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Original Article

Research on rapid source term estimation in nuclear accident emergency decision for pressurized water reactor based on Bayesian network☆

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ABSTRACT

Nuclear emergency preparedness and response is an essential part to ensure the safety of nuclear power plant (NPP). Key support technologies of nuclear emergency decision-making usually consist of accident diagnosis, source term estimation, accident consequence assessment, and protective action recommendation. Source term estimation is almost the most difficult part among them. For example, bad communication, incomplete information, as well as complicated accident scenario make it hard to determine the reactor status and estimate the source term timely in the Fukushima accident. Subsequently, it leads to the hard decision on how to take appropriate emergency response actions. Hence, this paper aims to develop a method for rapid source term estimation to support nuclear emergency decision making in pressurized water reactor NPP. The method aims to make our knowledge on NPP provide better support nuclear emergency.

Firstly, this paper studies how to build a Bayesian network model for the NPP based on professional knowledge and engineering knowledge. This paper presents a method transforming the PRA model (event trees and fault trees) into a corresponding Bayesian network model. To solve the problem that some physical phenomena which are modeled as pivotal events in level 2 PRA, cannot find sensors associated directly with their occurrence, a weighted assignment approach based on expert assessment is proposed in this paper. Secondly, the monitoring data of NPP are provided to the Bayesian network model, the real-time status of pivotal events and initiating events can be determined based on the junction tree algorithm. Thirdly, since PRA knowledge can link the accident sequences to the possible release categories, the proposed method is capable to find the most likely release category for the candidate accidents scenarios, namely the source term. The probabilities of possible accident sequences and the source term are calculated. Finally, the prototype software is checked against several sets of accident scenario data which are generated by the simulator of AP1000-NPP, including large loss of coolant accident, loss of main feedwater, main steam line break, and steam generator tube rupture. The results show that the proposed method for rapid source term estimation under nuclear emergency decision making is promising.

1. Introduction

Nuclear emergency preparedness and response is an essential part of the defense in depth to ensure the safety of nuclear power plant (NPP). Correct and timely nuclear emergency decision-making can provide operators with guidance and suggestions. It can reduce the release of radioactive materials, harm to the public,

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Nomenclature

ACC	Accumulators
ACC1-IV	Accumulators-1 isolation valve
ACC1-P	Accumulators-1 pressure
ACC1-SV	Accumulators-1 start valve
ACC1-WL	Accumulators-1 water level
ACC2-IV	Accumulators-2 isolation valve
ACC2-P	Accumulators-2 pressure
ACC2-SV	Accumulators-2 start valve
ACC2-WL	Accumulators-2 water level
ACP	AC power
ADS	Automatic depressurization system
APPRCS	Average primary pressure in a reactor coolant system
BC	Boron concentration
CHR	Containment cooling removal system
CIS	Containment isolation
CMT	Core makeup tanks
CP	Core power
CVS	Chemical and volume control
CWL-containment	Containment water level
CWL-core	Core water level
FCL (1)	Flow of coolant in loop 1
FCL (2)	Flow of coolant in loop 2
IRSWT	In-containment refueling water storage tank
LOCA	Loss of coolant accident
LMFW	Loss of main feedwater
MFWF	Main feedwater flow of steam generator
MSLB	Main steam line break
NPP	Nuclear power plant
NRHR	Normal residual heat removal
PC	Pressure of the containment
PCL	Pressure of second-loop
PCL(1)	Pressure of coolant in loop 1
PCL(2)	Pressure of coolant in loop 2
PPZ	Pressure of pressurizer
PRA	Probabilistic risk assessment
PRDEP	Primary depressurization in SGTR
PRHR	Passive residual heat removal
PSG (1)	Pressure in steam generator 1
PSG (2)	Pressure in steam generator 2
PWL	Pit water level
PWR	pressurized water reactor
RASCAL	Radiological assessment system for consequence analysis
RC	Radioactivity of the containment
RCP	Rate of coolant pressure
RECIRC	Water recirculation to RPV from the sump occurs
RSG (1)	Radioactivity in steam generator 1
RSG (2)	Radioactivity in steam generator 2
SDS	Shutdown signal
SFSG(1)	Steam flow in steam generator 1
SFSG(2)	Steam flow in steam generator 2
SFW	Startup feed-water
SGDEP	Secondary depressurization in SGTR by condenser
SGISO	Isolation of faulted steam generator
SGTR	Steam generator tube rupture
SMC	Super-cooling of main coolant
STE	Source term estimation
TC	Temperature of the containment
TCLL (1)	Temperature of the cold leg in loop 1
TCLL (2)	Temperature of the cold leg in loop 2
WLPZ	Water level in the pressurizer
WLSG (1)	Water level in steam generator 1
WLSG (2)	Water level in steam generator 2

and economic losses. Nuclear emergency decision-making usually includes the following key steps: accident diagnosis, source term estimation (STE), accident consequence evaluation, and protective action recommendations. Among them, accident diagnosis is the analysis and judgment of the state of NPPs; the STE refers to radioactive released from NPP through the containment or bypass to the environment; accident consequence evaluation refers to estimated harm of radioactive materials to the human body and environment; protective action recommendations provide appropriate and specific countermeasure including take stable iodine and so on [1] to avoid or reduce potential or projected harm.

STE is a key part of nuclear emergency decision-making. It has relatively large uncertainties and technical difficulties. STE provides input for subsequent steps such as accident consequence assessment. Only the STE is relatively accuracy and the feedback timely, the accident consequence assessment and protective action recommendations are more significant.

There are two methods of STE: forward and inverse STE method. Forward STE is based on the status of the reactor to calculate NPPs' release of radioactivity, including core inventory, and the state of core damage [2,3]; Inverse STE is based on environmental monitoring data to estimate the release of radioactivity [4].

Forward STE was first proposed in the WASH-740 report [5]. Due to the lack of experimental data, the method and related parameters were relatively simple, and the calculation results were too conservative. Subsequent US Nuclear Regulatory Commission issued WASH-1400 report [6], introduced the concept of probabilistic risk assessment (PRA), and proposed analysis of NPP risk methods. After the Three Mile Island nuclear accident, the industry and regulators had launched a large-scale severe accident research program. The industry had made important progress in understanding the severe accident mechanism. It had also developed some accident analysis procedures. The uncertainty of the STE had been analyzed and a large number of research results had been obtained [7]. Based on the results of these studies, a framework for emergency response for NPPs (NUREG-1228) [8] and a basis for parameterization of important physical processes (NUREG-1465) [9] was summarized. Scholars also conducted related research on STE, such as developing STE methods for different NPPs [10–13].

The representative methods of forward STE are the simulation of external source accident with medical imaging (SESAME) [14], response technical manual [15], and radiological assessment system for consequence analysis (RASCAL) [16]. RASCAL parameterized a large loss of coolant accident (LLOCA) based on previous research results. The difference between these methods was mainly reflected in that the parameterization was simpler or more complicated, and the accidents were covered more or less.

The inverse STE method was proposed after the Chernobyl nuclear accident. It is mainly based on the dose and concentration monitoring of NPPs to achieve STE [17,18]. The main bottleneck of inverse STE is difficult to guarantee the quality and quantity of measurement data. The uncertainty of STE is introduced by measurement data, meteorological model, and diffusion model. These factors have challenged the advancement of such methods.

In summary, the STE now faces the following common problems: (1) expert knowledge is not fully utilized. Once an accident occurs in a NPP, a large number of alarm signals may appear. At this time, experts are nervous and need to obtain key signal to judge the status of NPP. So expert knowledge is difficult to be fully utilized and the judgment speed is slow. (2) it has high demands on users (experts); (3) The application reactor for STE is relatively fixed; (4) it is difficult to achieve rapid STE. Based on the above problems, this study proposes an intelligent method for STE of a pressurized water reactor (PWR). This method is based on intelligent technology to automatically identify the status of NPPs and uses a PRA model to match all possible accident sequences to achieve STE.

STE is based on intelligent domain knowledge, including PRA models and engineering knowledge. Intelligent technology is implemented in nuclear emergency decision making. The intelligent technology can be summarized as "inference, diagnosis, and prediction", that is, it uses intelligent technology methods to analyze signal data, judge and predict the status of NPPs. Scholars had also made some researches on the application of intelligent technology in NPPs, such as the university of Tennessee [19] and Harbin engineering university [20]. The application of intelligent technology in NPPs is mainly applied in operation support systems, including process monitoring and fault diagnosis [21]. Process monitoring mainly analyzes the parameters of NPPs to judge whether the status of NPPs is operating normally. This process is "finding problems" [22]. The fault diagnosis is to determine what kind of failure occurred in an NPP. This process is "finding the cause".

Based on the above research, the framework of this paper is proposed. Firstly, this paper studies how to build a Bayesian network model for the NPP based on professional knowledge. It presents a method transforming PRA model (event trees and fault trees) into a Bayesian network model. To solve the problem that some physical phenomena which are modeled as pivotal events in Level 2 PRA, cannot find sensors associated directly with pivotal events, so it is difficult to build the Bayesian network model for it. A weighted assignment approach based on expert is proposed. Secondly, this paper implements the junction tree algorithm as the diagnosis method to judge the status of NPPs. Thirdly, the probabilities of possible accident sequences and the source term are calculated. Finally, the proposed method is checked by the simulator of AP1000-NPP, including LLOCA, loss of main feedwater (LMFW), main steam line break (MSLB), and steam generator tube rupture (SGTR).

2. A framework of PRA-based for rapid source term estimation

Since NPPs are mainly PWR, it is necessary to apply knowledge-based intelligent technology in PWR. At the same time, the system of AP1000-NPP is redundant and complex, and modeling is more universal. Therefore, this study selects AP1000-NPP as the research object.

2.1. Level 2 PRA calculation

The level 2 PRA accident sequence of AP1000-NPP is the nuclear accident emergency source term.

Release categories in level 2 PRA accident sequence of AP1000-NPP are shown in Table 1 [23]. The level 2 PRA accident sequence contains the analysis results of the source terms. Different accidents sequence represents the results of different source terms. The paper obtains the source term by matching the most likely accident sequence. Therefore, PRA knowledge can realize fast and relatively accurate STE.

Existing knowledge is used to directly match STE. The method is shown in Fig. 1. By judging the state of the NPP, the probability of success or failure of each event is as the input of the event tree, the probability of each accident sequence is calculated. The release category corresponding to the most probable accident sequence is the most likely source term.

Table 1
Release categories in level 2 PRA accident sequence.

Number	Name	Meaning
1	IC	Intact Containment
2	BP	Containment Bypass
3	CI	Containment Isolation Failure
4	CFE	Early Containment Failure
5	CFV	Containment Venting
6	CFI	Intermediate Containment Failure
7	CFL	Late Containment Failure

Taking the probability of each initiating and pivotal event status (success or failure) as inputs, probability of the accident sequence is calculated, as shown in formula (1):

$$p_i^* = P(\mathbf{I}_i) \cdot P\left(\overline{\mathbf{A}}\right) \cdot P(M) = P(\mathbf{I}_i) \cdot (1 - P(A)) \cdot P(M) \tag{1}$$

where the accident sequence calculated in formula (1) is represented by the red line in Fig. 1, $P(I_i)$ represents the probability of occurrence of the initiating event, $P(A)$ and $P(M)$ indicate the probability of the pivotal event A and M operating normally. $P(M)$ can be judged based on the operating status of the NPP, but the probability of level 2 PRA initiating event is calculated from the level 1 PRA accident sequence, so the level 1 PRA accident sequence needs to be analyzed first.

The level 1 PRA accident sequence is the input of the level 2 PRA. The analysis result of the level 2 PRA accident sequence is the source term. The relationship between level 1 PRA and level 2 PRA is shown in Fig. 2.

2.2. Level 1 PRA calculation method and classification

To calculate the level 1 PRA accident sequence, the status of each initiating event and the level 1 PRA pivotal event are calculated, which is the input of the event tree. The calculation method of the accident sequence of the level 1 PRA and the level 2 PRA is the same, as shown in formula (1). The difference is that the initiating event of level 1 PRA need to judge the status of NPP, as shown in Fig. 3.

The probability of all accident sequences in the level 1 PRA is calculated by formula (1), and the calculation results of the level 1 PRA are the input of the level 2 PRA. But not all the calculation results of the level 1 PRA accident sequence should be used as the input of the level 2 PRA. Because part of the accident sequence in the level 1 PRA represents that the core is not damaged, there is no large-scale release of radioactive materials, so the calculation results of the level 1 PRA need to be classified in Table 2.

For each type of the same results, it is divided into one category, and the accident sequence results are summed, and finally the frequency of each plant damage state is obtained by formula (2).

$$P_n = {P_n}^1 + {P_n}^2 + \ldots + {P_n}^k (n = 1, 2, \ldots, 9) \tag{2}$$

where P_n^k represents the probability of the n-th type of accident sequence, k represents the quantity for the type of $P_{n.}$ P_n indicates that same plant damage state.

2.3. Application of Bayesian network in source term estimation

The analysis and calculation results of the level 1 PRA are classified, but the calculations need to judge the status of NPP, and the

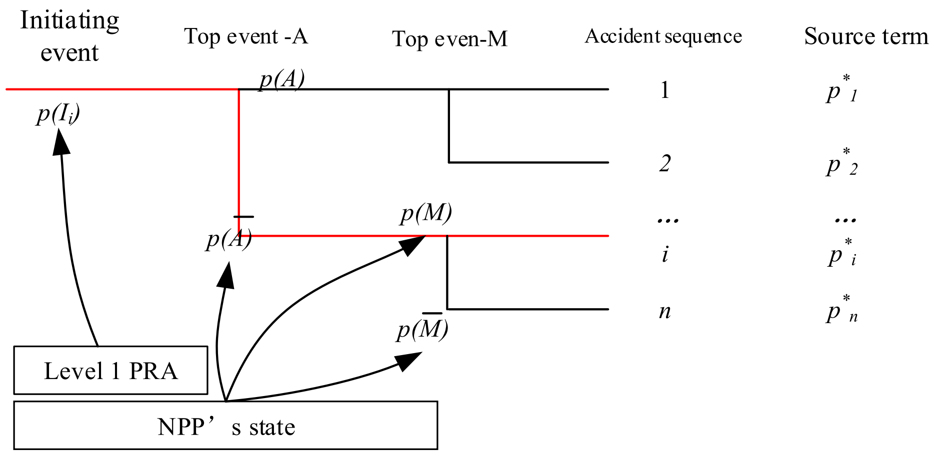

Fig. 1. Combination of level 2 PRA with the status of NPP.

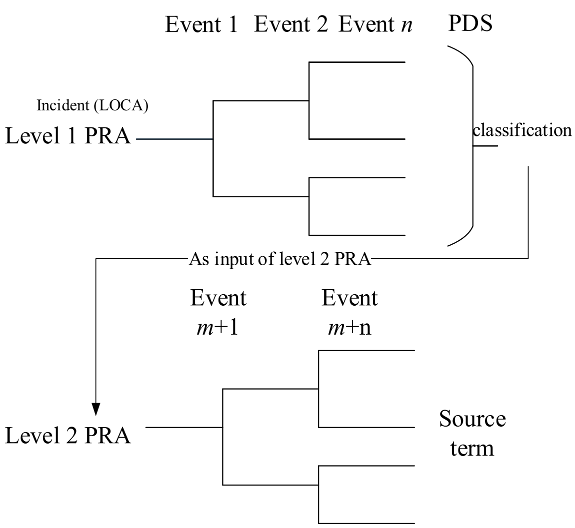

Fig. 2. Corresponding release category in PRA accident sequence.

reliability of the NPP state directly determines whether the STE is accurate and reliable. If the status of an NPP is judged by humans, diagnosis speed and reliability will be greatly reduced. As a complex industry system, an NPP may cause thousands of alarm parameters if the nuclear accident occurs. It is difficult for emergency personnel to quickly extract key information and accurately judge the status of the NPP. At the same time, emergency personnel is under tremendous psychological pressure, which makes it difficult for emergency personnel to judge the status of NPPs and hinders their knowledge. For example, in the Fukushima nuclear accident, poor communication, incomplete information, and complex situations made it difficult to determine the status of the NPP. Therefore, the paper introduces intelligent technology to judge the status of NPP to solve the above problems.

The application of intelligent technology is when the NPP is abnormal, and the abnormality of the parameters is automatically identified to determine what kind of failure has occurred in the NPP, such as expert systems, Bayesian network inference, etc. As a complex industrial system, an NPP has intricate, coupled, and uncertain information. Failures may manifest as multiple faults, associated faults, and other complex forms. Bayesian network can deal with these problems well, and it has the advantage of easy visualization because it is substantially a graphical model, the capability of making complex fault diagnosis, the capability of expressing uncertainty information, robustness for fault diagnosis, and the efficiency of parallel inference [24]. The Bayesian network is used in this paper.

3. Bayesian network

3.1. Principles of a Bayesian network

Bayesian network is a directed acyclic graph that consists of nodes and directed edges [25,33]. The system's parameters are represented by nodes. The node state generally represents the state of continuously updated parameters, such as temperature and pressure, which are evaluated initially with fuzzy theory. The relationships of nodes are expressed by edges, which are represented in conditional probability tables. An example Bayesian network model is shown in Fig. 4. In the figure, C and D have two states. When the state of C is 1, the probability of D being in state 1 or 2 is respectively 0.6 or 0.4, as given by the conditional probability tables.

3.2. Research on distributed Bayesian network modeling methods

Distributed modeling decomposes models into multiple modules, then these modules can be calculated individually and provide support for model calculations. A NPP is composed of multiple systems. It can perform distributed modeling of the NPP, which can divide the NPP into multiple modules [35].

Compared with other industrial systems, the NPPs system is more complex and redundant. There are 26 initiating events and 36 pivotal events in the level 1 PRA for AP1000-NPP [16]. Such a complex system, the Bayesian network model will lead to the explosion of node information and increase the difficulty of modeling. In this paper, a distributed modeling method is proposed. The modeling difficulty is reduced, and node explosion in Bayesian networks is solved.

In the AP1000-NPP, Bayesian network modeling is decomposed. Firstly, the event tree is divided into an initiating event and a pivotal event. Here, the initiating event is an event that causes the system operation to fail, such as LOCA; a pivotal event refers to the failure of the device to complete the specified task during the response process, such as the failure to open the safety valve. To achieve rapid STE, it is necessary to diagnose the status of the level 1 PRA initiating event, the level 1 PRA pivotal event, the level 2 PRA initiating event, and the level 2 PRA pivotal event. The state of the

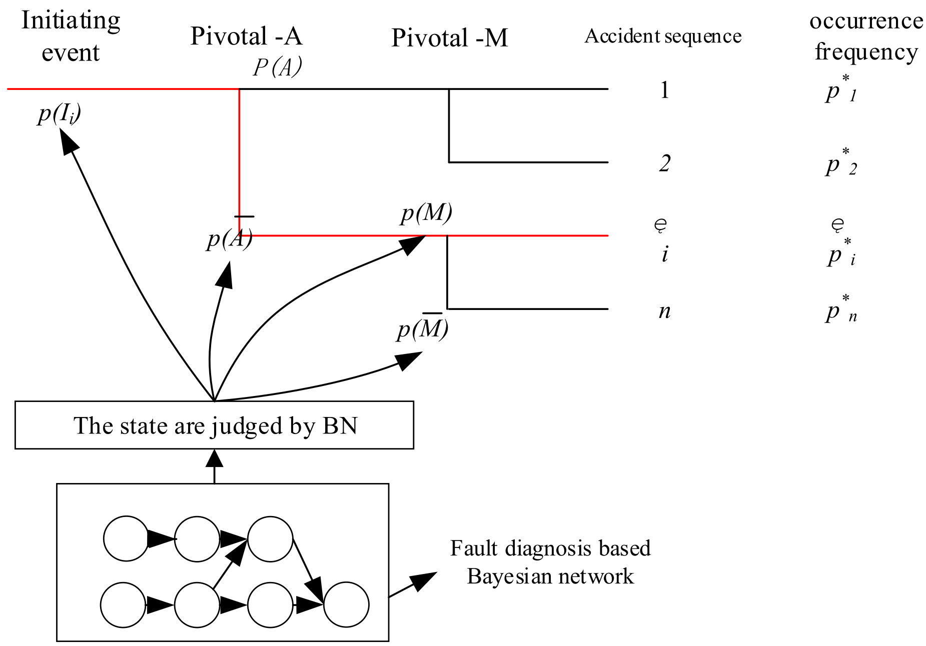

Fig. 3. Level 1 PRA accident sequence.

Table 2
Classification of level 1 PRA accident sequences.

Number	Name	Probability	Meaning
1	1A	P_1	High pressure of primary loop (small break accident)
2	1AP	P_2	Incomplete pressure relief at high primary loop
3	1D+3D	P_3	Partial pressure relief in the primary loop
4	3A	P_4	High pressure in the next loop in a transient accident
5	3BE	P_5	Primary loop has depressurized (Large LOCA)
6	3BR	P_6	Primary loop has depressurized
7	3BL	P_7	The primary loop has been depressurized (gravity injection succeeded, and pit recirculation failed)
8	3C	P_8	Damaged pressure vessel
9	6E+6L	P_9	Containment bypass
10	Other types		No further research

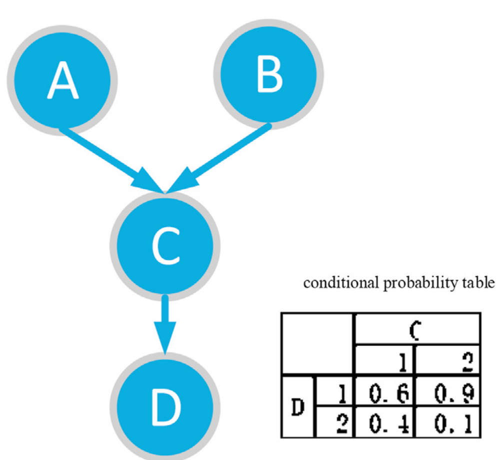

Fig. 4. Simplified BN model.

level 2 PRA initiating event is calculated and analyzed by the level 1 PRA accident sequence. Therefore, the Bayesian network modeling of AP1000-NPP mainly includes the following three categories:

(1) Level 1 PRA initiating event;
(2) Level 1 PRA pivotal event;
(3) Level 2 PRA pivotal event.

The level 1 PRA initiating events use the expert modeling and the expert group to build the Bayesian network model; existing knowledge (fault tree) are applied to build Bayesian network model in the level 1 PRA pivotal events; the level 2 PRA pivotal events, such as "hydrogen explosions", are too complicated. Considering factors such as limited accident awareness and fewer NPPs monitoring sensors, expert assessment methods are used to judge the status of the level 2 PRA pivotal events.

3.3. Level 1 PRA initiating event

A level 1 PRA initiating event is an accident that causes abnormal operation of the NPP. Bayesian network is a probabilistic graphical model for causal inference which is based on conditional probabilities. It is necessary to use expert knowledge to build the model as reasonably as possible. The initiating event modeling is divided into two steps: (1) acquiring existing domain knowledge; (2) using professional knowledge to build a reliable Bayesian network model. The first step is to acquire existing domain knowledge, mainly relying on the safety analysis report and PRA report of NPP. Chapter 19 of the AP1000 safety analysis report analyzes the symptoms of each initiating event [16]. It verifies and explains the trends of key parameters in accidents. The second step is to build a Bayesian network model by the expert group, based on the safety analysis report and PRA report. The steps are shown in Fig. 5.

After selecting the parameters, it is necessary to confirm the relationship between accidents and parameters. According to the description of the LOCA in the safety analysis report: when the accident occurs, with primary coolant flowing out, radioactive material leaks into the containment, and the dose in the containment increases. At the same time, the primary system leaks high-temperature and high-pressure coolant to containment, the pressure and temperature of the containment increase. As the primary coolant continues to flow out, the pressure of the primary system and water level in steam generators continue to decrease. The relationship of the LOCA Bayesian network established is shown in Fig. 6.

3.4. Level 1 PRA pivotal event

The safety analysis report contains the fault tree analysis of the level 1 PRA pivotal event, which also represents the expert's knowledge. Firstly, the fault tree is a directed tree-like network structure, and Bayesian can well include the graphical structure of the fault tree. Secondly, the logical gates of the fault tree can be transformed into Bayesian network conditional probability tables. Finally, this paper proposes a Bayesian network modeling method for NPP shown in Fig. 7.

The following describes the method of determining the conditional probability table of the Bayesian network through the fault tree structure [26]. The relationship between nodes in the fault tree is represented by logic gates. The following analysis analyzes how to convert the “OR gate” into a conditional probability table [34].

(1) OR gate

The OR gate indicates that as long as one node fails, the top node fails. The fault tree is transformed into a Bayesian network as shown in Fig. 8.

Both the Bayesian network and the fault tree are network structures, and the network nodes of the two can be transformed: OR gate condition probability table is shown in formula (3).

$$\begin{aligned}&P(G1=1|X1=0,X2=0)=0\\&P(G1=1|X1=0,X2=1)=1\\&P(G1=1|X1=1,X2=0)=1\\&P(G1=1|X1=1,X2=1)=1\end{aligned} \tag{3}$$

(2) AND gate

The AND gate means that the top event occurs when all bottom event occur. The conversion method is similar to the OR gate (as shown in Fig. 9), but the relationship between nodes is different. The conditional probability table is shown in formula (4).

$$\begin{aligned}&P(G1=1|X1=0,X2=0)=0\\&P(G1=1|X1=0,X2=1)=0\\&P(G1=1|X1=1,X2=0)=0\\&P(G1=1|X1=1,X2=1)=1\end{aligned} \tag{4}$$

The Bayesian network model is constructed based on the measurement points (In the modeling, it is necessary to consider whether the Bayesian network evidence nodes correspond to the sensor one by one). The structure of the Accumulators (ACC) Bayesian network is shown in Fig. 10. The ACC pressure and ACC water level are used to analyze the effect of valves.

3.5. Pivotal events of level 2 PRA

The pivotal event accident of Level 2 PRA is too complicated (it does not used ET/FT method), such as “hydrogen explosion”. People have limited awareness of such accidents, and there are fewer measuring points to monitor accidents, which makes it very difficult to establish a Bayesian network. Taking the event “Hydrogen Explosion” as an example, the measurement point is only the concentration of hydrogen, and it is difficult to construct a Bayesian network model. Therefore, the paper proposes “expert assessment” method to obtain the status of the event.

The linear weighted assessment method is the simplest but most effective statistical method and has been widely used. This method is used to evaluate the level 2 PRA pivotal events. In linear evaluation, the weights of the expert scores are determined. If the weights are the same, the weight coefficients are all 1; if they are different, different weight coefficients need to be set. Then the status of the pivotal event is calculated by formula (4). The steps are as follows [27]:

(1) There are n experts to evaluate whether an event has occurred. Considering the experts' experience in operation and engineering, each expert's weight is different. The weight of each expert is $W=\{w_i\}$ ($i=1,2,\ldots\ldots,n$).
(2) This paper designs three states: “success”, “uncertain” and “failure” of the level 2 PRA pivotal event, and each choice should correspond to the probability of the event successfully running. “Success”, “uncertain”, and “failure ” indicate that the probability of the event running successfully is 0.95, 0.5, and 0.05 respectively which is represented by $R=\{r_i\}$.
(3) The status of the level 2 PRA pivotal event is obtained based on the weighted average method. The calculation formula is shown in the following formula (5). The larger the value, the higher the degree of compliance. Probability for level 2 PRA pivotal event-A is obtained.

$$A=\frac{\sum_{i=1}^{n} w_i r_i}{\sum_{i=1}^{n} w_i} \tag{5}$$

where $i=1,2,\cdots\cdots n$ (n is the number of experts).

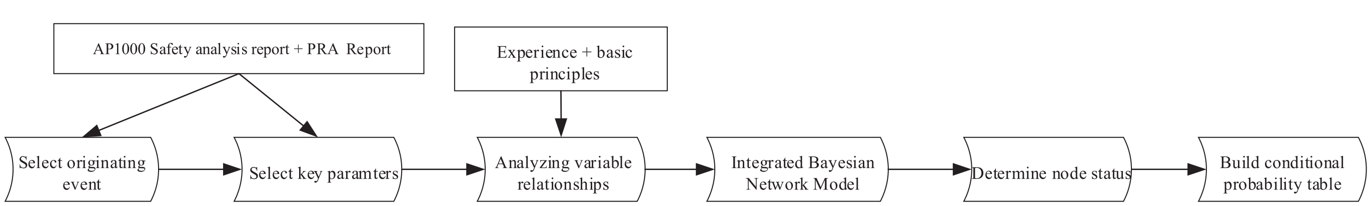

Fig. 5. Bayesian network modeling steps for level 1 PRA initiating events.

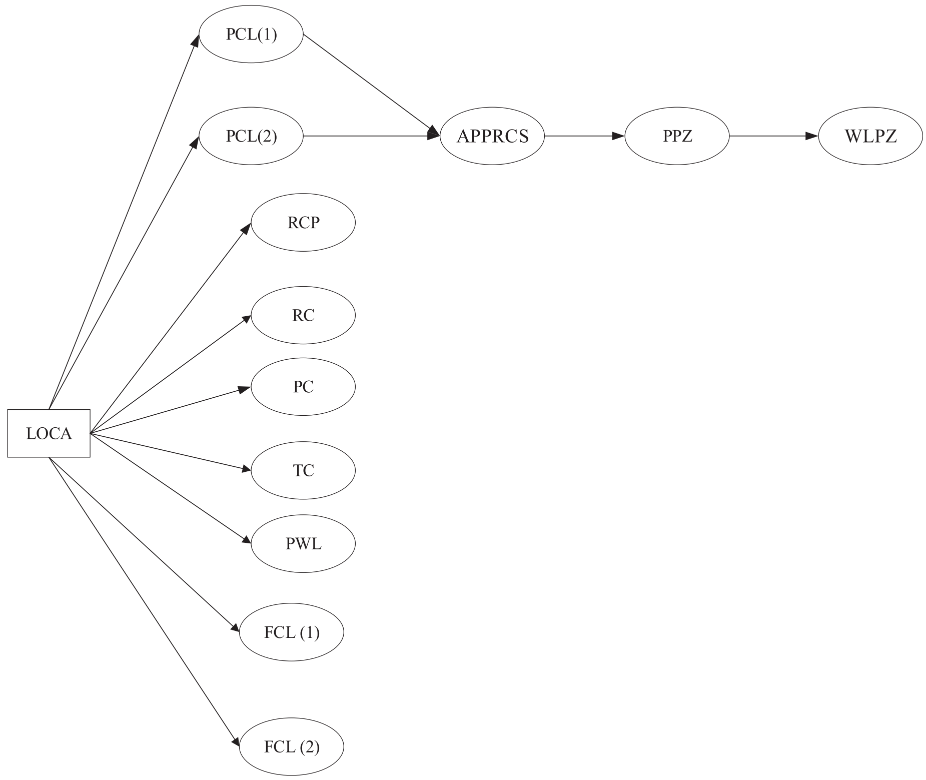

Fig. 6. Preliminary model of LOCA Bayesian network.

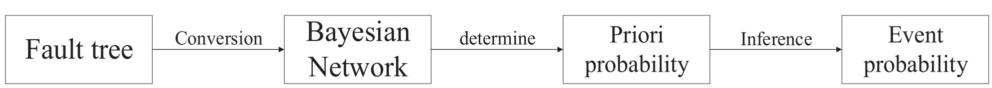

Fig. 7. Flowchart of a fault tree transformed into a Bayesian network.

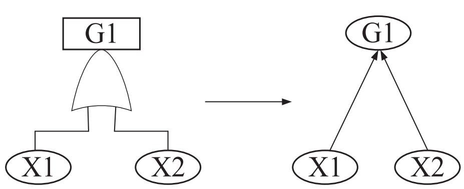

Fig. 8. OR gate into a Bayesian network.

4. Bayesian network inference

To achieve Bayesian network inference, a large number of scholars had proposed many different types of methods. Depending on whether the calculation results of the inference are accurate, the inference methods can be divided into two types of accurate inference and approximate inference [28,29]. Accurate inference means that when the Bayesian network makes inferences based on information, all inferred node state information must be accurate results. Approximate inference refers to the reasoning that the node state is an approximate solution. Bayesian networks use accurate inference when the structure is relatively simple and the reasoning speed is fast. For Bayesian networks with complex structures and slow inference calculation speeds, approximate inference is often used to improve inference speed [30]. The classification method is shown in Fig. 11.

According to the introduction of Bayesian network inference technology, the junction tree inference method has the advantages of easy to understand and fast calculation speed. It is one of the most common algorithms in Bayesian inference. The junction tree inference method is to transform the Bayesian network into a tree structure to achieve inference and diagnosis. The Bayesian network is transformed into a new network by the junction tree algorithm to solve the problem of conditional independence in Bayesian network inference. The calculation of the junction tree algorithm includes the following steps [31]: moralization, triangulation, construction of the junction tree, initialization, information transmission and collection, and marginalization. The flowchart is shown in Fig. 12 (Details for NPP refer to research group published article [32], section 2.3.3).

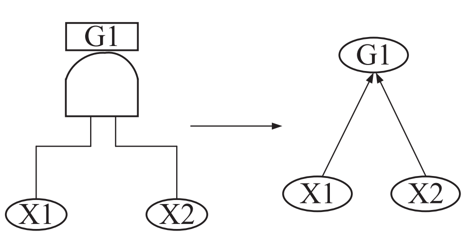

Fig. 9. Transformation of AND gate into Bayesian network.

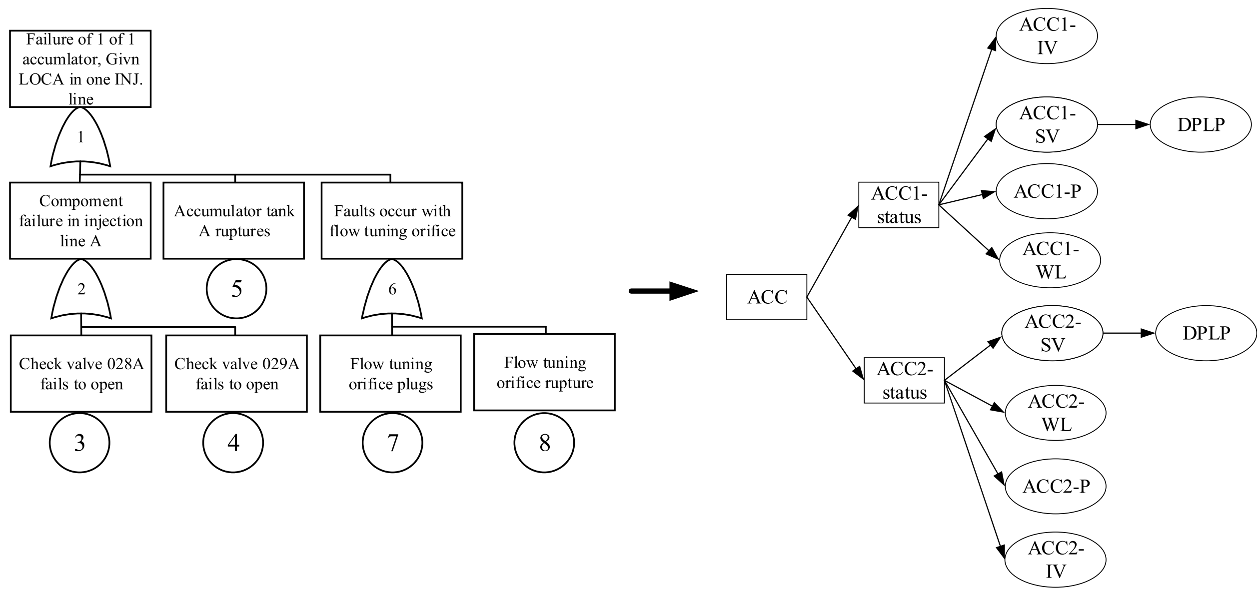

Fig. 10. ACC failure fault tree and Bayesian network model.

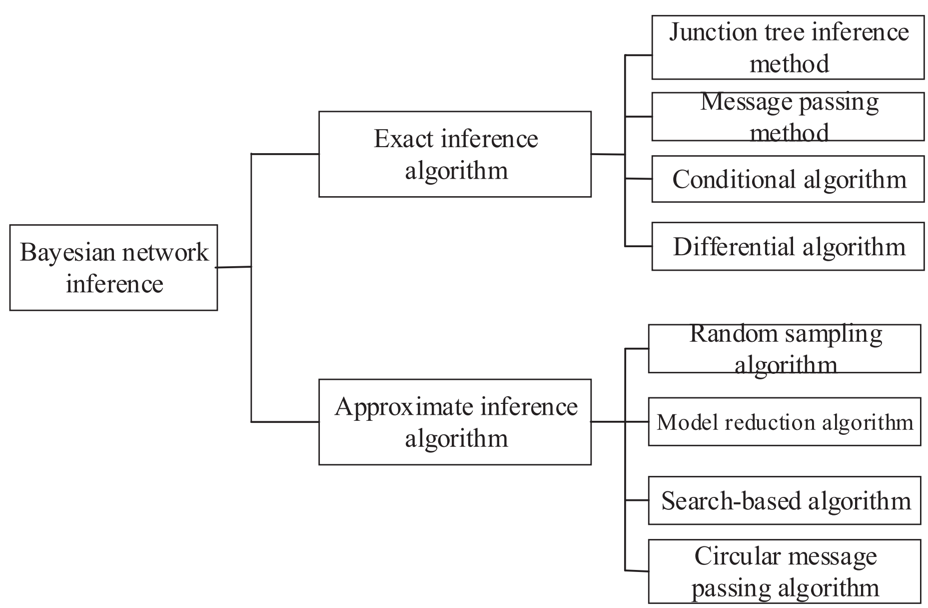

Fig. 11. Bayesian inference classification.

5. Case study

5.1. Bayesian network modeling for nuclear power plant

The proposed methods can achieve the Bayesian network modeling for all initiating and pivotal events. Bayesian network inference is used to judge the status of NPP for STE. In order to build a Bayesian network model with multiple faults and inference quickly and accurately, the paper proposes a distributed Bayesian network modeling method.

Based on the above modeling methods, the paper proposes a distributed modeling method suitable for NPPs. The paper selects three representative initiating accidents: LLOCA, SGTR, MSLB, and LMFW. Each pivotal event is an independent model and diagnosis module. This model is embedded in the network, as shown in Fig. 13.

The ACC node represents a complete pivotal event and a separate Bayesian network (ACC Bayesian network model is shown in Fig. 10). The red in Fig. 13 represents an independent Bayesian network model (just as ACC shown in Fig. 10). The following problems are solved by modeling in this way:

(1) Distributed modeling reduces the complexity of the model;
(2) Distributed modeling simplifies the model, which makes operators understand the model more clearly;
(3) The number of nodes of the model is reduced, the speed of inference is improved.

5.2. Case study

In order to demonstrate the proposed method, typical accidents of the AP1000 NPP are analyzed. By inserting the accident sequence into the simulator, the data of each sensor of the NPP can be obtained. The proposed method can be used to diagnose the operating status and possible accident sequences of NPP. The accident

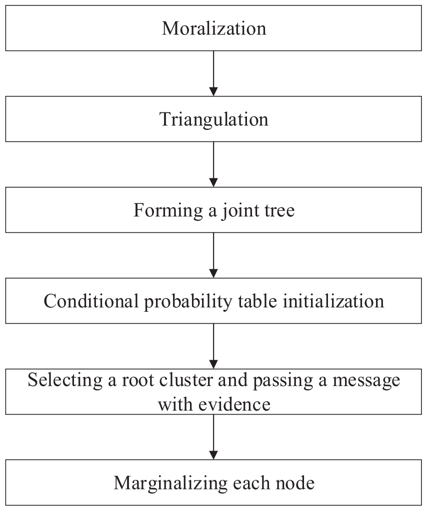

Fig. 12. Steps of junction tree algorithm inference.

sequence inserted by the simulator and the calculated accident sequence are compared and analyzed to verify the feasibility and accuracy of the method. The steps are shown in Fig. 14.

5.3. Parameter analysis

With the occurrence of LLOCA in the simulator, the pressure continues to decrease. Corresponding to the upper and lower limit thresholds of the regulator operation. According to the state analysis, the current pressure of the voltage regulator is in three states: “low”, “normal”, “high”, at probability 1, 0, 0. this evidence information is fed into the Bayesian network for diagnosis (Details for NPP refer to research group published article [32]).

5.4. Fault diagnosis results analysis

With the continuous input of evidence information, the results of the accident diagnosis are shown in Fig. 15(The research team developed the software). It is divided into four diagnostic modules: initiating event, device status, plant damage state, STE in Fig. 15. The curves indicate the probability of each fault occurred in Fig. 15. The higher the probability of each fault occurred, the greater the possibility that the fault is real. From the diagnosis result of the accident state in Fig. 15, it can be seen that the emulator diagnosed the accident as LLOCA in the eighth step after inserting the fault in the fifth step (one step stands for 5 s). When the fault is not inserted, the system is always in a normal operating state, and after the fault is inserted, the system responds quickly and can quickly identify the faults of NPP.

(1) Initiating event

It can be seen from Fig. 16 (initiating event) that the Bayesian network can quickly diagnose the initiating event after the emulator into an accident, and the fault is the same as the emulator

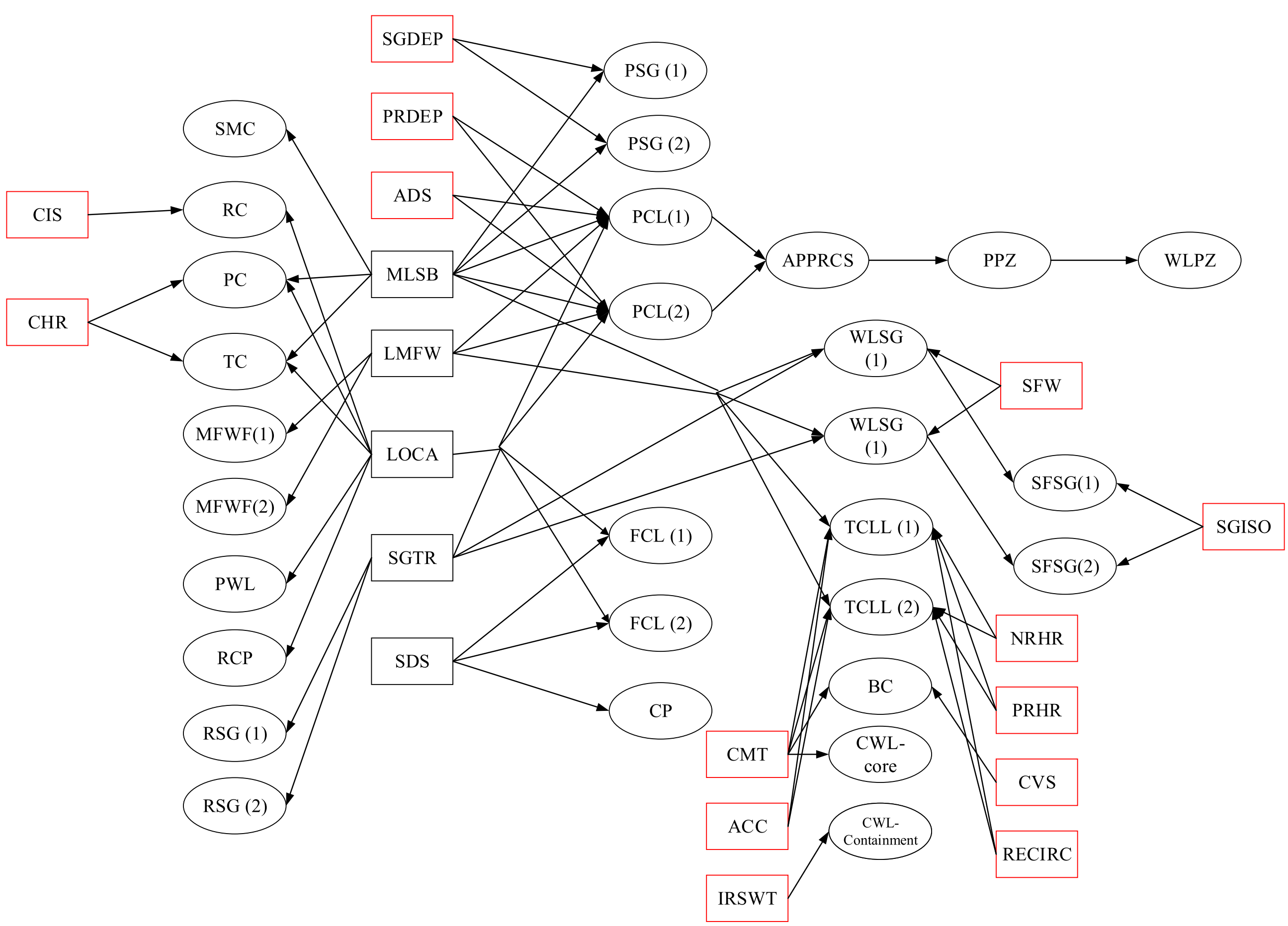

Fig. 13. Bayesian network integration model.

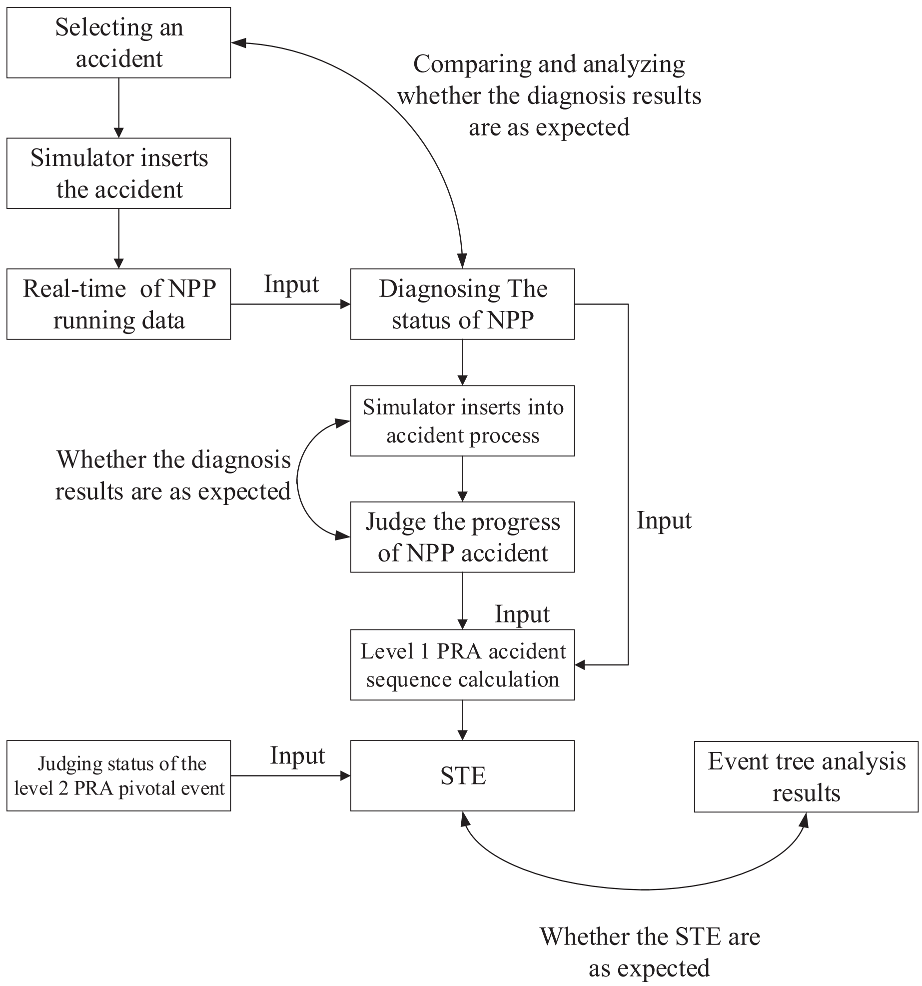

Fig. 14. Case analysis process of STE.

inserted in. This shows the accuracy of the diagnosis results and verifies the effectiveness of the Bayesian network diagnosis method proposed in the paper.

(2) Device status

With the occurrence of LLOCA accidents, protective measures have been used. The diagnosis results of the level 1 PRA pivotal events are shown in Fig. 15 (device status). When the NPP runs to 12 steps, the simulator is inserted into the ADS system and fails. According to the results of the equipment status diagnosis in Fig. 15, the ADS-F fault can be seen, which shows the effectiveness of the diagnosis of NPP ("0″ indicates that the event runs successfully, and "1″ indicates that the event failed to run.).

5.5. Analysis of STE results

(1) Calculation of level 1 PRA accident sequence

The accident sequence process is shown in Fig. 15 (plant damage state calculation results). The red color in the event tree (Fig. 16) represents the direction of the accident process judged above. It can be seen that the level 1 PRA accident sequence is 3D, and the system diagnoses the accident sequence "1D + 3D" with a probability of 1 (Fig. 15). The diagnostic results indicating the effectiveness of the calculation method for the level 1 PRA accident sequence.

(2) Level 2 PRA accident sequence

The level 1 PRA accident sequence is classified, and the probability that the core state "1D + 3D" occurs is 1, which is used as the input of the level 2 PRA to calculate the level 2 accident sequence. At this time, the level 2 PRA pivotal event is evaluated by experts shown in Table 3. Input through the interface. The result is shown in Fig. 15.

A level 2 PRA pivotal event status assessment is achieved by formula (5), where the assessment results are that other events successfully operated, but the IS system failed. The level 1 PRA calculation results are used as inputs to calculate the STE, as shown in Fig. 15. It can be seen that the source term with the highest matching degree is the CI release class. By analyzing the secondary PRA event tree, when IS fails, the event tree analysis accident sequence is shown in Fig. 17. It can be seen that the event tree analysis result is a CI release class, so the diagnosis result is the same as the event tree analysis. The STE method is feasible and reliable.

The proposed method is based on the professional knowledge of PRA, without recalculating the source term, and directly achieving the goal of rapid STE. In the case analysis, the method can match the release categories in 30 s. Compared with the speed of current STE,

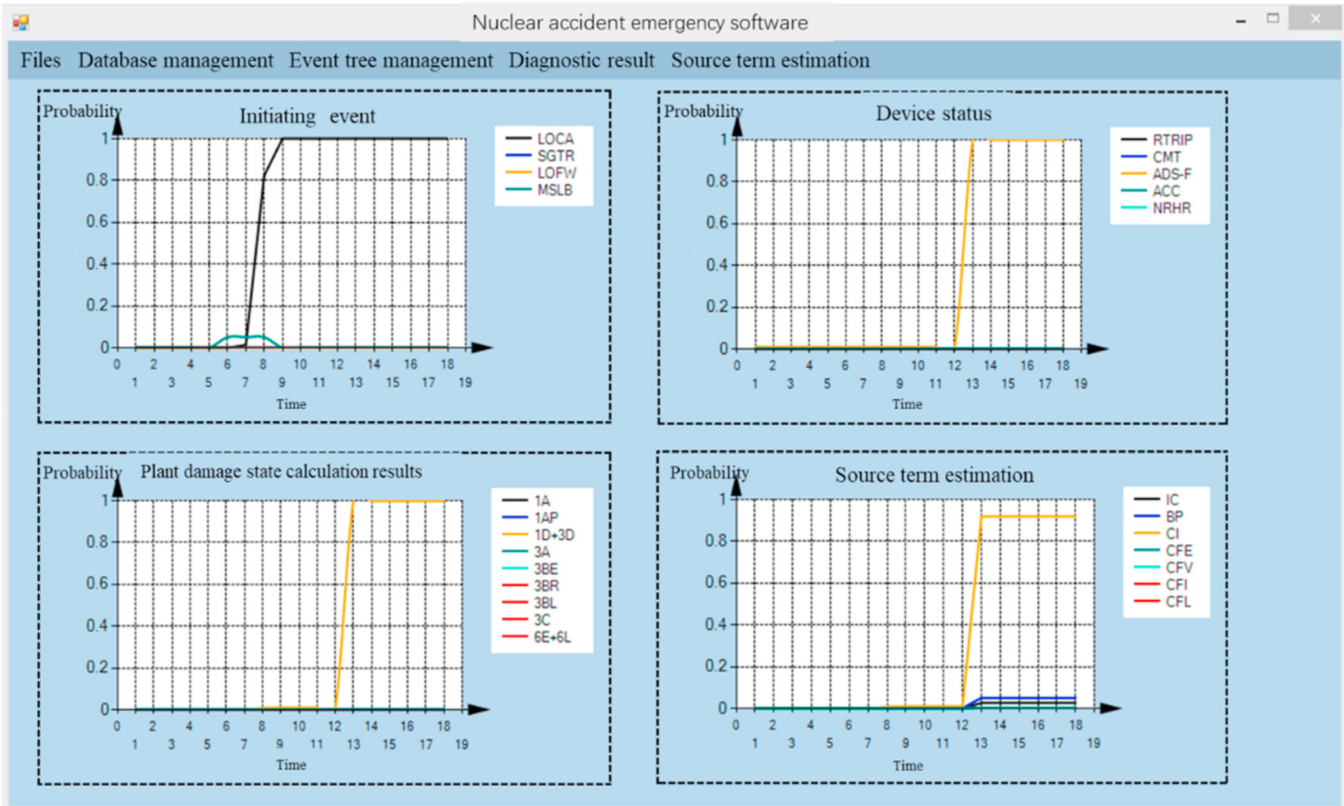

Fig. 15. LLOCA diagnostic results under faulty operating conditions.

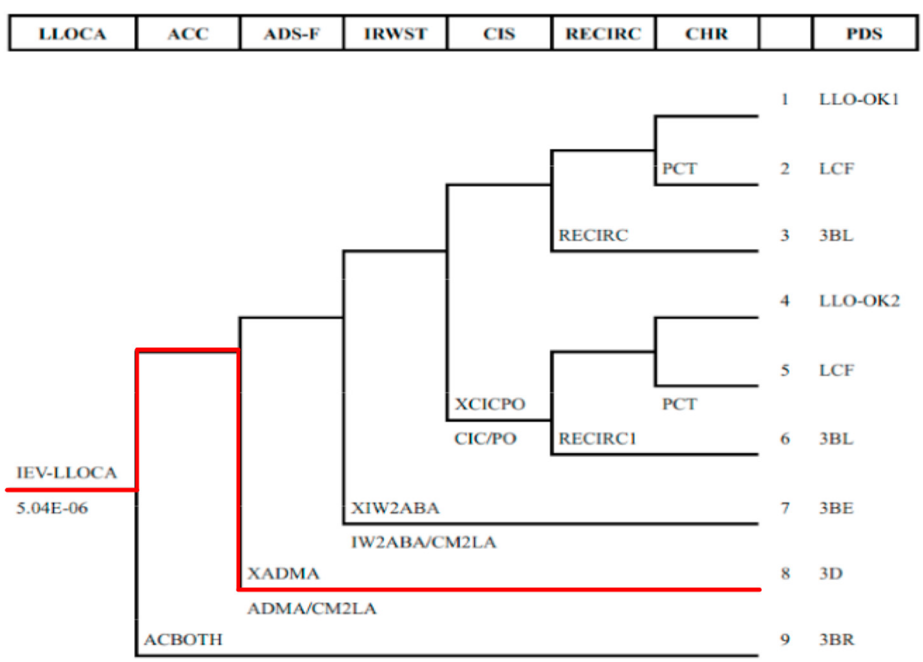

Fig. 16. LLOCA case level 1 PRA accident process analysis.

the method greatly improves the calculation speed of source term estimation.

6. Conclusion

In this paper, AP1000-NPP is used as the research object, and the diagnosis of the initiating event and the pivotal event in the level 1

Table 3
Level 2 PRA expert score.

Number	Event	Meaning	Expert A	Expert B	Expert C
1	DP	RCS Depressurization After Core Uncovery	success	success	success
2	IS	Containment Isolation	uncertain	failure	failure
3	IR	Reactor Cavity Flooding	success	success	success
4	RFL	Reflooding of a Degraded Core	success	success	success
5	VF	Debris Relocation to the Reactor Cavity	success	success	success
6	PC	Passive Containment Cooling	success	success	success
7	VT	Containment Venting	success	success	success
8	IF	Intermediate Containment Failure	success	success	success
9	IG	Hydrogen Control System	success	success	success
10	DF	Diffusion Flame	success	success	success
11	DTE	Early Hydrogen Detonation	success	success	success
12	DFG	Hydrogen Deflagration	success	success	success
13	DTI	Intermediate Hydrogen Detonation	success	success	success

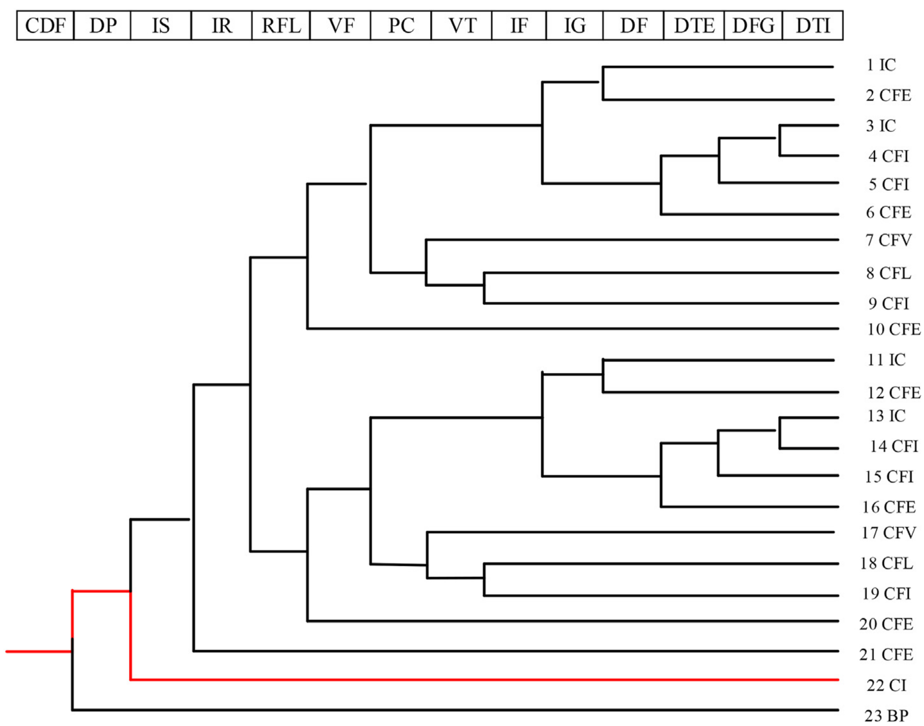

Fig. 17. Analysis result of level 2 PRA event tree.

PRA is realized based on the Bayesian network. The probability of each sequence is calculated based on the event tree model, the interface between the level 1 PRA and the level 2 PRA accident sequence is achieved. It quickly calculates the most likely release categories in the accident sequence and realize the rapid STE. The main work of this paper is summarized as follows:

(1) This paper uses intelligent inference and the existing PRA model to achieve rapid STE of the PWR based on calculating the level 1 and 2 PRA accident sequences.
(2) The state of the initiating event and the pivotal event in the level 1 PRA is diagnosed based on the Bayesian network and event tree.
(3) The method of building AP1000-NPP Bayesian network model is proposed.

After achieving the quick STE, how to instruct emergency commanders with the accident consequence evaluation can be further studied.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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