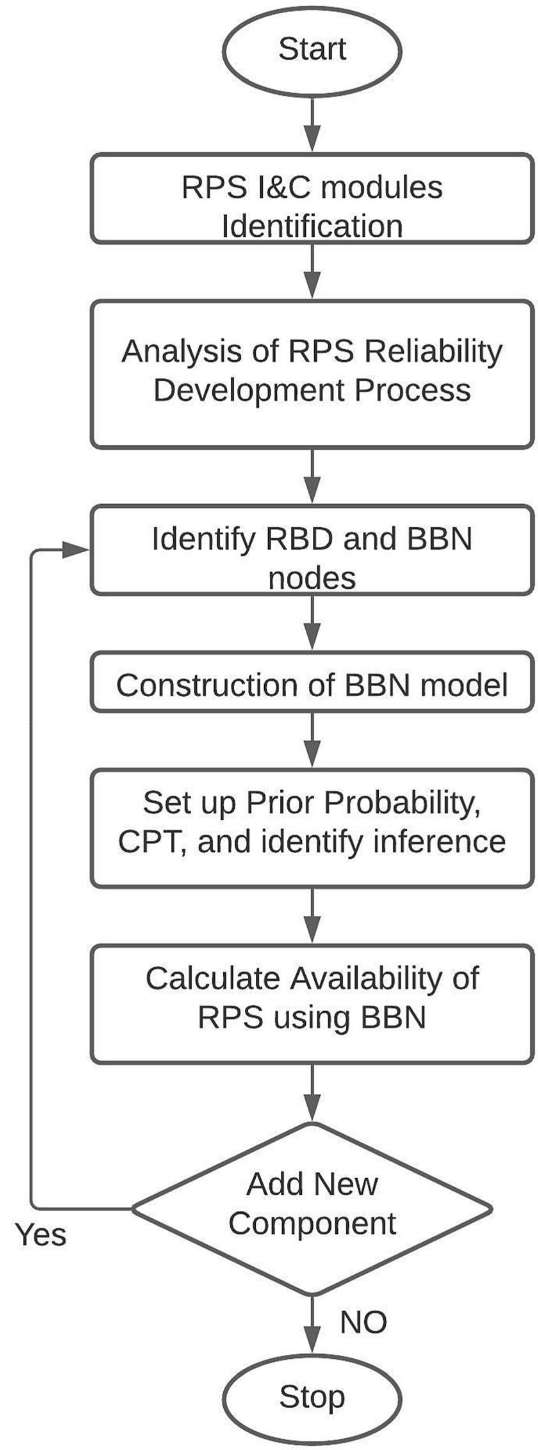


Fig. 3 Main steps for the proposed methodology

3.2 Proposed modeling of different RPS architectures using BBN based on RBD

Figures 4, 5, 6, 7, 8, 9, 10, 11 and 12 represent the RBDs and BBN models for the different arrangements of the digital RPS I&C components. The failure is propagated from the transmitter and sensor to the final trip failure. The signals generated by the sensors are converted to a pulse or digital volt and are then compared with set points in BP. The BP sends a signal to the CP after assessment. CP receives signals from the BPs of other channels and confirms the voting logic before initiating the reactor trip. The CB trips the reactor with 2oo4 voting logic. For the attainment of objectives, the RPS I&C system architecture was transformed to RBD for modeling ease in BBN. The four RPS channels are identified by symbols A, B, C, and D. Various arrangements of the digital RPS I&C components and modules are constructed by changing the redundancy of TR, PT, BP, CP, DO, BP&CP, BP&CP&DO, and CB to observe and evaluate the impact of these units on the overall RPS failure. The RBDs of different RPS I&C architectures have been developed and mapped to BBN models to demonstrate the effect of I&C components on the failure of the entire system. The details of the architectures are discussed below.

The configuration of Fig. 4 has no interchannel redundancy and consists of single TR, PT, AI, DI, BP, CP, DO, ST, UV, and CB modules. In the configuration of Fig. 5, two sensor and transmitter (TR_B1, TR_B2) modules were added to the architecture. The redundant pair of PT units (PT_D1, PT_D2) is added in Fig. 6. In Fig. 7, redundancy was added to the bistable processors (BP_A1, BP_A2) to demonstrate the effect of the BP component on the entire system failure. Two CP processors (CP_A1, CP_A2) joined the architecture shown in Fig. 8. A redundant pair of DO modules (DO_C1, DO_C2) was inserted in the architecture of Fig. 9. Dual redundancy in BP and CP components was inserted in the architecture of Fig. 10. The configuration of Fig. 11 had redundancy in the BP, CP, and DO modules. Finally, redundancy was added to the CB modules (CB_A1, CB_A2), as shown in Fig. 12.

3.3 BBN probability estimation

The failure rate or failure probability of I&C components is represented by λ. Table 1 shows the prior probability of a root node. Failure and success states are represented by 0 and 1, respectively. The conditional probabilities for other nodes (not root nodes) have to be evaluated with the knowledge of the state of its parent nodes. The digital RPS has various kinds of failures. When calculating the availability of RPS, we must take into consideration the causes of these failures, such as independent failure of components or failures caused by the failure of another component. The failure probability increasing factor for the creation of the CPT is proposed. This factor increases due to failures. It may be described as the ratio of availability of a specified node affected by its parent node failure, not by its own failure. For node "a," given that "b" is one of its parent nodes, the failure increasing factor is given by Eq. (2):

$$R_{x|y} = 1 - DT_{\mathrm{a|b}}/T - DT_{\mathrm{a}} \quad (2)$$

where T is the test interval, DT_{a} is the downtime of node "a" caused by its failure, and $DT_{\mathrm{a|b}}$ is the downtime of node "a" caused by the failure of its parent node "b". Table 2 shows the conditional probabilities for nodes with four-input "2oo4" voting logic of the digital RPS I&C modules. There are 16 combinations due to four inputs, 11 combinations classified as failure state, and five combinations classified as success state. For the failure state, the probability of failure is equal to $\lambda R_{\mathrm{a|b}}$, whereas the probability of success is equal to $(1 - \lambda)R_{\mathrm{a|b}}$. For the success state, the probability of failure is equal to failure rate λ, whereas the probability of success is equal to $1 - \lambda$. The generic main information of the RPS I&C components is represented in Table 3 [29, 30].

4 Results and discussion

Figure 13 shows the availability and unavailability comparisons between the different architectures of the digital RPS I&C components depicted in Sect. 3, based on the generic data for the RPS I&C components in Table 3, and the CPT for a node with four-input 2oo4 logic of the digital RPS I&C modules in Table 2. By substituting from generic data into CPT, we obtain the inputs to the BBN. By using the MSBNx tool for implementing the different RPS I&C component architectures, the availability and unavailability are obtained. The first architecture with no redundancy in I&C modules is counted as the main architecture with an availability of 0.999944. Architectures no. 2 with redundancy added in TR component, no. 3 with redundancy added in PT, no. 6 with redundancy added in DO, and no. 10 with redundancy added in the UV module have the same availability as the main configuration with no redundancy. Therefore, redundancy in TR, PT, DO, and UV components does not increase or decrease the availability of RPS I&C modules. The availability of the digital RPS decreased to 0.999785 in architecture no. 4 with redundancy added in the BP component and to 0.999719 in architecture no. 9 with redundancy added in CB. However, the availability increased in architecture no. 5 with redundancy added to CP; in architecture no. 7 with redundancy added to BP and CP components; and in

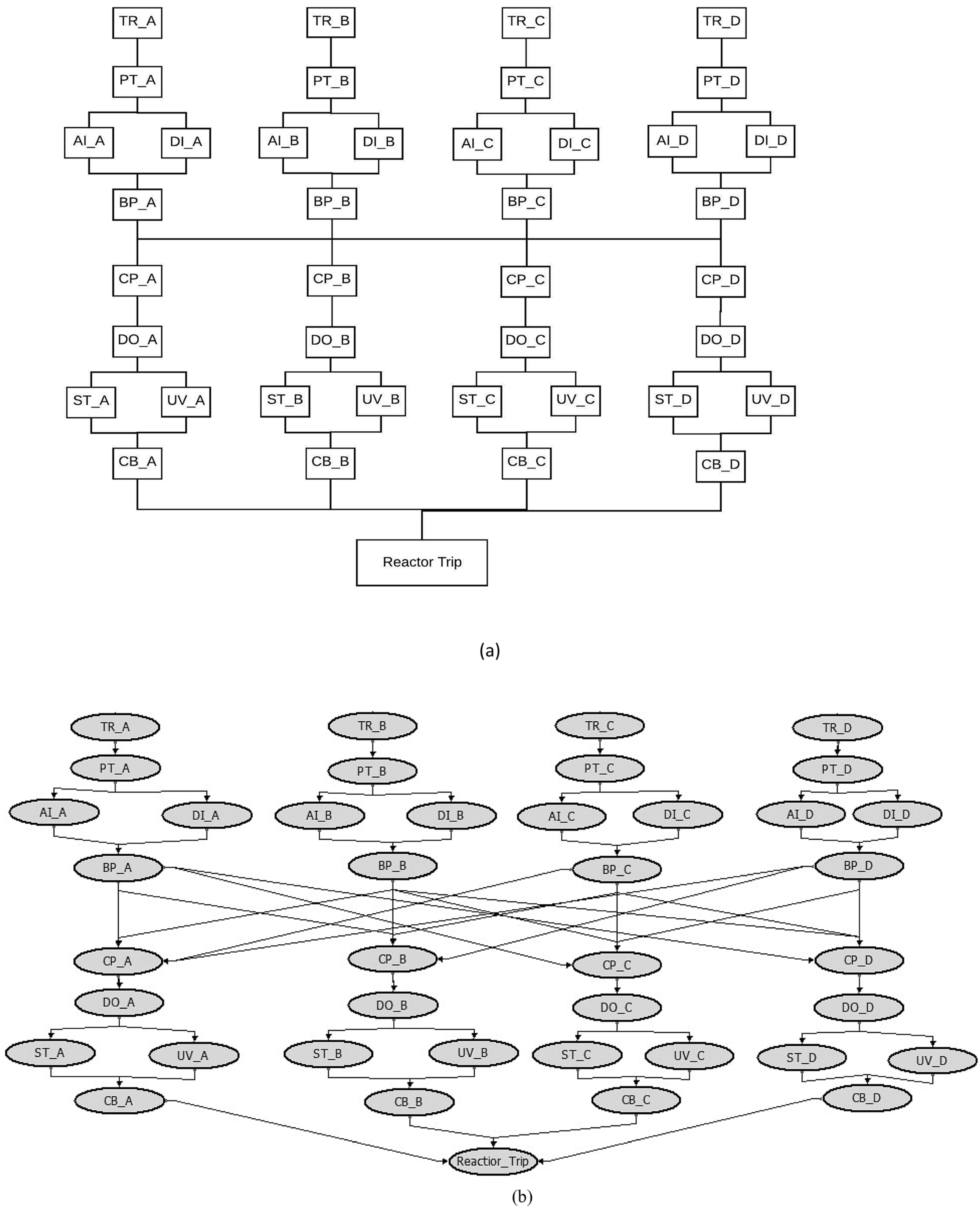
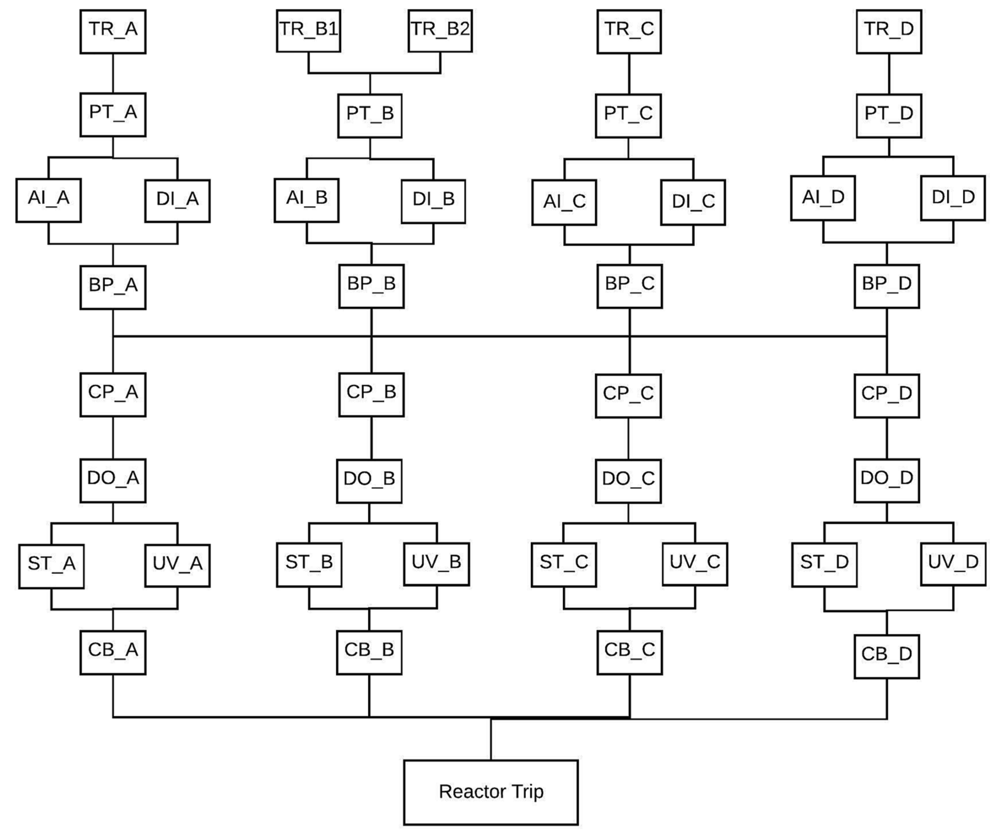
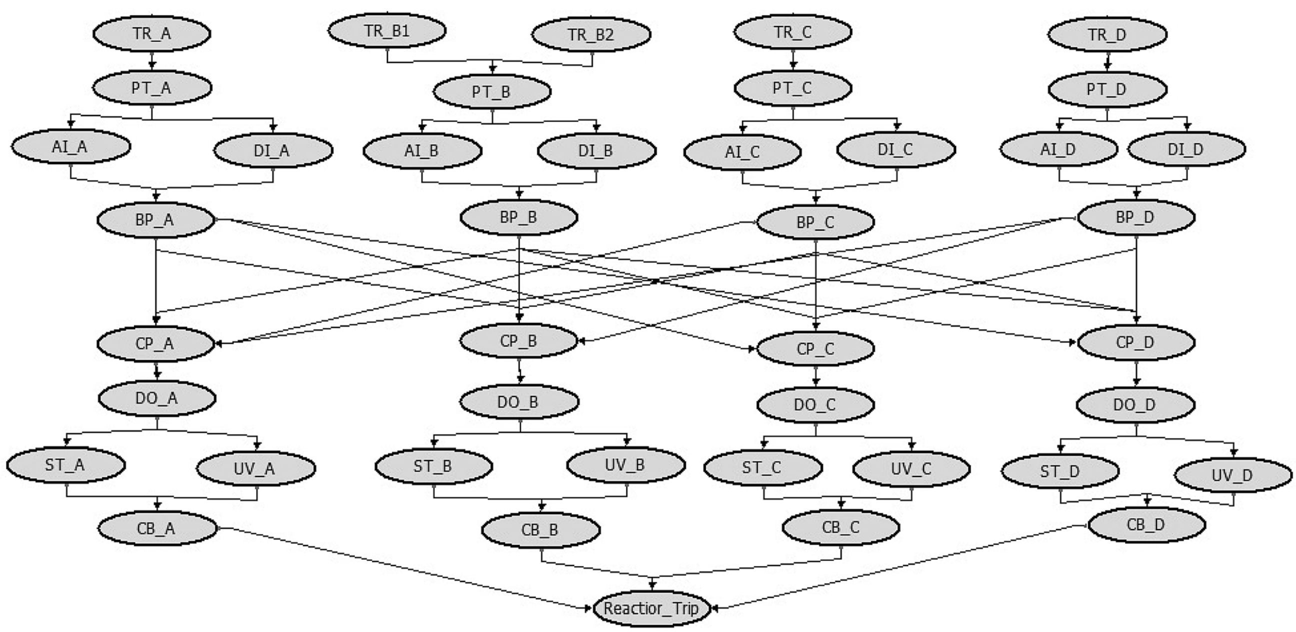


Fig. 4 (**a**) RBD with no redundancy and (**b**) BN model with no redundancy

architecture no. 8 with redundancy added in BP, CP, and DO components to 0.999966, 0.999967, and 0.9999998, respectively. The results demonstrate that architecture no. 8 with redundancy added to BP, CP, and DO components is



(a)



(b)

Fig. 5 (**a**) RBD with TR redundancy and (**b**) BN model with TR redundancy

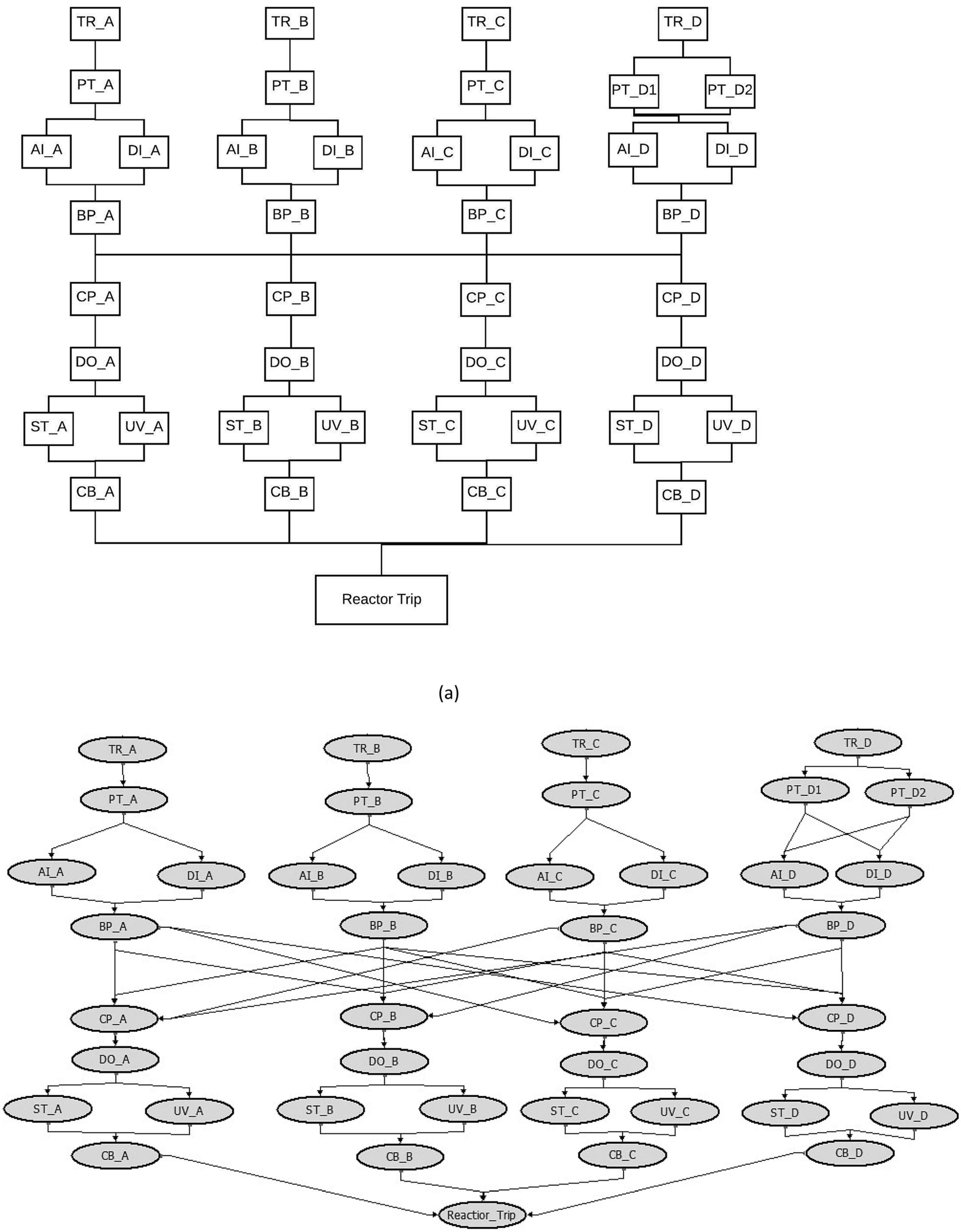


Fig. 6 (**a**) RBD with PT redundancy and (**b**) BN model with PT redundancy

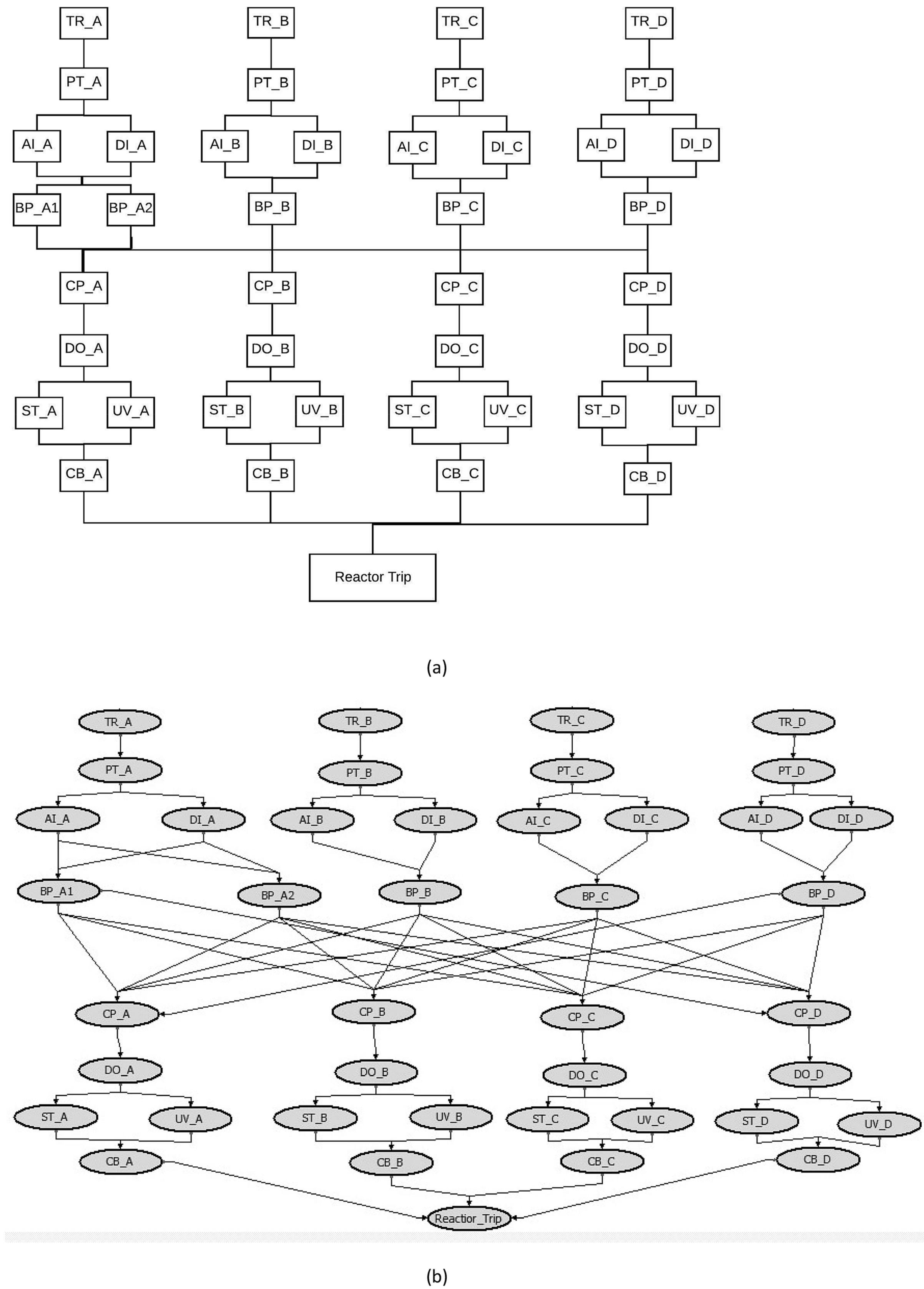
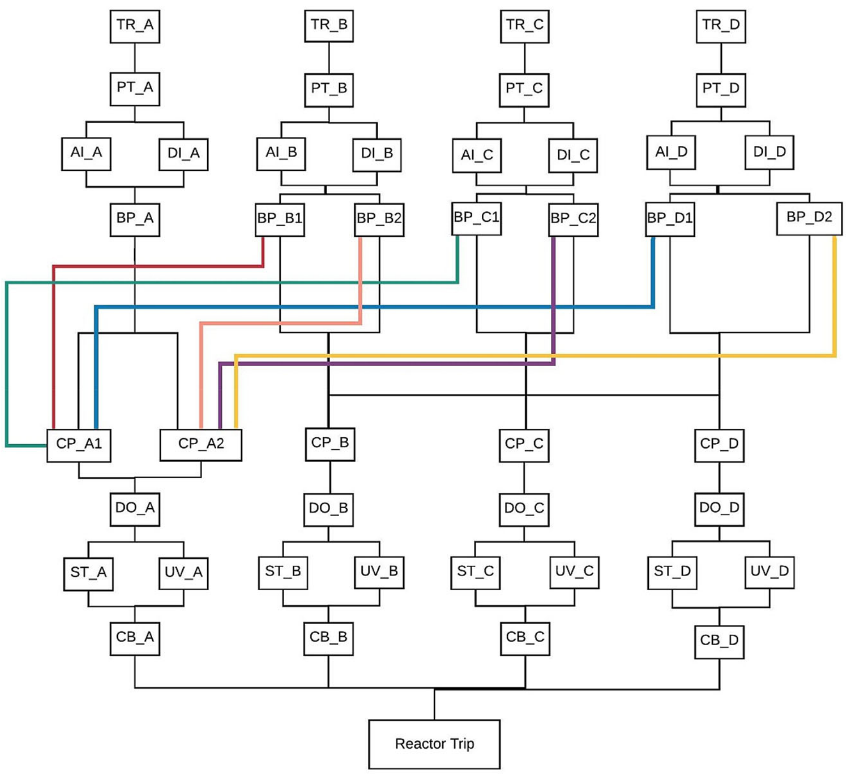
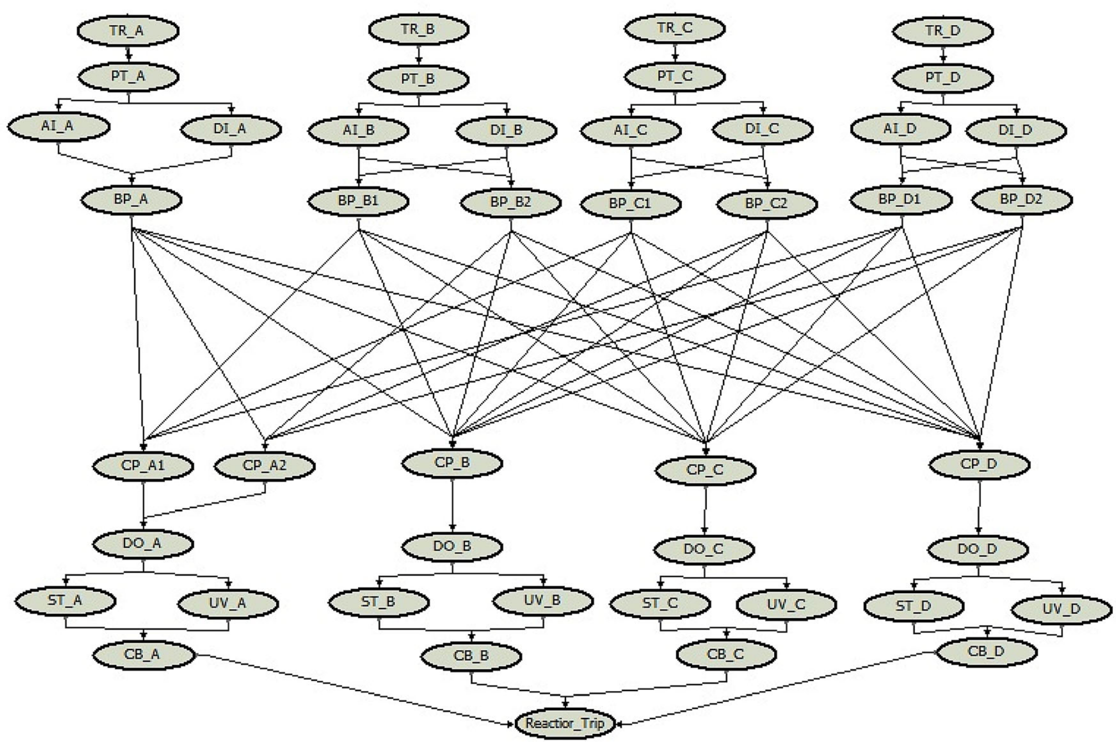


Fig. 7 (a) RBD with BP redundancy and (b) BN model with BP redundancy



(a)



(b)

Fig. 8 (**a**) RBD with CP redundancy and (**b**) BN model with CP redundancy

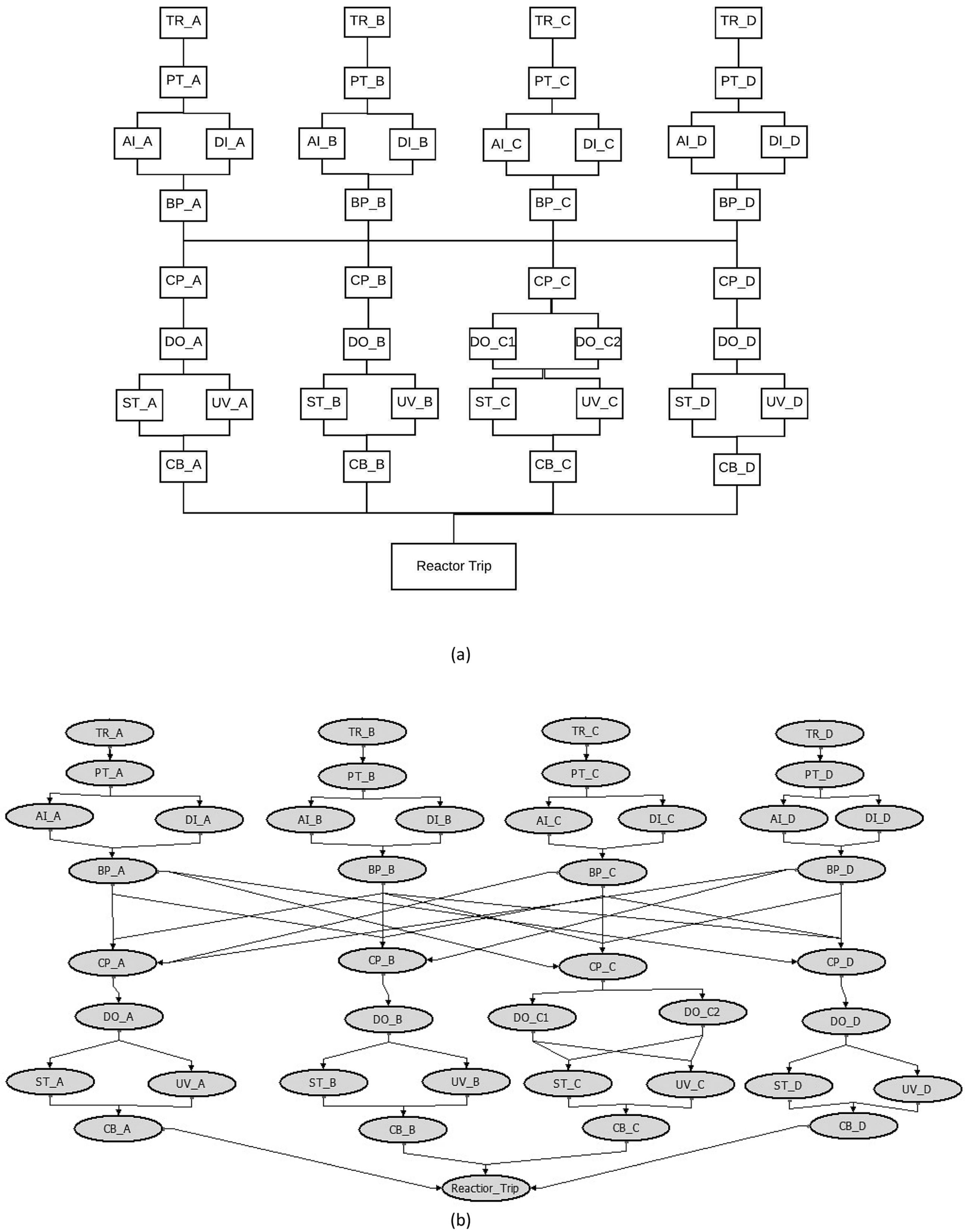


Fig. 9 (**a**) RBD with DO redundancy and (**b**) BN model with DO redundancy

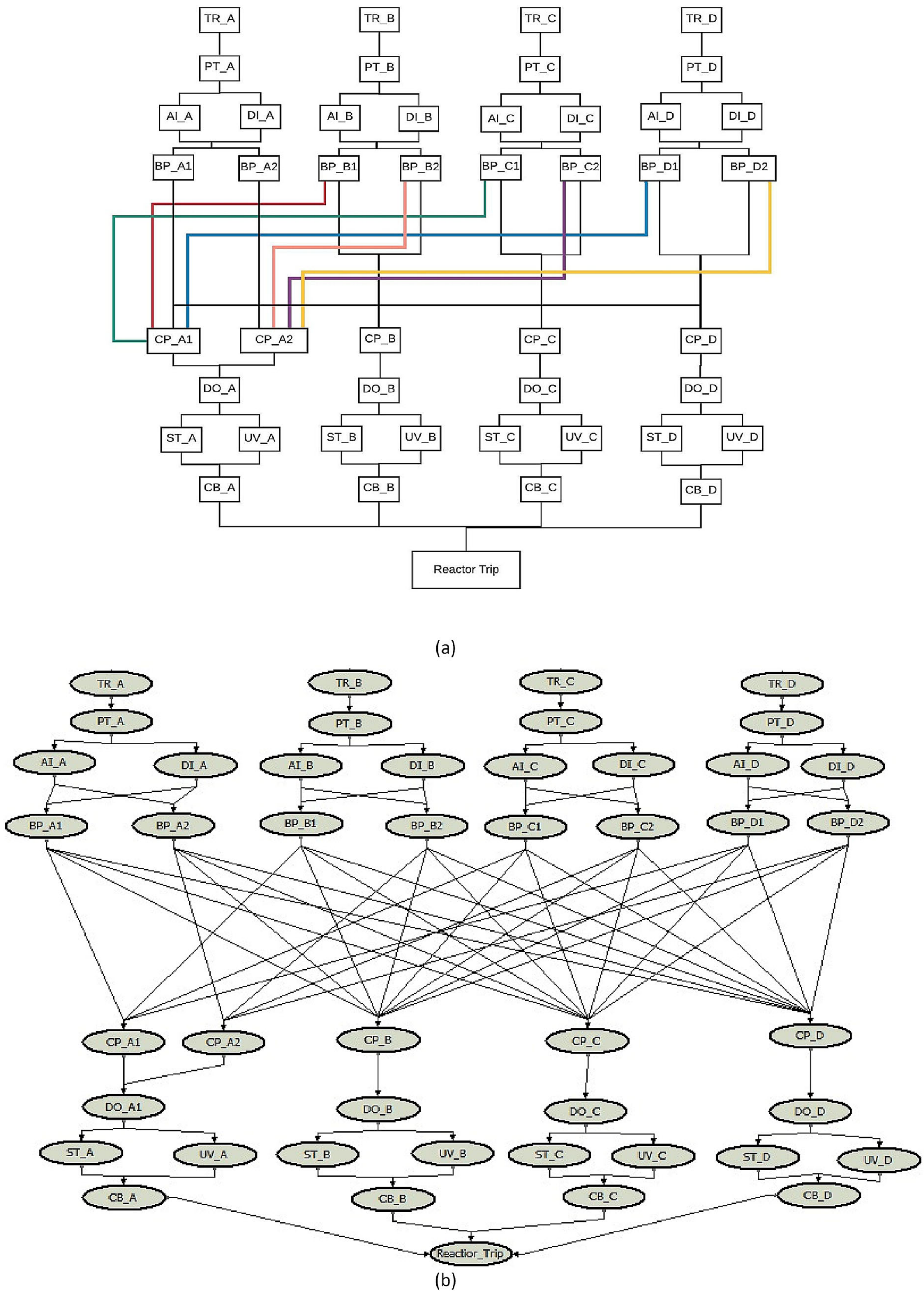


Fig. 10 (**a**) RBD with redundancy in BP and CP and (**b**) BN model with redundancy in BP and CP

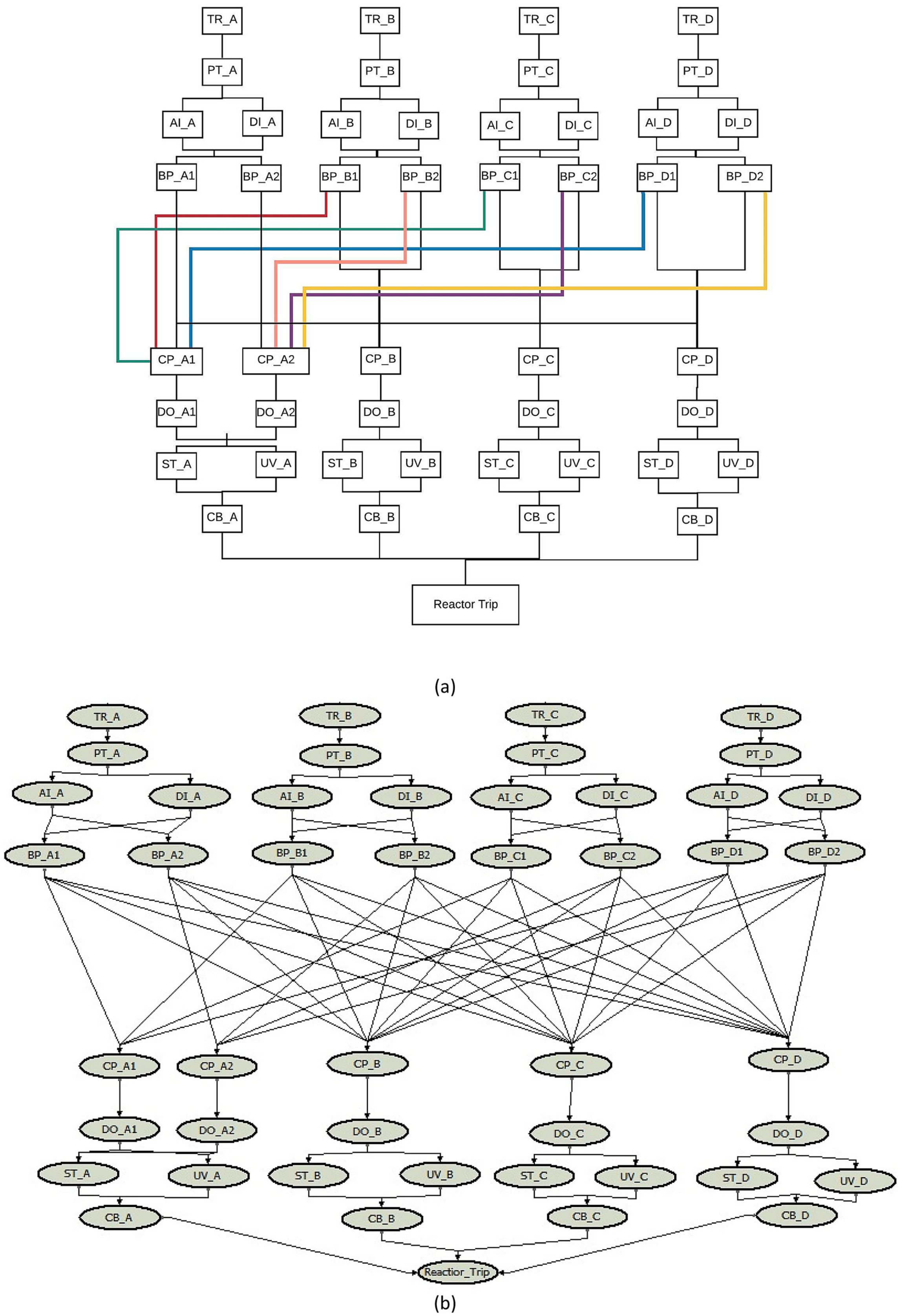


Fig. 11 (**a**) RBD with redundancy in BP, CP, and DO and (**b**) BN model with redundancy in BP, CP, and DO

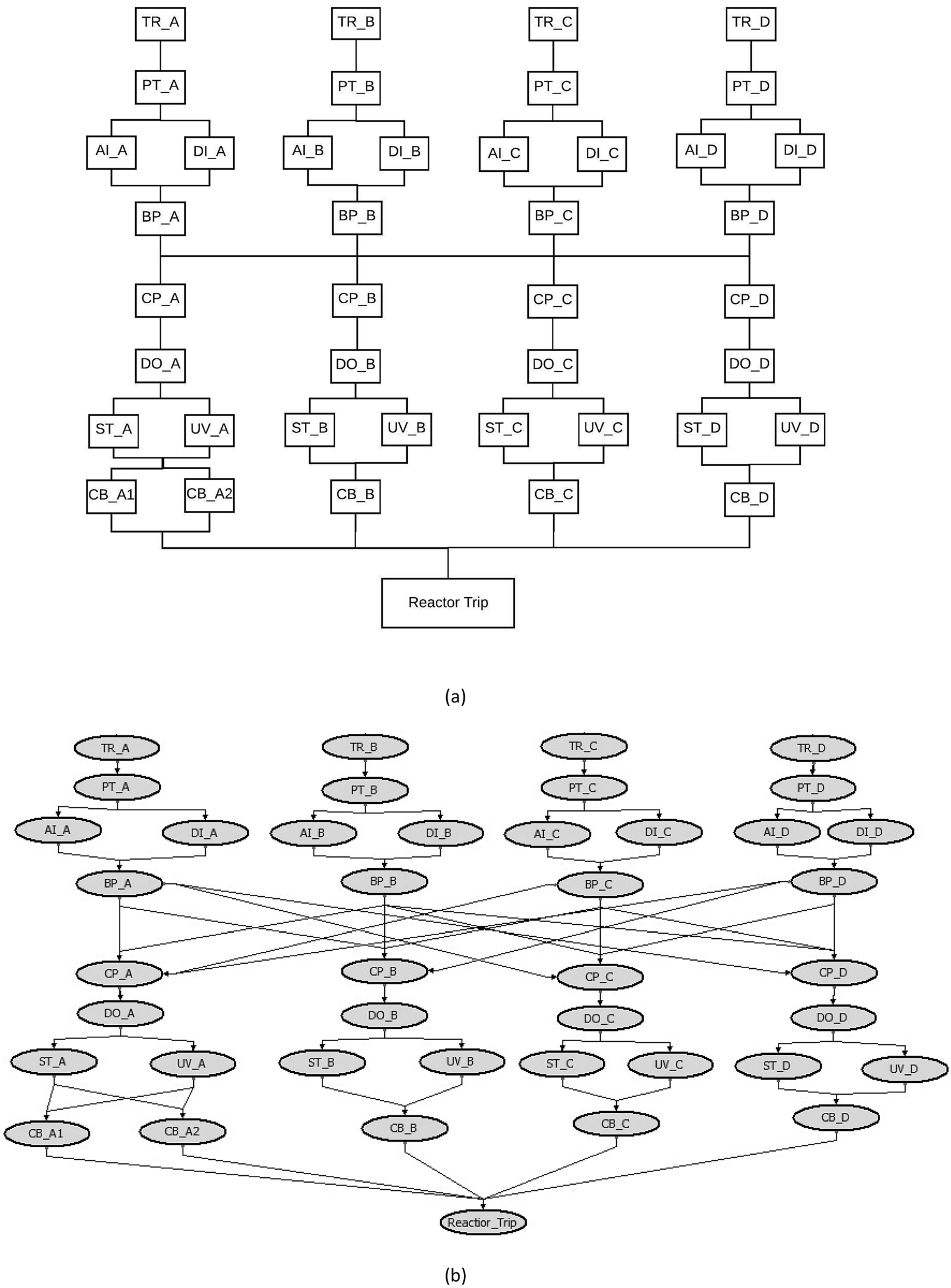


Fig. 12 (**a**) RBD with redundancy in CB and (**b**) BN model with redundancy in CB

the optimal architecture for the design of RPS I&C modules, because it has the highest availability of 0.9999998 compared to the other architectures. Figure 14 shows the unavailability of the digital RPS using the present methodology compared to other methods based on minimum unavailability requirements [8]. The unavailability of the proposed method gives a minimum value equal to 1.43E−07 compared to values of 8.08E−07, 1.52E−03, 1.00E−03, 7.85E−01, and 1.13E−05 calculated using other methodologies.

The results prove the superiority of the present study. The comparison of the supposed model's result to the other different methods' results is based on the requirement of minimum unavailability of the RPS, as stated in the NUREG/ CR-5500 [8]. Component importance measures are defined as a means to measure the impact and contribution of a component on the total system risk. Popular importance measures include Birnbaum, Fussell–Vesely (FV), risk reduction worth (RRW), and risk achievement worth (RAW). The RRW is defined as the decrease in risk when a component is functioning or perfectly reliable, whereas RAW is defined as the relative increase in risk when a component is in a failure state [31]. The RRW is the ratio of the unreliability of the entire system to the system unreliability if component i is reliable, as shown in Eq. 3. The RAW is the ratio of the system unreliability if component i fails to the actual system unreliability, as shown in Eq. (4):

$$I^{\mathrm{RRW}}(it) = 1 - h(p(t))/1 - h(1_i, p(t)). \tag{3}$$

$$I^{\mathrm{RAW}}(it) = 1 - h(0_i, p(t))/1 - h(p(t)) \tag{4}$$

The actual system unreliability is $1 - h(p(t))$. The system unreliability when component i is reliable is $1 - h(1_i, p(t))$, where the failure rate of the corresponding component i is set to 0 in the BN model. The system unreliability when component i fails is $1 - h(0_i, p(t))$, where the failure rate of the corresponding component i is set to 1 in the BN model. Table 4 presents the values of the RRW and RAW importance measures for each component. The components of the RPS can be classified into high, medium, and low sensitivity to risk components based on US Nuclear Regulatory Commission Regulation (NUREG) standards for risk importance measures. Components with

Table 1 Prior probability table of a root node

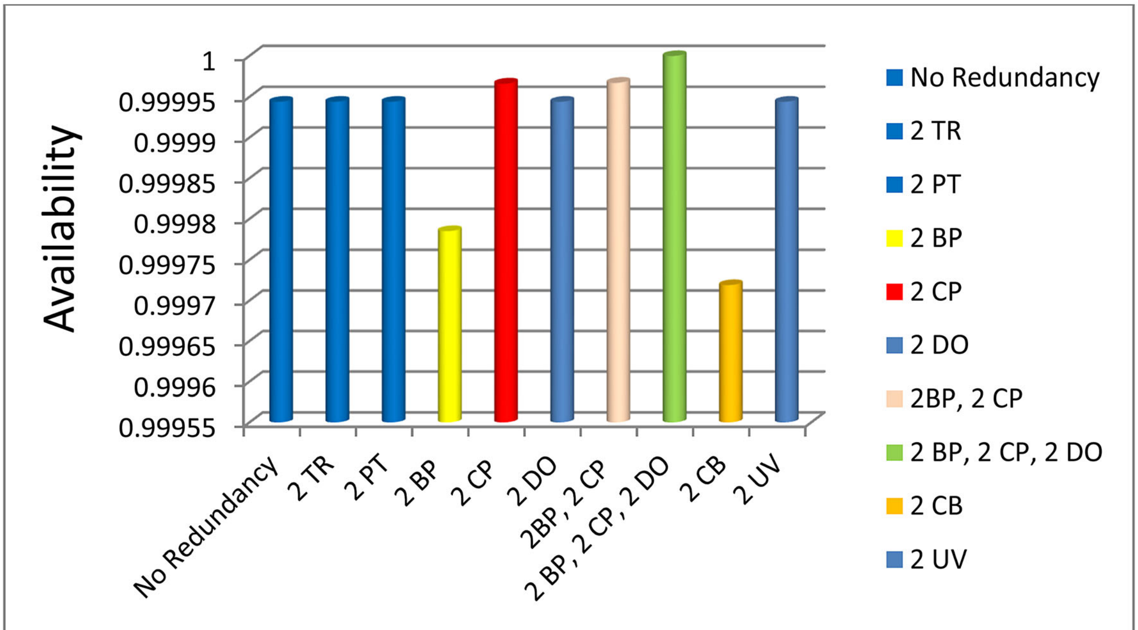
Root node	0	1
	λ	$1 - \lambda$

Table 2 CPT for a node with 2oo4 logic

Parent node inputs	Module state	Child node	
		Failure	Success
0000, 0001, 0010, 0011, 0100, 0101, 0110, 1000, 1001, 1010, 1100	0	λR_{alb}	$(1 - \lambda)R_{\mathrm{alb}}$
0111, 1011, 1101, 1110, 1111	1	λ	$1 - \lambda$

Table 3 Generic I&C components for RPS basic information

Component ID	Component name	Unit	Failure mode	Failure rate (λ)	Distribution	Factor	Value
1	Sensors and transmitters (TR)	h	Sensor fails	1.7×10^{-6}	Log normal		
2	Pressure/level transmitter (PT)	h	Fails to provide	4.4×10^{-6}	Log normal	$R_{2\|1}$	0.8254
3	Analog input (AI)	h	Fails to generate trip output	2.0×10^{-6}	Log normal	$R_{3\|2}$	0.8593
4	Digital input (DI)	h	Fails to generate trip output	8.96×10^{-7}	Log normal	$R_{4\|2}$	0.8146
5	Bistable processor (BP)	d	Fails to operate	5.0×10^{-4}	Log normal	$R_{5\|3}$	0.8601
						$R_{5\|4}$	0.8607
6	Coincidence processor (CP)	d	Processor logic modules fail	1.6×10^{-4}	Log normal	$R_{6\|5}$	0.8532
7	Digital output (DO)	h	Fails to generate trip output	8.2×10^{-7}	Log normal	$R_{7\|6}$	0.8324
8	Shunt circuit (ST)	d	Fails to energize	1.2×10^{-4}	Log normal	$R_{8\|7}$	0.8526
9	Undervoltage circuitry (UV)	d	Fails to energize	1.7×10^{-3}	Log normal	$R_{9\|7}$	0.8117
10	Circuit breaker (CB)	d	Fails to open/close	4.5×10^{-5}	Log normal	$R_{10\|8}$	0.843
						$R_{10\|9}$	0.847



Architecture	Architecture description	Availability of RPS	Unavailability of RPS
1	No Redundancy	0.999944	5.61774e-5
2	2 TR	0.999944	5.60984e-5
3	2 PT	0.999944	5.59405e-5
4	2 BP	0.999785	2.15118e-4
5	2 CP	0.999966	2.92531e-5
6	2 DO	0.999944	5.58561e-5
7	2BP, 2 CP	0.999967	3.28276e-5
8	2 BP, 2 CP, 2 DO	0.9999998	1.43215e-7
9	2 CB	0.999719	2.80981e-4
10	2 UV	0.999944	5.61791e-5

Fig. 13 Availability and unavailability of RPS for different architectures

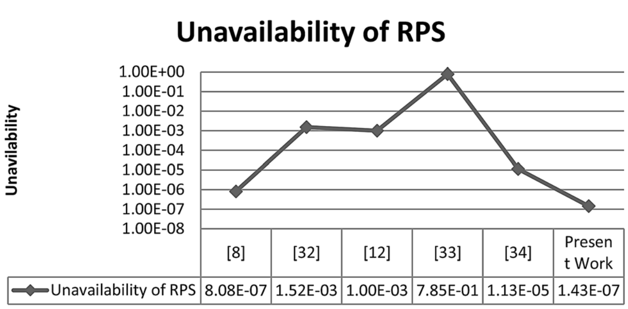


Fig. 14 RPS unavailability comparison for various methods

RRW greater than 1.005 or RAW greater than 2.0 are classified as high-risk impacts [8].

The values demonstrate that, for architecture 1, the TR, PT, and CB components are more sensitive to risk, whereas BP and CP components are less sensitive based on their RRW value. The CB component is more sensitive to risk, whereas the TR, PT, BP, CP, and DO components are less sensitive, while the ST and UV are slightly sensitive based on their RAW value. For architecture 4, the TR and PT components are more sensitive to risk, whereas the BP and CB components are less sensitive based on their RRW value. The CB component is more sensitive to risk, whereas the TR, PT, BP, CP, and DO components are less sensitive, while UV is slightly sensitive according to RAW value. For architectures 5 and 7, the TR, PT, and CB components are more sensitive to risk, whereas BP is less sensitive based on their RRW value. The CB component is more sensitive to risk, whereas UV is less sensitive, whereas CP, DO, and ST modules are slightly sensitive according to their RAW value. For architecture 8, CB is more sensitive to risk, whereas TR, PT, BP, CP, and DO

Table 4 RRW and RAW importance measures values for various architectures

Component name	RRW						RAW					
	Arch						Arch					
	1	4	5	7	8	9	1	4	5	7	8	9
TR	1.24	2.07	1.45	1.43	1.01	1.001	5.02	5.06	1.02	1.02	1.03	8.03
PT	2.21	3.06	2.47	2.46	1.02	1.003	5.02	5.06	1.02	1.02	1.03	8.03
AI	1.00	1.0001	1.00	1.00	1.00	1.00	1.00	1.79	1.00	1.00	1.00	1.002
DI	1.00	1.0001	1.00	1.00	1.00	1.00	1.00	1.27	1.00	1.00	1.00	1.0007
BP	1.05	1.02	1.01	1.01	1.03	1.01	5.02	5.06	1.02	1.002	1.004	8.03
CP	1.02	1.007	1.006	1.007	1.10	2.42	7.5	6.41	2.84	2.83	5.22	10.61
DO	1.006	1.001	1.002	1.002	1.023	1.17	7.5	6.41	2.84	2.84	5.22	10.61
ST	1.00	1.00	1.002	1.002	1.003	1.0006	2.02	1.69	3.90	3.85	6.25	1.9
UV	1.00	1.00	1.002	1.002	1.003	1.0006	3.33	2.57	7.62	7.62	13.19	3.06
CB	1.25	1.08	1.56	1.58	4.37	1.32	30.96	21.17	86.02	86.03	157.5	38.33

are less sensitive based on their RRW value. The CB component is more sensitive to risk, whereas CP, DO, ST, and UV are less sensitive based on RAW value. For architecture 9, the CP component is more sensitive to risk, whereas the BP, DO, and CB components are less sensitive based on their RRW value. The CB component is more sensitive to risk, whereas the TR, PT, BP, CP, and DO components are less sensitive, while UV is slightly sensitive based on their RAW value. Based on previous comparisons, one can conclude that there are some components that are equal in importance. Components TR, PT, BP, CP, and CB are identified as more sensitive to risk according to their RRW values. Components TR, PT, BP, CP, DO, UV, and CB are more sensitive components owing to their RAW values. While RRW and RAW importance measures focus on components TR, PT, BP, CP, and CB as highly sensitive to risk, these components should be taken into consideration during the design of RPS to improve reliability and decrease risk and cost.

5 Conclusions and recommendations

The prohibition of accident mitigation consequences, the fulfillment of suitable operating conditions, and improving reliability in the protection of the nuclear site are the main tasks for the safety and effectiveness of NPPs. This research set about applying the BBN model to improve reliability inference and assessment of the digital RPS I&C systems for NPPs. BBNs are a popular method for modeling uncertain and complex systems. They provide a robust and mathematically consecutive structure for the reliability analysis of various systems. Different scenarios of RBDs and their related BN models of the digital RPS I&C component arrangements were established. The failure data and downtime of the I&C components were utilized in the reliability study. Many experiments were carried out using BBN to measure and quantify the unavailability of digital RPS I&C for different architectures. The architecture with redundancy added to BP, CP, and DO components is the optimal architecture for the design of RPS I&C modules because it has the highest availability of 0.9999998 compared to other architectures. The availability of the digital RPS applied in the present study is compared with other related methods. The results confirm the feasibility, capability, and notability of the present methodology using BBN for evaluating and improving the reliability of digital RPS I&C modules.

The significance of the I&C component was determined using component importance measures RRW and RAW, which confirm its impact on the risk of the entire system. The components TR, PT, BP, CP, and CB are classified as highly sensitive to risk by both measures and must be considered by the operator during the design stage to achieve the desired availability and safety. In addition, recommendations for high reliability of the RPS needs, reduction in the test interval to every week or every day, replacing critical components with higher reliability components, increasing the channel and component redundancy, and reducing common components or sources will reduce common cause failures. Further work on continuous BN reliability modeling is essential to construct more realistic models and generate more accurate and approximate inferences. In addition, neural networks and support vector machine algorithms can be useful for BN topology and parameter learning.

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