



Article

Development of Importance Measures Reflecting the Risk Triplet in Dynamic Probabilistic Risk Assessment: The Concept and Measures of Risk Importance [†]

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Abstract

Although dynamic probabilistic risk assessment (PRA) techniques have advanced in their ability to represent the progression of events over time, the formulation of suitable risk importance measures for these methods still poses a substantial challenge. In particular, it is difficult to reflect the full breadth and multidimensional character of the risk information produced by dynamic PRA. In this study, we introduce a set of new importance measures derived from the risk triplet perspective: (i) Timing-Based Worth (TBW), which expresses diversity in scenario occurrence time; (ii) Frequency-Based Worth (FBW), which captures the probability of different scenarios; and (iii) Consequence-Based Worth (CBW), which characterizes scenario consequences. Formal definitions of these three indices are provided, and a conceptual scheme for integrated importance evaluation is proposed to support multidimensional analysis. As an initial demonstration, TBW and FBW are applied to a simplified reliability case using a dynamic PRA framework built on the continuous Markov chain Monte Carlo (CMMC) approach. This application is used to test their interpretability and the internal consistency of the proposed scheme. The findings suggest that TBW and FBW make it possible to conduct more holistic importance evaluations, taking into account resilience effects and temporal diversity in addition to conventional frequency-based perspectives. Such an extension is expected to increase the usefulness of dynamic PRA outputs for risk-informed decision-making.

Keywords: dynamic PRA; CMMC; risk importance measure; risk triplet; resilience



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1. Introduction

Probabilistic risk assessment (PRA) has been widely used in the safety analysis of nuclear power plants since the 1970s [1–4]. In particular, PRA methods based on event trees (ETs) and fault trees (FTs)—hereafter referred to as static PRA—have offered a systematic and comprehensive framework for analyzing accident scenarios and quantifying the risk

contributions of individual elements, including equipment failures and human actions. These capabilities have established PRA as a foundational tool for supporting risk-informed decision-making (RIDM) in diverse domains such as design improvement, maintenance planning, and regulatory development [5–7].

Within this context, risk importance measures (RIMs) [8]—such as Risk Achievement Worth (RAW), Fussell-Vesely (FV), Risk Reduction Worth (RRW), and the Birnbaum measure—have played a central role in quantifying risk contributions and informing decision-making. A typical application is the risk-informed categorization of structures, systems, and components (SSCs), which has been implemented in RIDM practices [9–13]. However, static PRA requires predefined event sequences and their associated temporal characteristics during accident progression, making it difficult to accurately capture the dynamics of physical phenomena and operator responses. Moreover, its binary treatment of event outcomes—typically modeled as simple occurrence/non-occurrence—fundamentally limits its ability to reflect variations in timing and consequences.

To overcome these limitations, dynamic PRA methodologies have been developed [14–17]. Dynamic PRA enables the quantitative evaluation of more realistic accident scenarios by incorporating dynamic features such as time dependence, operator interventions, and the progression of physical phenomena through step-by-step simulation of system state transitions. In particular, dynamic PRA enables the direct quantification of accident consequences through simulation, thereby eliminating the need to predefine event sequences or success criteria.

These features make dynamic PRA especially well-suited for consistently addressing the three fundamental elements of risk, commonly referred to as the risk triplet [18,19], defined by the following equation:

$$Risk = \{ \langle S_i, L_i, X_i \rangle \}_c, \quad i = 1, 2, \dots, N, \quad (1)$$

where *Risk* is the risk associated with the system or activity, S_i is the i th risk scenario, L_i is the likelihood of the scenario occurring, and X_i is the consequence if the scenario actually occurs. The subscript c indicates “complete”, meaning all significant scenarios, or at least those that should be included as scenarios, are considered.

The representative methodology for dynamic PRA is the dynamic event tree (DET) method [15,20–22]. Although structurally similar to conventional ETs, the DET method differs in that it does not require the analyst to predefine the sequence of system responses following an initiating event. Instead, the response timing and ordering are determined dynamically based on a time-dependent system model and branching conditions defined by the analyst. This framework enables the consistent treatment of both epistemic and aleatory uncertainties within a unified phenomenological and probabilistic model, allowing for more comprehensive and systematic coverage of possible event sequences compared to existing ETs/FTs approaches.

Among other dynamic PRA methodologies, the continuous Markov chain Monte Carlo (CMMC) method [23–25]—technically corresponding to a Continuous-Time Markov Chain Monte Carlo approach—is regarded as a broadly applicable and high-resolution method for dynamic PRA, owing to its capacity to simultaneously capture time dependencies, sequence effects, and inter-event dependencies [16]. By combining continuous-time Markov processes with Monte Carlo sampling, this method facilitates consistent quantification of both the frequency and consequence of accident scenarios. Specifically, state transition probabilities for individual system elements at each time point are determined based on physical variables such as temperature and pressure obtained from accident analysis codes. These probabilities are then compared against random numbers to update component

states sequentially. The resulting time-dependent plant states are propagated to the next time step, enabling the progressive construction of accident scenarios.

While the development of dynamic PRA methodologies has progressed in recent years, RIMs that quantitatively evaluate the significance of components and operator actions based on dynamic PRA outputs remain underdeveloped. Existing importance measures, such as RAW and FV, are predicated on static ETs/FTs structures and are not well-suited to accounting for the temporal evolution and complex branching behavior inherent in dynamic PRA.

To address this limitation, efforts have been made to extend existing measures to dynamic contexts—for example, Mandelli et al. have proposed approaches to adapt RAW and FV for use in dynamic PRA [26]. Furthermore, RIMs for dynamic PRA have been introduced, including the dynamic importance measures (DIMs) [27] and the core damage frequency (CDF)-based importance measure [28,29]. Among these, DIMs explicitly considers how uncertainties in system elements affect the progression of accident scenarios and how variations in event timing influence overall system risk. As such, it reflects certain dynamic features of dynamic PRA. However, these prior studies primarily focus on a single dimension of risk—either frequency or consequence—and do not establish a framework that decomposes the risk triplet (scenario, likelihood, and consequence), defines importance from each perspective, and integrates them into a comprehensive interpretation of importance. Such a multidimensional and integrative approach to importance evaluation has yet to be fully developed.

To address the identified methodological gap, this study proposes a framework for the integrated evaluation of risk importance, explicitly reflecting the risk triplet based on outputs from dynamic PRA. The framework introduces three dedicated RIMs—Timing-Based Worth (TBW), Frequency-Based Worth (FBW), and Consequence-Based Worth (CBW)—each corresponding to one dimension of the risk triplet. Their formal definitions and theoretical foundations are systematically presented, along with a conceptual framework for integrated importance evaluation. As a preliminary demonstration, TBW and FBW are applied to a simplified reliability model to evaluate their interpretability and the coherence of the proposed conceptual framework. A dynamic PRA using the CMMC method is used to simulate accident scenarios for this demonstration. The plant-scale application of the proposed framework and all three RIMs including CBW, is reported separately in Zheng et al. [30].

This article is a revised and expanded version of a paper entitled Narukawa et al. [31].

2. RIMs Reflecting the Risk Triplet

This work introduces RIMs for dynamic PRA from the standpoint of the risk triplet, with a focus on capturing time dependence, assessing resilience including accident management (AM), and ensuring consistency with existing RIMs. The three measures proposed are: (1) Timing-Based Worth (TBW), which reflects the diversity of scenario occurrence times; (2) Frequency-Based Worth (FBW), which represents the likelihood (probability) of scenarios; and (3) Consequence-Based Worth (CBW), which characterizes the associated scenario outcomes (consequences). Their formal definitions are provided below.

1. TBW

$$TBW^{SorF} = \log_{10} \left(\frac{E_{I=SorF}[T(R)]}{E[T(R)]} \right) \text{ for } E[T(I = S \text{ or } F)] \leq E[T(R)], \quad (2)$$

where R denotes the evaluation event (e.g., core damage or containment failure), while I refers to the basic event (e.g., a component function or AM action). $E[T(R)]$ is the expected time at which R occurs during the entire analysis, $E[T(I = S \text{ or } F)]$ denotes the expected

time of occurrence of I , where I can be either success (S) or failure (F). Finally, $E_{I=SoF}[T(R)]$ expresses the expected time of R conditional on the outcome of I .

Figure 1 illustrates how $E[T(R)]$, $E[T(I = S \text{ or } F)]$, and $E_{I=SoF}[T(R)]$ are related.

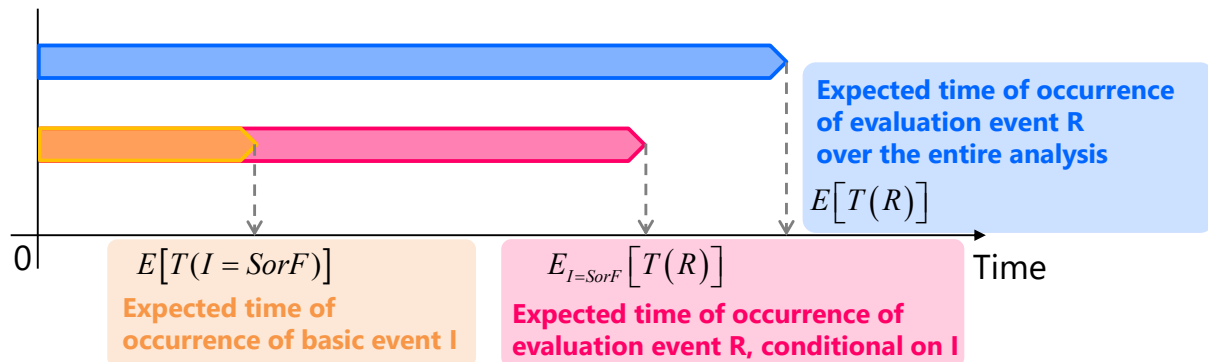


Figure 1. Relationship among $E[T(R)]$, $E[T(I = S \text{ or } F)]$, and $E_{I=SoF}[T(R)]$. Reprinted from Ref. [31].

2. FBW

$$\text{FBW}^{\text{SoF}} = -\log_{10}\left(\frac{E_{I=SoF}[F(R)]}{E[F(R)]}\right). \quad (3)$$

Here, $E[F(R)]$ denotes the expected frequency of R throughout the analysis, and $E_{I=SoF}[F(R)]$ represents the expected frequency or probability of R given I .

FBW is linked to the existing measures FV, RAW, and RRW [8], as expressed in the following equations, which highlight its consistency with existing RIMs.

$$\text{FBW}^S = -\log_{10}(1 - \text{FV}), \quad (4)$$

$$\text{FV} = \frac{E[F(R)] - E_{I=S}[F(R)]}{E[F(R)]}, \quad (5)$$

$$\text{FBW}^F = -\log_{10} \text{RAW}, \quad (6)$$

$$\text{RAW} = \frac{E_{I=F}[F(R)]}{E[F(R)]}, \quad (7)$$

$$\text{FBW}^S = \log_{10} \text{RRW}, \quad (8)$$

$$\text{RRW} = \frac{E[F(R)]}{E_{I=S}[F(R)]}. \quad (9)$$

3. CBW

$$\text{CBW}^{\text{SoF}} = -\log_{10}\left(\frac{E_{I=SoF}[C(R)]}{E[C(R)]}\right). \quad (10)$$

Here, $E[C(R)]$ denotes the expected consequence of R across the entire analysis, and $E_{I=SoF}[C(R)]$ expresses the expected frequency or probability of R given I .

The overall concept of risk importance evaluation with these measures is depicted in Figure 2. Positive values of all the measures correspond to safety improvement. The main distinctions from existing RIMs arise with TBW and CBW. TBW provides the time margin before an evaluation event occurs, which is particularly relevant for assessing the feasibility and success probability of AM, thereby contributing to resilience assessment. CBW, on the other hand, captures the consequences (e.g., the release of fission products)

and functions as a measure for evaluating the consequence-mitigation capability of AM and related actions.

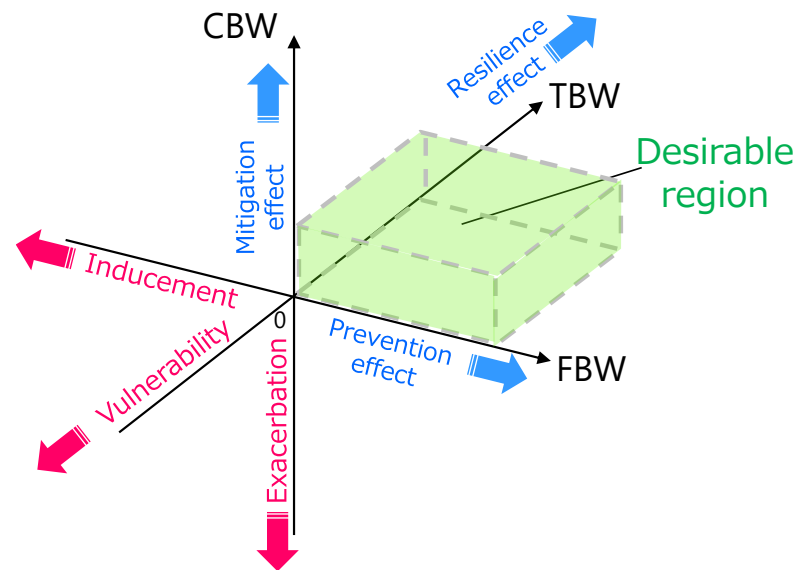


Figure 2. Conceptual view of risk importance evaluation reflecting the risk triplet. Reprinted from Ref. [31].

Accordingly, employing the three measures proposed in this study enables risk importance evaluation that incorporates both resilience and consequence-mitigation aspects—areas that have been difficult to address using existing importance measures focused solely on scenario frequency.

3. Application to Dynamic PRA

To illustrate the applicability and interpretability of the proposed RIMs, a dynamic PRA was applied to the Holdup Tank problem [32]. For comparative purposes and verification, a corresponding static PRA was also conducted using the ET/FT-based approach. Among the three proposed measures, this study focuses on TBW and FBW as a preliminary investigation using a simplified reliability model. The primary objective is to demonstrate the feasibility and interpretability of a multidimensional importance evaluation framework that reflects the risk triplet. CBW, the third measure, was not evaluated here because the Holdup Tank model does not include quantitative consequence parameters such as release magnitude or damage extent. Nevertheless, CBW is a general measure applicable to any problem in which scenario consequences can be quantitatively assessed. A comprehensive application of all three RIMs—including CBW—to a full-scale nuclear power plant, along with an integrated demonstration of the framework, are reported in Zheng et al. (2025) [30].

The states of operation of the valve and pumps are determined by the tank's water level. Table 1 summarizes how the water level corresponds to the states of each component. When the level of is around the midpoint, the valve remains open, pump 1 is running (on), and pump 2 is idle (off). If the water level rises from this condition, pump 1 shuts down (off), shifting the state of operation to lower the level. In contrast, when the water level drops, the valve closes and both pump 1 and pump 2 are activated, thereby moving the operational state toward raising the level.

Table 1. Operational states of valve and pumps. Reprinted from Ref. [31].

Water Level (x)	Valve	Pump 1	Pump 2
$a_1 < x < a_2$	Open	On	Off
$a_2 < x$	Open	Off	Off
$x < a_1$	Closed	On	On

3.1. Holdup Tank Problem

Figure 3 illustrates the Holdup Tank model. The model includes a water storage tank equipped with a single valve and two pumps (pump 1 and pump 2). When the valve is open, water flows out of the tank, whereas operation of the pumps results in water being injected into it.

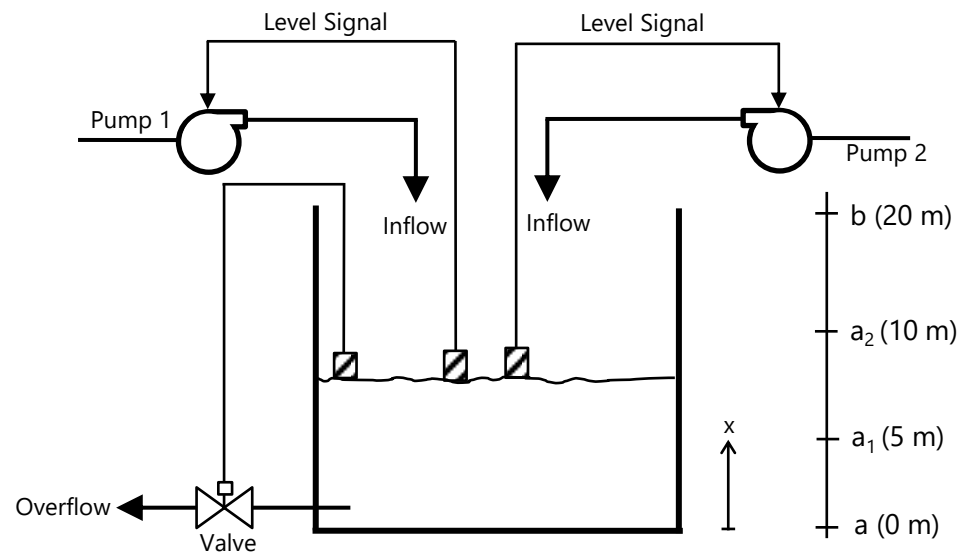
**Figure 3.** Schematic representation of the Holdup Tank model. (Reprinted from Ref. [31].).

Table 2 lists the flow rate, failure modes, and failure rates of the valve and pumps. The failure modes are divided into demand failures and operational failures. We assume Poisson processes for the latter (operational failures). For the failure states, the valve is assumed to have both open and closed states, while the pumps are assumed to have both on and off states. To simplify the analysis, variations in flow rate due to changes in water level are not taken into account.

Table 2. Summary of flow rate, failure modes, and failure rates for the valve and pumps. Reprinted from Ref. [31].

Component	Flow Rate (m ³ /h)	Failure Mode	Failure Rate
Valve	1.0	Demand failure (open/closed)	0.05 (/demand)
		Operational failure (open/closed)	0.001 (/h)
Pump 1	1.0	Demand failure (on/off)	0.05 (/demand)
		Operational failure (on/off)	0.001 (/h)

Table 2. *Cont.*

Component	Flow Rate (m ³ /h)	Failure Mode	Failure Rate
Pump 2	0.5	Demand failure (on/off)	0.05 (/demand)
		Operational failure (on/off)	0.001 (/h)

The situation in which the tank's water level drops to a (0 m) is referred to as “dryout,” whereas exceeding the allowable height *b* (20 m) is termed “overflow.” These two states are treated as evaluation events. In the Holdup Tank model, both static and dynamic PRAs were performed, focusing on the initiating event where pump 1 failed off.

3.2. PRA Methods

3.2.1. Static PRA Method

The static PRA was performed with an event tree developed following the earlier study [32]. Figure 4 shows a simplified, hardware-oriented event tree constructed for the Holdup Tank model. From this event tree, the frequencies of dryout and overflow were obtained analytically.

Initiating event	Additional responses		Endstate	Sequence
Pump 1	Valve	Pump 2		
Failed off	Irrelevant		Level under control	1
	Irrelevant		Dryout	2
	Failed open	Irrelevant	Level under control	3
	Failed closed	Failed on	Overflow	4
		Failed off	Level under control	5

Figure 4. Hardware-oriented event tree for the Holdup Tank model. (Reprinted from Ref. [31]).

3.2.2. Dynamic PRA Method

For the dynamic PRA, the CMMC method [23–25] was applied. In this approach, system state transition are modeled as a Markov chain, and Monte Carlo simulation is used to capture the system's dynamic behavior. The overall calculation process is illustrated in Figure 5, and the analytical conditions are summarized in Table 3.

Table 3. Summary of analytical settings for the CMMC method. Reprinted from Ref. [31].

Item	Set Value
Time step Δt (h)	0.1
End time t_{end} (h)	50
The number of simulation n_{all} (-)	10,000

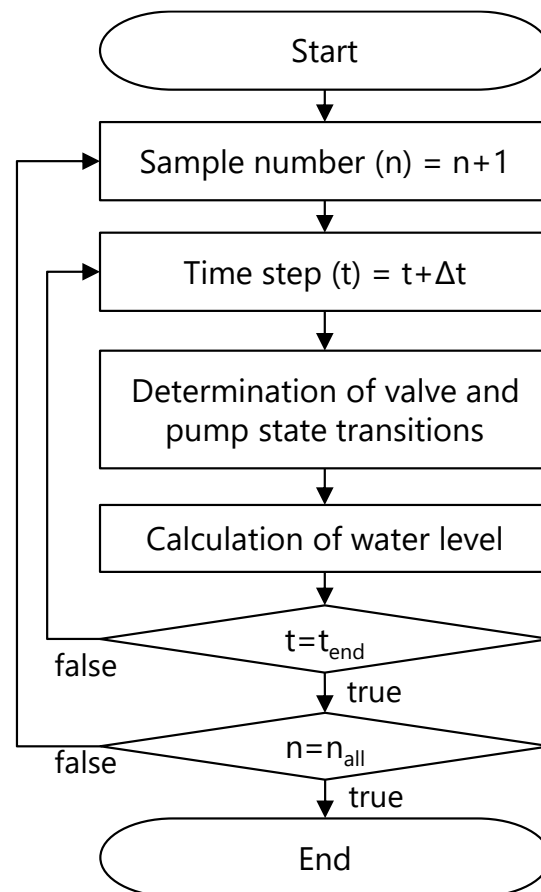


Figure 5. Calculation flow of the CMMC method. Reprinted from Ref. [31].

In the CMMC implementation, the transition probabilities among the operational states summarized in Table 1 were constructed based on the failure modes and rates in Table 2. The model combines continuous-time transitions due to operational failures (modeled as Poisson processes) with discrete, demand-triggered transitions occurring when the water level crosses the thresholds that define the state conditions.

3.3. Results and Discussion

3.3.1. Time Evolution of Water Level and Components Status

Figure 6 presents the time evolution of the tank's water level together with the operational states of the components, as estimated using the CMMC method. Following the initiating event in which pump 1 failed off occurred, the water level decreased. Changes in the valve and pump states were observed when the water level reached a_1 (5 m). Afterward, multiple demands were triggered in the early phase of the event as the tank level fluctuated.

Although Figure 6 shows that some valve and pump state changes occur before the water level reaches a_1 (5 m), these early transitions correspond to time-dependent operational failures that may occur in the initial stage of the simulation.

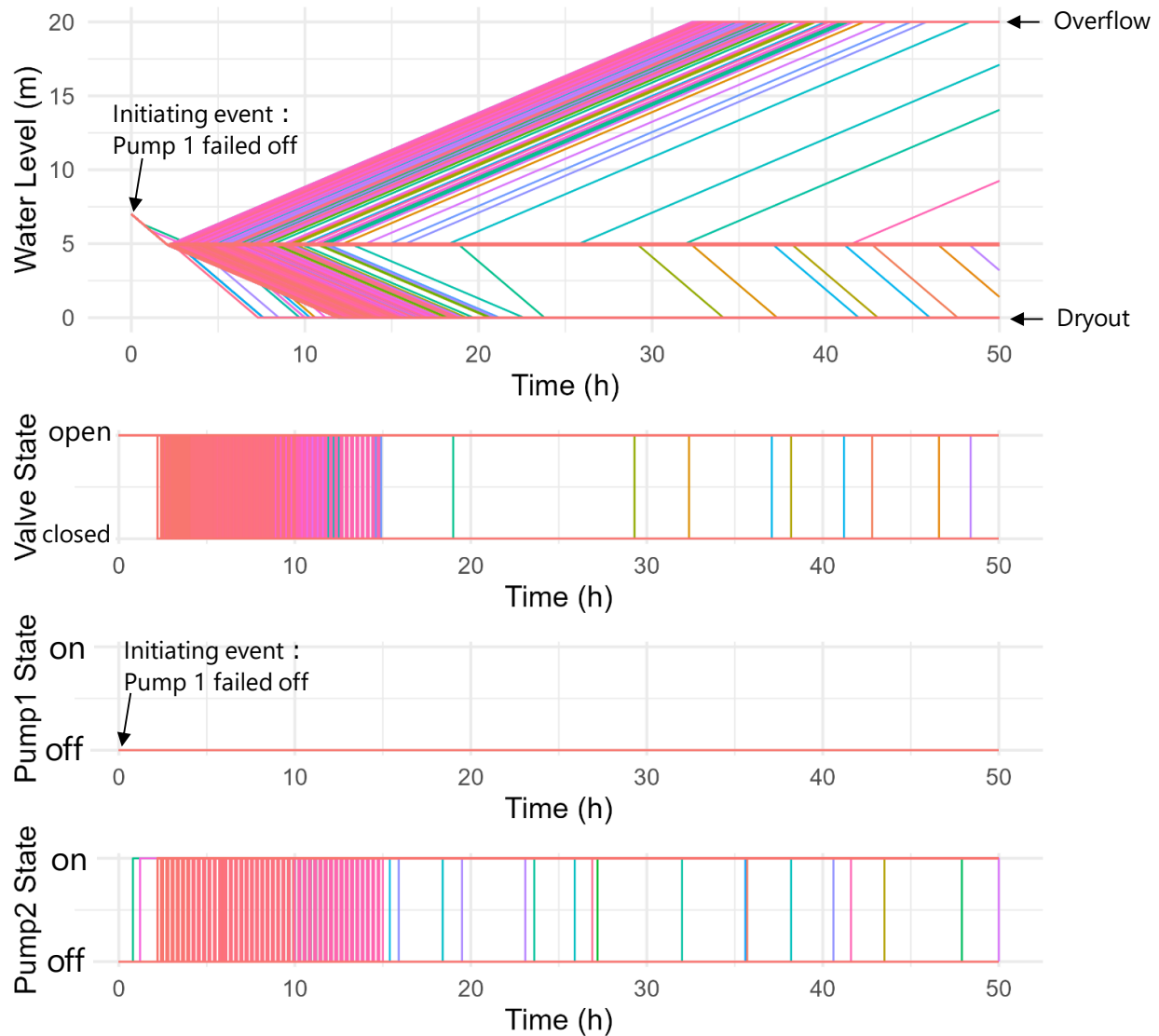


Figure 6. Time evolution of the tank's water level and operating states of valve and pumps. (Only the initial 1000 samples are shown. Reprinted from Ref. [31]).

3.3.2. Comparison of Existing RIMs with Static PRA

We verified the results of dynamic PRA by comparison with those of the static PRA. For this purpose, the existing importance measures RAW and FV were employed.

Table 4 lists the calculated values of FV and RAW, where the maximum value for each index is marked with an asterisk. In both static and dynamic analyses, pump 2 was found to have little influence on dryout.

Table 4. Results of FV and RAW calculations for static and dynamic PRAs. (An asterisk (*) marks the highest value in each column. Reprinted from Ref. [31]).

Evaluation Event	Basic Event	FV		RAW	
		Static	Dynamic	Static	Dynamic
Overflow	Valve demand failure	0.49	0.99 *	10.38 *	1.35
	Valve operational failure	0.51 *	−0.01	10.37	0.10
	Pump 2 demand failure	0.49	0.91	10.38 *	1.87 *
	Pump 2 operational failure	0.51 *	0.02	10.37	1.67

Table 4. Cont.

Evaluation Event	Basic Event	FV		RAW	
		Static	Dynamic	Static	Dynamic
Dryout	Valve demand failure	0.49	0.88 *	10.38 *	1.31
	Valve operational failure	0.51 *	0.02	10.37	2.03 *
	Pump 2 demand failure	0.00	−0.30	1.00	0.70
	Pump 2 operational failure	0.00	0.01	1.00	1.23

In contrast, differences appeared in the treatment of demand and operational failures. For both dryout and overflow, the static PRA produced high RAW values for both demand and operational failures, whereas the dynamic PRA yielded high FV values mainly for demand failures. Two reasons account for this: (1) in the dynamic PRA, the probability of demand failures is relatively high due to the large number of demands occurring in the early stages of the event (see Figure 6); and (2) in the static PRA, the probability of operational failures is estimated as the product of the failure rate and the end time (t_{end}), giving a comparatively larger value.

Overall, while the numerical results differ due to the unique features of dynamic PRA, such as its explicit treatment of state transitions, the importance measures derived from the dynamic PRA remain generally consistent with those from the static PRA.

As defined in Equation (5), the Fussell–Vesely (FV) measure includes a difference term between conditional and baseline probabilities; therefore, FV can take negative values when the occurrence probability of the evaluation event becomes lower under the conditioning. In our holdup-tank setup, this arises, for example, for dryout under the demand failure of Pump 2 (Table 4), where the failure stops the decrease in water level because the pump's non-operation prevents further valve-demand actions. As a result, the probability of valve demand failures decreases, which in turn lowers the overall likelihood of dryout.

3.3.3. Measurement of Risk Importance Reflecting the Risk Triplet

Figure 7 presents the results of the proposed measures, FBW and TBW, calculated through the dynamic PRA using the CMMC method. Figure 8 illustrates the concept of risk importance evaluation using FBW and TBW.

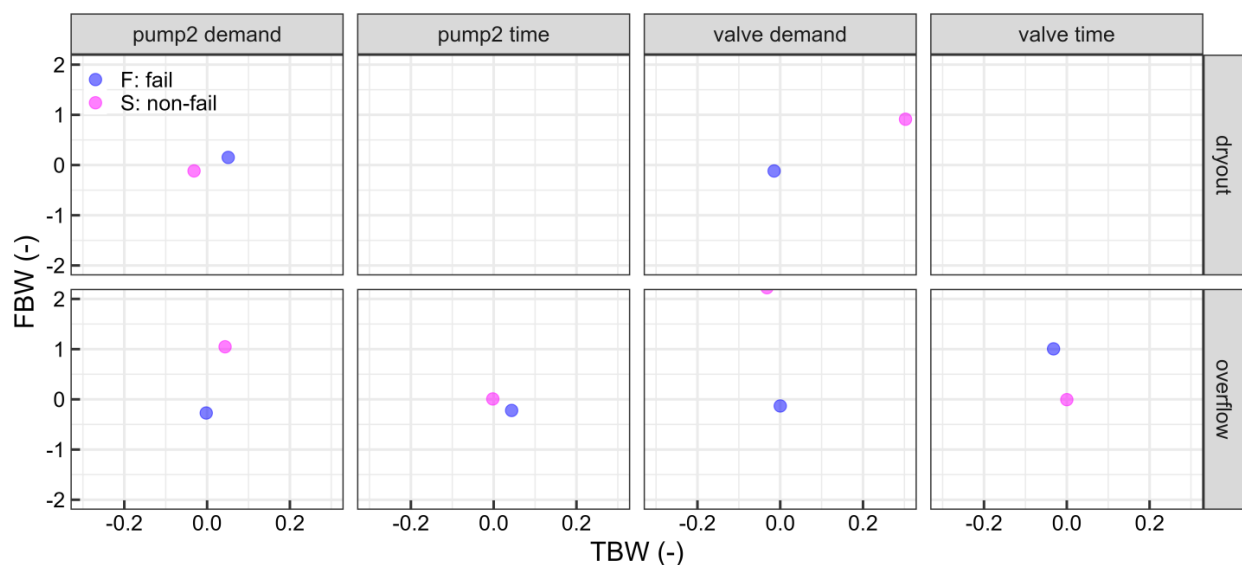


Figure 7. Calculation results of FBW and TBW. (Adapted from Ref. [31]).

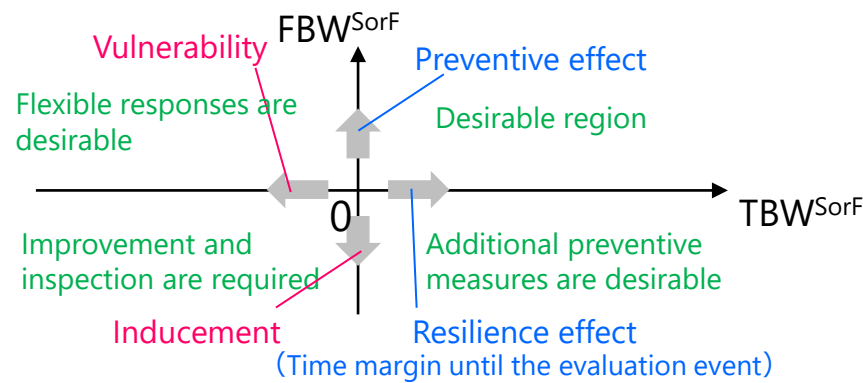


Figure 8. Conceptual view of risk importance evaluation using FBW and TBW. Reprinted from Ref. [31].

Among the four basic events (demand and operational failures of pump 2 and valve), the conditional dryout associated with operational failures of pump 2 and valve did not satisfy the TBW criterion, since their expected occurrence times were later than that of the dryout.

In contrast, for the conditional dryout caused by pump 2's demand failure, both TBW and FBW yielded positive values, reflecting preventive as well as resilience effects. Here, a positive TBW indicates a delay in the occurrence of the evaluation event, representing a favorable resilience margin, whereas a negative TBW implies accelerated event progression or a lack of resilience. The magnitude of TBW should be interpreted in a relative sense across systems or scenarios, as no universal threshold can be defined independently of system characteristics. The present case study illustrates how a positive TBW represents the system's resilience capability, as follows. In the conditional dryout scenario caused by Pump 2's demand failure, the failure corresponds to a fail-to-start event triggered when a start demand occurs at a low water level. Under these conditions, the valve remains closed and pump 1 is in the failed-off state, which prevents further changes in the tank's water level. Consequently, the valve's demand failure rate becomes zero, which lowers the probability of dryout and postpones its occurrence under operational failure conditions. This delay provides additional time for recovery actions such as pump repair before dryout occurs, thereby representing the resilience effects captured by a positive TBW.

Conversely, the conditional overflow for pump 2's demand failure, together with the conditional dryout and overflow for the valve's demand failure, produced negative values for both TBW and FBW. This indicates the absence of preventive or resilience effects. As illustrated in Figure 6, the numerous demands occurring in the early phase of the event make the demand failures of the valve and pump 2 dominant contributors to dryout and overflow, thereby shortening the time margin.

These findings confirm that the proposed RIMs enables a multidimensional risk importance evaluation that explicitly incorporates resilience effects—an aspect difficult to capture with existing measures that rely only on scenario frequency.

4. Conclusions

While dynamic PRA methodologies that incorporate the time-dependent progression of events have significantly advanced, the development of corresponding RIMs remains underdeveloped. Existing RIMs, primarily designed for static PRA, typically address only a single aspect of risk—such as frequency or consequence—and are inadequate for capturing the full range of information provided by dynamic PRA. This methodological gap limits the practical utility of dynamic PRA in RIDM.

To address this gap, the present study proposed a framework for the integrated evaluation of risk importance, explicitly reflecting the risk triplet based on outputs from dynamic PRA. The framework introduces three dedicated RIMs—Timing-Based Worth (TBW), Frequency-Based Worth (FBW), and Consequence-Based Worth (CBW)—each corresponding to one dimension of the risk triplet. Their formal definitions and theoretical foundations were systematically presented, along with a conceptual framework for integrated importance evaluation.

As a preliminary demonstration, TBW and FBW were applied to a simplified reliability model using dynamic PRA based on the CMMC method, in order to evaluate their interpretability and the coherence of the proposed conceptual framework.

The results confirm that TBW and FBW enable a more comprehensive evaluation by accounting for resilience effects and temporal diversity—features that cannot be captured through frequency-only importance measures evaluated within the static PRA framework. This advancement is expected to support broader and more effective utilization of dynamic PRA outputs in RIDM.

The proposed risk importance measures are not limited to the CMMC framework; in principle, they can also be applied to other dynamic PRA methodologies such as the DET approach as long as time-dependent scenario frequencies and consequences are available. Such an extension would allow for a more direct comparison with static Event Tree-based importance evaluations and further broaden the applicability of the proposed framework.

The present study focused on demonstrating the feasibility of the proposed framework using a simplified reliability model. A plant-scale application of the framework, including all three RIMs and detailed consequence modeling, has been reported separately in Zheng et al. [30], providing complementary validation under more realistic system conditions.

Collectively, these studies demonstrate the potential of the proposed framework to enhance the interpretability and practical utilization of dynamic PRA in risk-informed decision-making.

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Abbreviations

AM	Accident Management
CBW	Consequence-Based Worth
CDF	Core Damage Frequency
CMMC	Continuous Markov chain Monte Carlo
DET	Dynamic Event Tree
DIM	Dynamic Importance Measure
ET	Event Tree
FBW	Frequency-Based Worth

FT	Fault Tree
FV	Fussell-Vesely
PRA	Probabilistic Risk Assessment
RAW	Risk Achievement Worth
RIDM	Risk-Informed Decision Making
RIM	Risk Importance Measure
RRW	Risk Reduction Worth
SSC	Structures, Systems, and Component
TBW	Timing-Based Worth

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