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Review Article

Recent research towards integrated deterministic-probabilistic safety assessment in Korea

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ABSTRACT

For a long time, research into integrated deterministic-probabilistic safety assessment has been continuously conducted to point out and overcome the limitations of classical ET (event tree)/FT (fault tree) based PSA (probabilistic safety assessment). The current paper also attempts to assert the reason why a technical transformation from classical PSA is necessary with a re-interpretation of the categories of risk. In this study, residual risk was classified into interpolating- and extrapolating-censored categories, which represent risks that are difficult to identify through an interpolation or extrapolation of representative scenarios due to potential nonlinearity between hardware and human behaviors intertwined in time and space. The authors hypothesize that such risk can be dealt with only if the classical ETs/FTs are freely relocated, entailing large-scale computation associated with physical models. The functional elements that are favorable to find residual risk were inferred from previous studies. The authors then introduce their under-development enabling techniques, namely DICE (Dynamic Integrated Consequence Evaluation) and DeBATE (Deep learning–Based Accident Trend Estimation). This work can be considered as a preliminary initiative to find the bridging points between deterministic and probabilistic assessments on the pillars of big data technology.

1. Introduction

Since the publication in the US of the first PSA (probabilistic safety assessment) study known as WASH-1400, PSA has developed into an effective and systematic means for identifying hazards as well as for evaluating and prioritizing the risks in nuclear facilities. Attempts to enhance the safety of NPPs (nuclear power plants) in diverse applications include design modifications, operational improvements, and countermeasures against abnormality in the framework of PSA [1–6]. Moreover, as of today, many countries in the world legislate the safety goals of their nuclear programs on the basis of the PSA framework [7].

Despite such achievements, PSA, functioning as an important tool for safety assessment and management, has generated many discussions on its limitations and technical challenges, especially after the Fukushima Daiichi accident. The critical point seems well summarized in the following question: whether PSA can reasonably check for faithful implementation of DiD (defense in depth) [5]. Other viewpoints sharing the same motivation discuss the fulfillment of organized or systematic management for epistemic and aleatory uncertainties [8] and the combination of known-unknown phenomena [9]. If the focus moves to the Republic of Korea, PSA has been legislated in the framework of PSRs (periodic safety reviews) and AMPs (accident management plans) in recent years [10]. These legal requirements are more or less associated with multi-unit considerations due to the technical issues involved with external events and/or inter-unit shared systems, even though those requirements are inherently organized to treat single units. Both Korean regulators and utilities are establishing their own multi-unit PSA methodologies and producing results to accommodate this issue and to address social concerns [11], as consistent with international activities [12,13]. Forecasting the situation in the future, the issues of epistemic and aleatory uncertainties or known-unknown phenomena as described above seem evolved from the transition from single-unit to multi-unit subjects, resulting in increased operating modes, increased combinations of initiating events, and diversified to intra-as well as inter-unit dependencies. These trends will bring continuous and

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even stronger challenges in all levels of PSA (i.e. Level 1 for design basis accidents, Level 2 for severe accidents, and Level 3 for emergency preparedness).

The authors presupposed that the nature of such challenges originates from the fact that more than what can be observed within the frame of static event trees (ETs) and fault trees (FTs) is required. Even though the classical PSA considers the dynamics of scenarios, the ETs/FTs involved are preemptively deterministic and implicitly set up based on safety analysis and operating procedures. They are, therefore, not likely to be sufficient to cope with future needs.

As potential enabling methodologies to make a breakthrough for such technical tasks, several meta-studies have been published that highlight the benefit of dynamic (also called integrated deterministic and probabilistic) approaches [8,14], which can be complementary with the use of static logic trees. As opposed to the classical static approaches, the dynamic approaches explicitly model the behavior of a system over time that could result from complicated interactions between hardware and human operators.

This study looks for the benefits brought by the integrated deterministic and probabilistic approaches on the basis of the risk categories populated from existing studies in Chapter 2. According to this, Chapter 3 introduces two research activities holding complementary characteristics to effectively and efficiently address the risk categories. Although this field has already seen substantial progress internationally, it can be said that it is in the beginning stages in the Republic of Korea. Therefore, this paper aims to explain the development status of the methods and toolbox as well as to introduce Korean initiatives. Related discussion and conclusions are given in Chapter 4.

2. Exploration of unknown risk

2.1. Origin and nature

Nuclear incidents and/or accidents can occur from recognized or even unrecognized situations. Both cases should be prevented or mitigated to ensure that the public and the environment are not affected under the principle of DiD.

Even though the inherent risk stays bounded depending on the nature of a system, common sense dictates that the concern of risks associated with nuclear facilities tends to steadily increase if special measures are not taken, because of both social and technical aspects. In terms of the social aspect, it is crucial to point out the statement by the US Nuclear Regulatory Commission (USNRC) in 1986. According to this statement (also known as the 0.1% rule[1]), the risk of cancer fatalities to the population near an NPP should not exceed 0.1% of the sum of cancer fatality risks from all other causes. This means that the target risk of nuclear facilities has to decrease as time goes by because of the development of related technologies improving the quality of our daily lives, which cut down the number of cancer fatalities. At the same time, it is possible to consider that technical aspects may increase the risk sources of nuclear facilities, such as the emergence of new cross-over technologies, natural phenomena that can lead to new initiating events, degradation or aging of SSCs (structures, systems, and components), and more difficult emergency response due to advanced social network conditions. In addition, it is clear that the interactions between different types of nuclear facilities, for example, a power station and a storage facility or among multiple units, have become more complex. This goes without saying if we start to consider the domain of security. Since security generally talked about on nuclear industry is related with an intentional attack, the situation gets more complicated unlike safety which is caused by randomness but can be estimated.

The important point is that, in dealing with the increase of risk sources discovered from such technical concerns, while we can check and respond to their fluctuation for *controlled* situations in advance, it is relatively more difficult to assess the impact of *residual* situations. Eventually, the purpose of PSA should be to reduce the unknown risk belonging to both situations by anticipating their consequences as precisely as possible so that reasonable decisions can be made with limited resources [7,15]. However, to grasp such missed situations, that is, the accident scenarios that are not deterministically covered by PSA models, there is a contradiction of having to wait for such risks until they emerge. The PSA methodology itself does not “discover” the scenarios; rather, it is to a large extent a way of documenting and organizing analysts’ discoveries [3,6].

PSA, along with safety analysis, is a technique that must be used to satisfy the safety standards set forth by legal requirements. In order to confirm that the safety standards are satisfied, the amount of unknown risk originating from either and/or both of controlled and residual situations should be minimized by analyzing all potential scenarios. This paper tries to argue that the integrated deterministic and probabilistic approaches are more effective in identifying such unknown risk than the existing methods. And by dividing them into two categories, we intend to further solidify their exploration. We note first though that it is worth reconsidering the risk categories; the classification of risks may be interpreted somewhat differently depending on which part is given meaning.

For example, the concepts of both controlled and residual risk are comparable with those mentioned by Yang [5]. Meanwhile, the unknown risks distinguished are supposed to be decomposed into two types (interpolating-censored and extrapolating-censored), as explained in the next section.

2.2. Classification of unknown risk

A part of the unknown risk in the previous section would be classified into two challenges depending on the accessibility of knowledge.

2.2.1. Interpolating-censored risk

The first challenge is related with the ‘shadow’ unknown risks, highlighting that they are hidden. For these, the authors selected the term *interpolating-censored*, which has already been pointed out in previous studies [14,16–18]. We can imagine that the total inherent risk would be bounded along a certain boundary (Fig. 1,

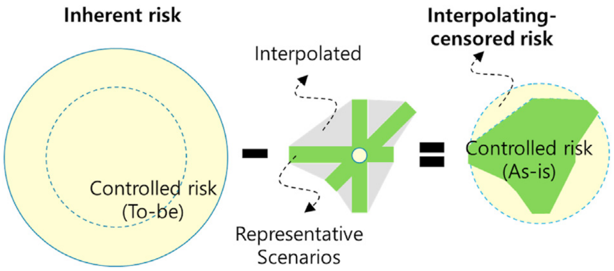

Fig. 1. Identification of controlled risk using classical approaches.

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[1] “The policy statement concludes the risk of cancer fatalities to the population near a nuclear power plant should not exceed 0.1% of the sum of cancer fatality risks from all other causes.” Available at: https://www.nrc.gov/reading-rm/doc-collections/fact-sheets/reactor-risk.html.

left), the inside of which we try to cover as much as possible with current knowledge levels and regard as controlled risk. In order to pursue an ease of analysis (usually simplification) on the basis of belief in the phenomenon governed by fundamental physical and/or chemical principles, a few representative scenarios are selected with conservative assumptions. If the conservatism of the representative scenarios is sufficient, it is expected that the amount of risk attributable to the rest of the scenarios that were not actually taken into account can be covered by the interpolation of risks originating from the representative scenarios.

Through interpolation of representative scenarios, accordingly, the area of a controlled risk is re-established (Fig. 1, middle). However, the expected controlled risk may not equal the one to be analyzed due to the censored scope between the representative scenarios (Fig. 1, right), which corresponds to a part of the unknown risk inside the controlled risk. Even though the representative scenarios are conservatively investigated, situations between them have the potential to not be covered.

If we put the concept of interpolating-censored risk into the PSA framework, it can be reduced by increasing the resolution of the headings in an ET and by allowing flexible timelines. This should accompany the simulation driven by physical models with setting up the structure of the ETs. In other words, this method can be summarized as a wide spectrum of realizations for accident scenarios using ETs with higher degrees of freedom (Fig. 2, middle). In addition, it is expected that the representative scenarios would be modified in such a way that more optimal calculation is possible (Fig. 2, right).

2.2.2. Extrapolating-censored risk

The more difficult challenge is to find emerging, growing, and *trans*-mutating unknown risk belonging to residual risks beyond the current knowledge level. In Figs.1 and 2, inherent risk was assumed to be bounded, but in fact should be much larger than the predictable controlled risk due to limitations of the current knowledge level. In order to distinguish it from the aforementioned unknown risk, the authors selected the term *extrapolating-censored*, meaning that the representative scenarios are no longer useful to find hazards. In other words, the amount of risk to be additionally clarified can be amplified by forming a singularity driven by the nonlinear relationship that occurs in a particular combination of hardware and human factors.

For instance, when unanticipated operator actions are taken outside the anticipated manner specified in a procedure, this case cannot be excavated within the current framework (Fig. 3, right). Actually, this claim could be irrelevant in the case of NPPs because most of safety significant actions to be done by human operators are described in diverse procedures. However, in reality, it is widely perceived that following a procedure as written does not guarantee the safety of NPPs [19]. The excerpt below emphasizes this aspect [20]:

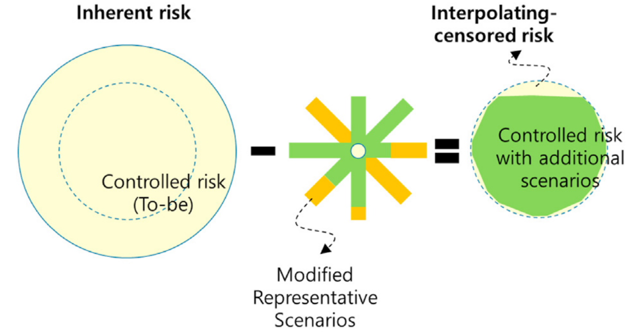

Fig. 2. Reduction of interpolating-censored risks with modified representative scenarios.

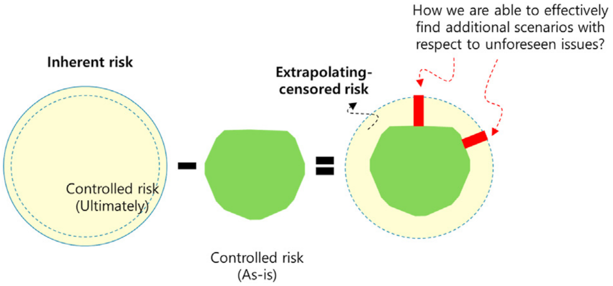

Fig. 3. Reduction of extrapolating-censored risks.

“Procedures are in investment in safety – but not always. Procedures are thought to be required to achieve safe practices – yet they are not always necessary, nor likely ever sufficient for creating safety. Procedures spell out how to do the job safely – yet following all the procedures can lead to an inability to get the job done (p. 98).”

If we adopt the abovementioned aspect, it is possible to expect that there are times when human operators need to intentionally deviate from a procedure in order to operate NPPs more safe manner. This kind of response namely *noncompliance behavior* has been reported for many decades from diverse industries [20]. Here, it should be emphasized that the nature of noncompliance behaviors is the result of active responses to be done by human operators who want to find out effective countermeasures to optimize the safety and/or the productivity of NPPs [21,22]. This strongly implies that, in terms of searching novel scenarios that can affect the safety of NPPs, it is indispensable to consider the effect of noncompliance behaviors on the progression of diverse accident conditions.

The interactive simulations of multiple physical models coping with the stochastic nature may bring a technical breakthrough. Finding and reducing the extrapolating-censored risk requires the ability to create a wider range of combinations of variables in the scenarios, but unfortunately, such an approach would generate a nearly infinite number of cases to be investigated, meaning that this can be considered as an NP-hardness problem. It should be effective to reduce the number of simulations through an optimized random approach or to lessen the computing time using a super-fast surrogate model.

2.3. Attempts to explore unknown risks

The integrated deterministic and probabilistic approach may not be the only way to come closer to both interpolating– and extrapolating-censored risks. However, one must-have aspect is the incorporation of stochastic scenario branches obtained from physical models in order to take into account the dynamic interactions of hardware and human factors. The stochastic nature comes from the behavior of interactive agents such as successes, failures, recoveries, errors, or intentional actions. Of course, the computation of the probability of the sequence of each scenario and its uncertainty analysis should be conducted in this framework such that the benefits of the classical PSA can be maintained.

This integrated deterministic and probabilistic approach, sometimes called dynamic PSA or computational risk assessment [23], is not fully matured in practice; for instance, the associated codes and standards have not yet been established, and even the current justification for improving nuclear safety or verifying DiD is controversial. For this reason, the authors investigated how such challenges had been handled from the perspective of the classical PSA, particularly in terms of Levels 1, 2, and 3, focusing on recently published papers. The research to develop methodologies, tools, or pre-/post-processing and to delineate overviews was excluded, while specific applications published within the last 10 years were excerpted. The collection regarding the finding of residual risks is summarized in Table 1. The numbers in the table indicate the references, the horizontal axis quotes the specific PSA levels, and the vertical axis separates interpolating- and extrapolating-censored risks to show the applicability of the integrated approaches.

Although the search was limited to the last decade, the references are generally concentrated on Level 1 with relatively fewer for Levels 2 and 3. This can be interpreted that the integrated approaches are also focusing on the issues of design basis accidents corresponding to Level 1 because classical PSA is still focused on the fundamental safety issues related with them. In the case of Level 1, there have been many studies to analyze the interpolating-censored risk, while for newly designed reactor types, integrated approaches have been employed since there are likely a lot of unforeseen pending issues that correspond to the extrapolating-censored risks.

In case of external events, the actual phenomena inside an NPP will show similar aspects to those of internal events. Therefore, it is expected that the analysis methods for internal and external events may be able to be shared. However, the contributors of these works justified their simulation-based approaches by mentioning that the existing methods were insufficient to be available and reasonable for flooding, fire, and seismic analysis. In the case of a wide-ranging disaster bringing extensive damage, it is highly likely that multiple NPPs will be affected and the conditions of the event will appear in a complex pattern.

Levels 2 and 3 are being studied in connection with each other. As the scope of PSA widens, the complexity of the technical issues will increase, and so the sources of risks are more likely to be hidden and unrecognized. Particularly, since there is room for non-deterministic human tasks in severe accident management guidelines, authors have emphasized the necessity of the integrated approaches. According to Ref. [44], multi-unit PSA has adopted the integrated approaches. Even though it is a just starting phase, this direction is expected to become dominant in the future.

3. On-going research in Korea

This chapter introduces two recent studies for developing enabling techniques related to the integrated deterministic and probabilistic approach in South Korea. These two studies aim to address both the interpolating- and extrapolating-censored risk. The methods should be equipped with at least a physical model (i.e., phenomenological simulation), reliability models for the SSCs, a human model, and a kind of scheduler that can run these models and obtain results consecutively.

3.1. Integrated toolbox: DICE

Basically, PSA is based on a combination of ETs and FTs to evaluate scenarios, meaning their likelihood and consequence. The integrated approach can further assess the effect of stochastic realization resulting from hardware (e.g. SSCs) or human (e.g. operators) elements in a timeline.

Table 1
Literature survey for identifying residual risks.

	Level 1		Level 2	Level 3
	Internal Event	External Event		
Interpolating-censored	[24–37]	[45–47]	[50–54]	[57–59]
Extrapolating-censored	[38–44]	[48,49]	[55,56]	N/A

The DICE, or Dynamic Integrated Consequence Evaluation, is being developed in Kyung Hee University with other collaborators as a computational tool to implement the integrated framework [60–63]. DICE adopts the discrete dynamic event tree (DDET) approach to overcome the technical issues arising from the fixed structure of classical ETs. Therefore, time-dependent and condition-driven branches are one of the most important concepts. Eventually, depending on how flexible the timing and the number of branches are, it is possible to observe the residual risks. Meanwhile, it should be noted that such flexibility is totally dependent on computational resources [64,65]. Nevertheless, DICE tries to maximize its coverage by decomposing branches in a mutually exclusive and collectively exhaustive (MECE) manner for the time domain as well as the success/failure domain. This will be explained in the 'Diagnosis module' subsection below.

The underlying structure of DICE is shown in Fig. 4. Implementing the DDET method requires (1) a scheduler responsible for the overall management of the modules, (2) a physical module determined by the corresponding purpose, (3) a diagnosis module that evaluates whether the branching condition is reached based on the real-time results of the physical module, and (4) a reliability module that computes the availability of the SSCs and decides the actuations.

3.1.1. Scheduler

As a core module of the DDET-base DICE, the scheduler is responsible for the exchanging of information between each module. Based on this information, the event sequences are decomposed as a means of generating branches in an ET. In addition, the scheduler can continue or terminate simulations of the event sequence depending on the status of the physical model. At this stage of development, the scheduler judges event sequences into 'Safe' or 'Damaged' at termination, and 'Cut-off' for very low probability ones.

3.1.2. Physical module

The physical module is in charge of calculating a system's behavior depending on the interests of the analysts. It can be thought of as a kind of computational simulation as opposed to a real system. Currently, DICE is interested in the analysis of internal events corresponding to Level 1 PSA, so MARS-KS (Multi-dimensional Analysis of Reactor Safety KINS Standard, i.e. the Korean regulatory safety analysis code) [66] was embedded in the physical module. DICE is designed such that any other simulation codes can be connected as long as the protocol between the physical module and the scheduler is maintained.

The physical module sends the values calculated by the simulation code to the scheduler, and receives information on the input settings for the simulation code from the scheduler.

3.1.3. Diagnosis module

The diagnosis module determines the timings for the branches triggered either automatically or manually. The automatic function deals with the branching rules registered in a system; for example, the branches caused by the actuation of the RPS (reactor protection system) or ESFs (engineered safety features) belong to this category. The manual function handles operator behaviors. While the automatic diagnosis module is simply composed of logical statements for system variables, the manual diagnosis module needs a human model so that it can imitate the decisions of the operators. As of now, DICE employs a separately developed artificial

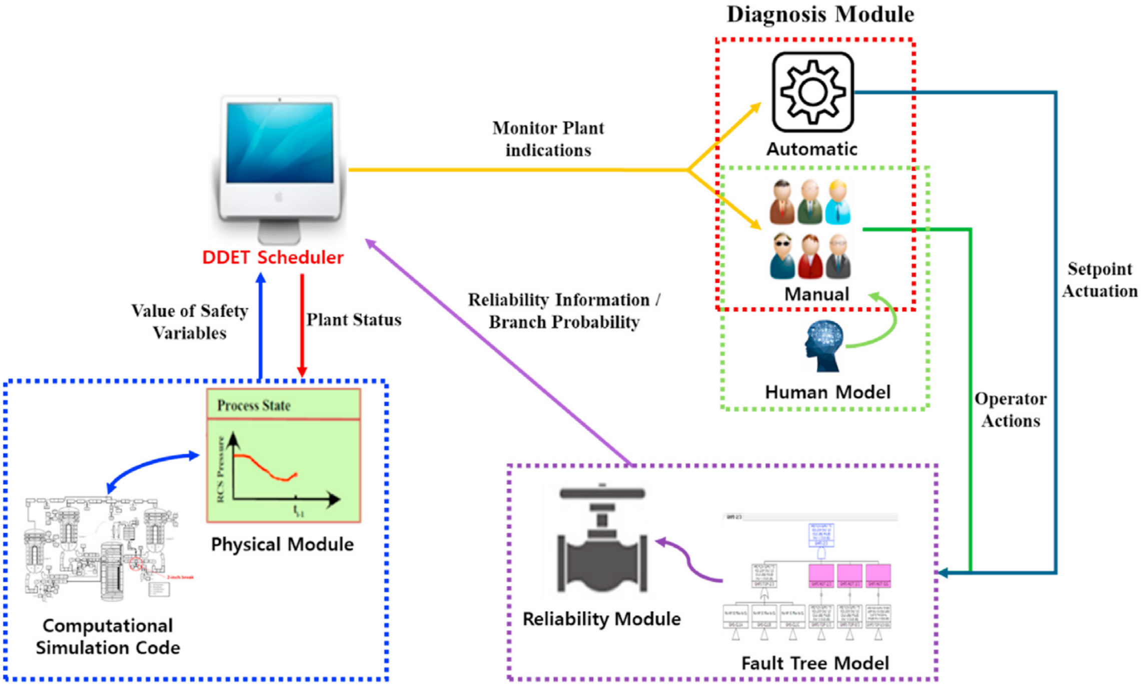

Fig. 4. Structure of DICE (dynamic integrated consequence evaluation).

intelligence model [67] based mainly on EOPs (emergency operating procedures).

One significantly different concept between these two submodules is the method to fulfill the MECE requirement in decomposing the branches, as shown in Fig. 5. In the case of the automatic function, the branches are generated at a single point according to the success or failure of the SSCs.

For example, if there are three pumps and an actuation signal is triggered to start them up, the branches would be zero, one, two, and three pumps in operation. In the manual function, the branches are created at multiple points by dividing the execution time where the operator performs an action. For example, the first branch is created when the manual function decides a certain task, and the next branches are created with a specified time window, with all time windows making up the entire timeline in an MECE manner. The probability of each time window is computed by the human model.

Fig. 6 shows an example of the form of DDET that is created when DICE is running. The diagnosis module receives information on the variables calculated by the physical model from the scheduler, and sends branching points (such as t_1, t_2, and t_3 in Fig. 6) to the reliability module for the realization of meaningful branches.

3.1.4. Reliability module

When a branching point is determined from the diagnosis module, it calculates the branch probability in consideration of the failure modes of the SSCs. Regardless of the diagnosis types, as the final actuation is related with the SSCs, this module checks the possibility of each branch and assigns the proper probability. All results go to the scheduler. In its current form, DICE applies classical fault tree analysis for the quantification of the branch probability (i.e., p_{1-x} and p_{2-x} in Fig. 6). However, for the branches decomposed by a manual action, the final probability is computed by multiplying the component availability by the human action probability (i.e. p_{3-x} in Fig. 6).

In order to make the running time of DICE manageable, DICE works on multi-cores and multi-machines in a server-client manner. In other words, if the computing resources are sufficient, the total running time of a huge amount of simulations can be reduced to some extent. Another strategy to overcome this issue will be introduced in the next section, that is, the development of super-fast surrogate models. However, even if the number of scenarios is optimized and the running time is reduced, it is obviously still true that the amount of data to be produced is enormous. Therefore, a post-processing function, such as grouping scenarios in

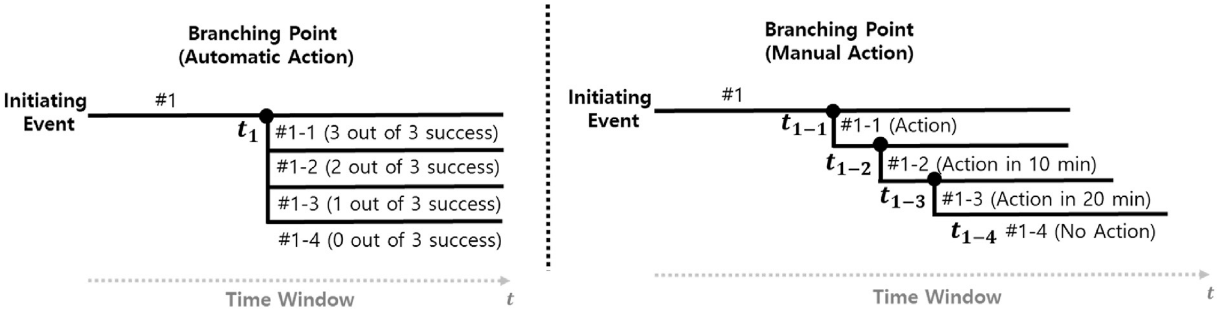

Fig. 5. Decomposition of the branches according to actuation type.

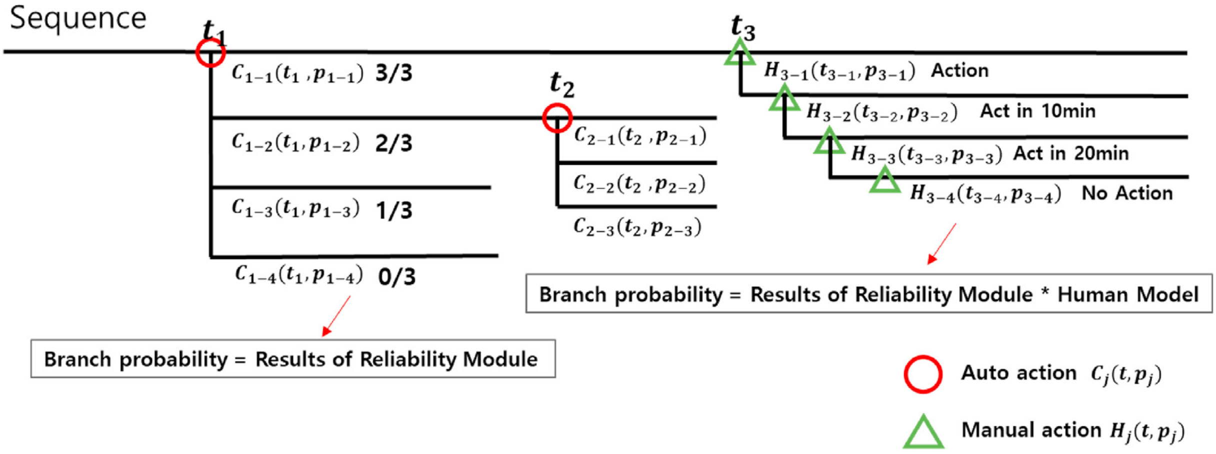

Fig. 6. Example of the DDET in DICE.

various ways, is also required to efficiently analyze them [68,69]. Fig. 7 shows one of the post-processing functions of DICE. Users can define the end states such as 'safe' or 'damaged' by registering logical statements about the variables, and all scenario branches can arrive at one of the end states.

There is also a cut-off state, which means that the probability of the scenario reaches below a specified value so that it is very unlikely to occur. The logical statements of the variables can be extended to suggest additional filtering conditions depending on analysis purposes. This function enables the singularity of each scenario to be found, or in other words, to confirm that the anticipated safe scenarios pose no risks or that the scenarios previously thought were risky are in fact not. DICE also provides log data for each branch and sequence, separately. The name itself of each sequence represents the consecutive results of the diagnosis module. At any particular branching point, the branching time, conditional branch probability, and sequence probability that determine the cut-off state are recorded. In addition, all information of the physical module at that point are checked in, which not only supports additional filtering conditions and the truncation criteria, but also allows users to check changes in the variables over time. Cutsets in the log data are another important source of information that can help risk-informed decision making, and be used to identify the causes decomposing branches.

3.2. High-speed surrogate: DeBATE

In the case of DICE, a high-precision simulation code (e.g., MARS-KS) plays as the physical model to calculate the results of the diverse conditions that can be generated by combining the statuses of the SSCs and the responses of human operators, as shown in Fig. 4. In other words, the primary role of the physical model is to predict (or determine) the final state of any given condition in terms of key process parameters or variables.

From a theoretical standpoint, or with sufficient time, the running time does not matter for analysis. Unfortunately, in reality, this option is inefficient or even infeasible. For example, if some final states of interest could be affected by the binary states (e.g., Open/Close) of 20 components and 10 operator responses with three time-windows (e.g., Early/Adequate/Late), then the maximum number of producible branches would be $2^{20} \times 3^{10} = 61{,}917{,}364{,}224$. Despite significant improvements in computing power these days as well as the rapid development of new techniques such as parallel processing, it is still not easy to reduce the required calculation time for cases such as above to an acceptable level. That is why the current DICE model aims to find the interpolating-censored risk, rather than the extrapolating-censored risk that requires more extensive simulations. Accordingly, it is indispensable to secure a breakout technique that allow us to find the final state of each branch or scenario within a second, for instance. Indeed, this problem has been the main obstacle hampering the introduction of an integrated deterministic and probabilistic approach in the past and even still these days.

In this regard, the Korea Atomic Energy Research Institute is developing a system called DeBATE, or Deep learning–Based Accident Trend Estimation, which can provide the overall trend of the

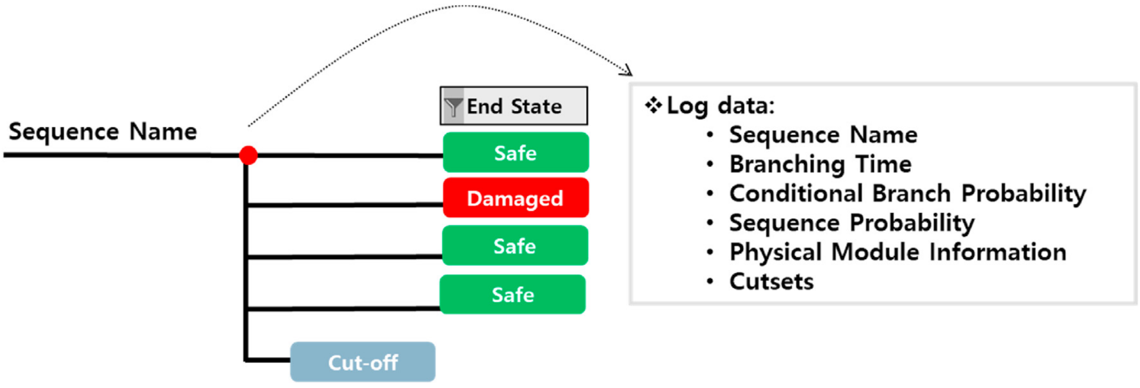

Fig. 7. Post-processing methods of DICE.

key process parameters calculated from any physical model after training with the associated input. In order to understand the ultimate purpose of DeBATE, let us consider Fig. 8.

Although there could be many different pathways to develop this notion, one promising solution is to create a surrogate (or reduced order) model using a deep learning technique. In other words, if the inputs and the associated outputs of a certain physical model can be properly trained, it is possible to generate the outputs of any given input expected from the physical model. This implies that the most important technical challenge is how to train the inputs and the associated outputs of the physical model; for this, DeBATE adopts a structure consisting of two stages, as depicted in Fig. 9.

First of all, in order to capture the variability of the outputs generated from a physical model with a couple of dimensions, the first stage determines a ‘latent space’ that corresponds to a map of the key features in representing the outputs. To this end, the typical structure of a conditional autoencoder (cAE) was adopted as the training structure of the first stage. Once the content of the latent space has been successfully extracted from the first stage, the second stage training is performed.

The purpose of the second stage is to train the deep learning model to create the expected output of the physical model based on integrated information from two different sources: the content of latent space and the original inputs. When the deep learning model is properly trained, it can be used as a tool to generate the outputs of any given inputs (even those not included in the training data sets), which are supposed to be generated from the physical model with the associated inputs. This two-staged training structure is not unique, having already shown good performance in other domains such as biochemistry [70].

In order to confirm the feasibility of DeBATE, Kim et al. carried out a series of validation tests [71]. They prepared a total of 8000 inputs with associated outputs calculated by MARK-KS, and demonstrated that the two-staged learning structure is feasible for developing DeBATE because, for a given input, the output was generated in less than in 0.2 s with about 3% error on average. This indicates that, on average, the trends of the key process parameters generated by DeBATE were well matched with those from MARK-KS. The more interesting result is that DeBATE properly generated the expected outputs of inputs that were not previously trained. Although there are several cases that showed a relatively large error bounded to 16% in the generation of expected outputs by using untrained inputs, it is possible to say that Kim et al. proposed a new, trailblazing pathway to overcome the largest hurdle of the integrated deterministic and probabilistic approach [71].

4. Discussions and conclusions

In this paper, it is argued that the classical PSA approach should be aimed at becoming a dynamically integrated method in order to effectively address and characterize residual risks. As a basis for this, the related literature in this field over the past 10 years was investigated. In general, the research is moving from Level 1 PSA to Level 2 and Level 3 PSA as the related methodologies mature, and it can be seen that stochastic issues are moving from hardware elements to human factors including operators and/or organizations. In addition, it is expected that complex issues caused by wide-range disasters will accelerate the need for the dynamically integrated method.

Meanwhile, two research activities conducted to realize the functioning of advanced PSA as aforementioned in South Korea were presented. In the case of DICE, the main focus is on checking the interpolating-censored risk. Attention is given to observing whether there is no underestimate of the event scenarios by branching the moment where stochastic issues occur in line with the MECE concept. However, since the branch itself is only possible through already established engineering judgment, it is still difficult to explore the extrapolating-censored risk. In addition, as the number of scenarios exponentially increases as the branches are decomposed in detail, limitations of computing resources in terms of time and storage capacity arise. For such issues, the solution is being explored through DeBATE. The scheduling function of DICE can be modified so that stochastic phenomena can occur at every time step, and the calculation of the physical model to be changed accordingly is shortened through DeBATE. When random failures and operator responses are taken at every time step, the search for infinite unknown areas other than the previously recognized scenarios can be potentially possible and will eventually contribute to finding the extrapolating-censored risk. Currently, it is inevitable that this is based on a simple trial-and-error approach rather than a systematic searching, so even if the accuracy of the physical model is sacrificed a little, the speed needs to be very fast due to the large number of simulations. This characteristic is expected to be used as a tool to support decision-making, especially in the high-uncertainty situations in Levels 2 and 3 PSA.

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.

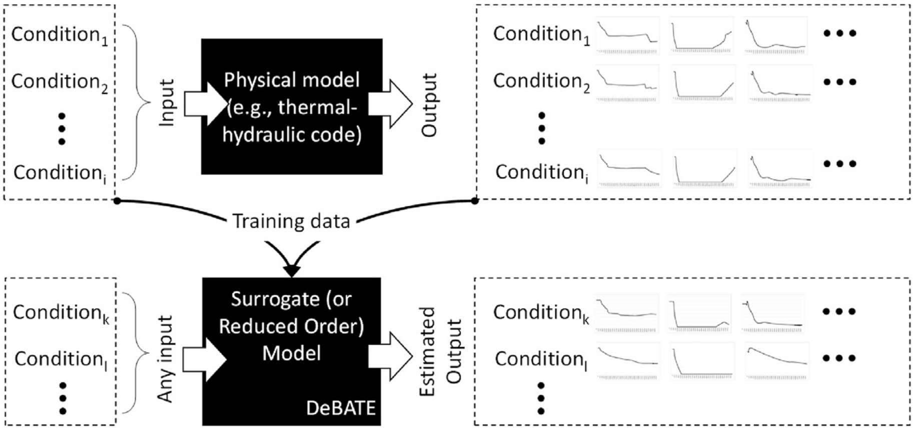

Fig. 8. Function of a physical model (upper) and that of DeBATE (lower).

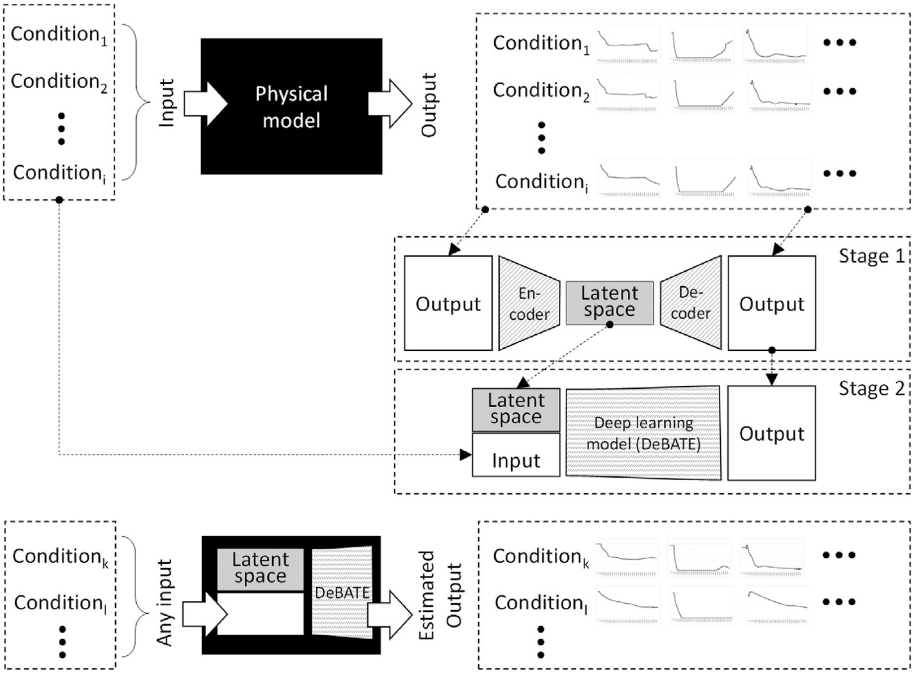

Fig. 9. Schematic diagram of the training structure of DeBATE.

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